THE NON-ALCOHOLIC BEVERAGE MARKET IN THE UNITED STATES: DEMAND INTERRELATIONSHIPS, DYNAMICS, NUTRITION ISSUES AND PROBABILITY FORECAST EVALUATION

A Dissertation

by

KALU ARACHCHILLAGE SENARATH DHANANJAYA BANDARA DHARMASENA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2010

Major Subject: Agricultural Economics

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ABSTRACT

The Non-Alcoholic Beverage Market in the United States: Demand Interrelationships, Dynamics, Nutrition Issues and Probability Forecast Evaluation. (May 2010)

Kalu Arachchillage Senarath Dhananjaya Bandara Dharmasena,

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There are many different types of non-alcoholic beverages (NAB) available in the United States today compared to a decade ago. Additionally, the needs of beverage consumers have evolved over the years centering attention on functionality and health dimensions. These trends in volume of consumption are a testament to the growth in the NAB industry.

Our study pertains to ten NAB categories. We developed and employed a unique cross-sectional and time-series data set based on Nielsen Homescan data associated with household purchases of NAB from 1998 through 2003.

First, we considered demographic and economic profiling of the consumption of NAB in a two-stage model. Race, region, age and presence of children and gender of household head were the most important factors affecting the choice and level of consumption.

Second, we used expectation-prediction success tables, calibration, resolution, the Brier score and the Yates partition of the Brier score to measure the accuracy of

predictions generated from qualitative choice models used to model the purchase decision of NAB by U.S. households. The Yates partition of the Brier score outperformed all other measures.

Third, we modeled demand interrelationships, dynamics and habits of NAB consumption estimating own-price, cross-price and expenditure elasticities. The Quadratic Almost Ideal Demand System, the synthetic Barten model and the State Adjustment Model were used. Soft drinks were substitutes and fruit juices were complements for most of non-alcoholic beverages. Investigation of a proposed tax on sugar-sweetened beverages revealed the importance of centering attention not only to direct effects but also to indirect effects of taxes on beverage consumption.

Finally, we investigated factors affecting nutritional contributions derived from consumption of NAB. Also, we ascertained the impact of the USDA year 2000 Dietary Guidelines for Americans associated with the consumption of NAB. Significant factors affecting caloric and nutrient intake from NAB were price, employment status of household head, region, race, presence of children and the gender of household food manager. Furthermore, we found that USDA nutrition intervention program was successful in reducing caloric and caffeine intake from consumption of NAB.

The away-from-home intake of beverages and potential impacts of NAB advertising are not captured in our work. In future work, we plan to address these limitations.

DEDICATION

This dissertation is dedicated to my dear wife Inoka.

ACKNOWEDGEMENTS

I must thank my dissertation committee chair, Dr. Oral Capps, Jr., and his family for their support throughout my graduate career here at Texas A&M University. He not only gave me academic guidance, but also assisted me by providing a golden stepping stone to enter into the field of employment that I desire. I enjoyed being taught by him and always liked the way he looks at problems. I like his quote “when one door closes, another one or perhaps many opens” and also his encouragement that he gives me to become a “differentiated product”. The love Dr. Capps and Mrs. Capps have for me, my wife and my two kids, is really heartwarming and touching.

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CHAPTER I

INTRODUCTION

In this dissertation we concentrate on four major topics related to the non-alcoholic beverage industry in the United States[1]. We first consider demographic profiling of the consumption of non-alcoholic beverages in a two-stage modeling exercise. In the first stage, we model factors affecting the decision to consume non-alcoholic beverages followed by the second stage where economic and demographic drivers of consumption of non-alcoholic beverages are explored. Characteristics of at-risk populations in the consumption of non-alcoholic beverages are identified (this study is referred to as *"Demographic Study"* hereinafter). Next, relevant policy implications important to private and public interest groups with respect to consumption of non-alcoholic beverages are discussed.

Secondly, we use novel techniques to evaluate probabilities generated from qualitative choice models used to model the purchase decision of non-alcoholic beverages by a household. The evaluation of qualitative choice models in terms of issuing forecast probabilities are identified using a host of new parameters (this study is referred to as *"Probability Forecast Evaluation Study"* hereinafter).

Thirdly, we model demand interrelationships of non-alcoholic beverage consumption using a static and a dynamic systemwide framework to identify own-price, cross-price and expenditure elasticities. In this analysis, we also investigate

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This dissertation follows the style of the *American Journal of Agricultural Economics.*

[1] Specific non-alcoholic beverages considered in this dissertation are isotonics, regular soft drinks, diet soft drinks, high-fat milk, low-fat milk, fruit juices, fruit drinks, bottled water, coffee and tea.

substitutability and complementarity effects across non-alcoholic beverages. Inventory behavior and/or habit persistence of consumption of non-alcoholic beverages also is examined. Various policy alternatives pertaining to levying a tax on sugar-sweetened beverages (SSB) is explored here (this study is referred to as *"Demand Systems Study"* hereinafter).

Finally, we investigate nutritional contributions of non-alcoholic beverages to the U.S diet and the impact of the United States Department of Agriculture (USDA) dietary guidelines for Americans put forward in the year 2000 (this study is referred to as *"Nutrition Study"* hereinafter). Characteristics of at-risk populations in the intake of calories, calcium, vitamin C and caffeine derived from consumption of non-alcoholic beverages are identified. Finally, potential policy implications that can be put forward by private and public institutions are discussed.

Chapter I is organized as follows. Foremost, we offer background information, a general description about the problem, and the justification for each study. General and specific objectives of each study subsequently are discussed. The final section of this chapter gives the structure and the organization of this dissertation.

Background Information, Problem Statement and Justification

In the following section, we offer a narrative on background information, problem statement and justification related to each study.

Demographic Study and Demand Systems Study

There are so many different types of non-alcoholic beverages available today compared to say a decade ago. Support for this contention is evident with a visit to the non-alcoholic beverages isle of any grocery store. As we show in Figure 1.1, “need states” have evolved from 1970 to present centering attention on functionality and health dimensions desired by beverage consumers (Beverage Marketing Corporation, 2009).

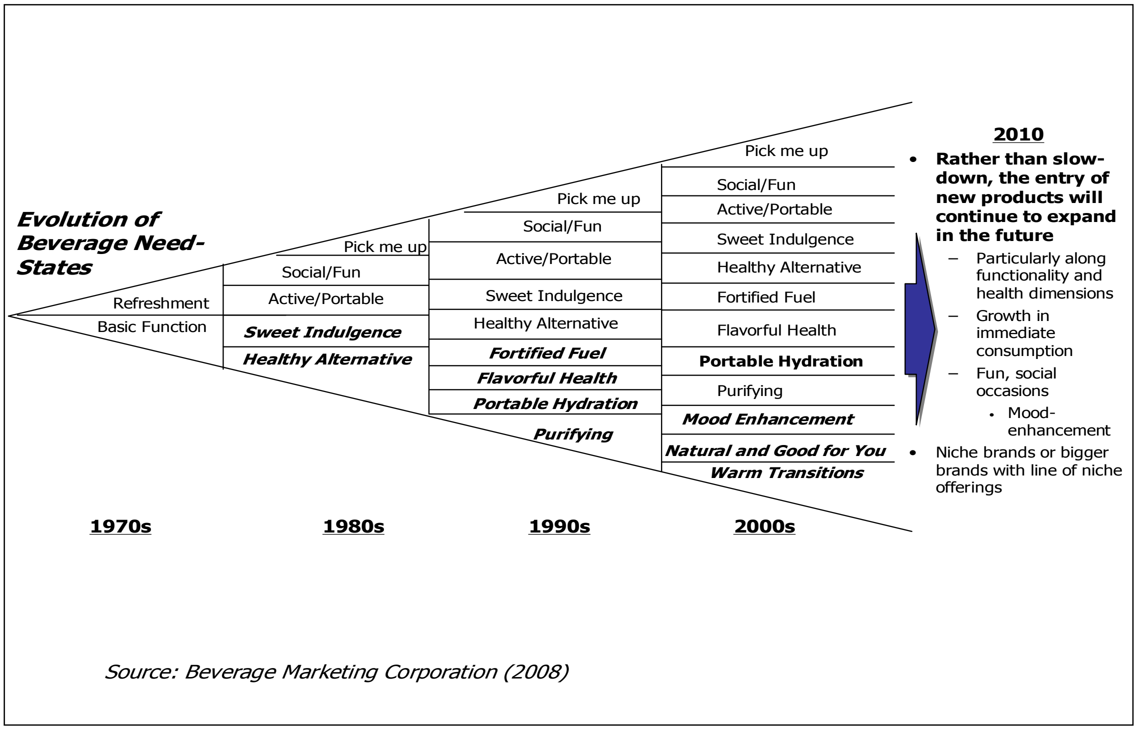


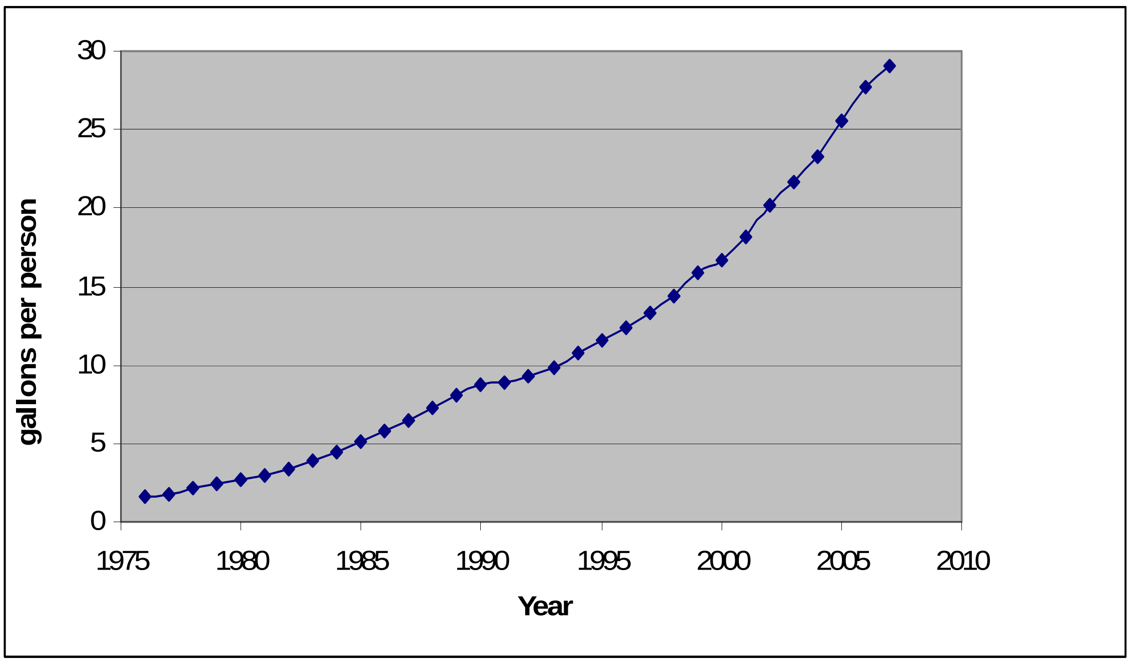
Figure 1.1: Beverage marketplace trends

Furthermore, non-alcoholic beverages provide consumers not only with a basic refreshment function, (as they did in 1970s), but also beverages are available today for mood enhancement, for the satisfaction of sweet indulgences, for specific social occasions and for the nutrient fortification, etc.

According to trends given from the *Statistical Abstract of the Unites States* (2006) and United States Department of Agriculture (USDA), Economic Research

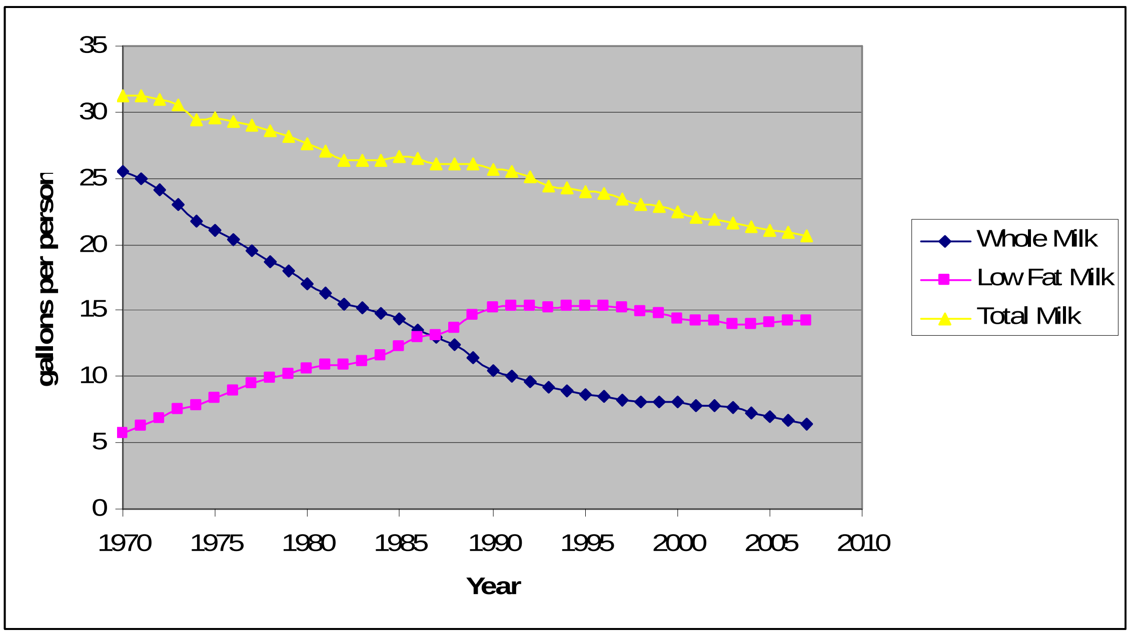
Service (ERS) (2009), the non-alcoholic beverage industry has changed dramatically over the past decade.

For example, there is a phenomenal growth in the consumption of bottled water; where per capita consumption increased from 1.6 gallons per year in 1976 to 29 gallons per year in 2007 (see Figure 1.2 to visualize the trend in the growth in bottled water consumption over the past three decades).



Source: USDA, Economic Research Service (2009)
Figure 1.2: Trend in per capita bottled water consumption in the United States: 1976-2007

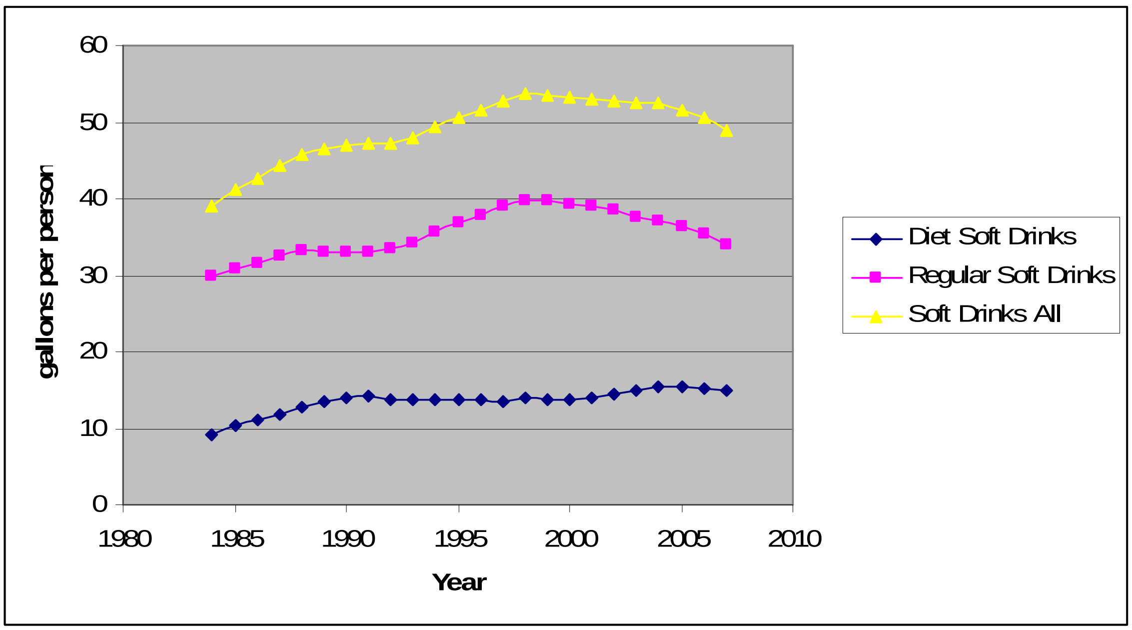
On the other hand, as shown in Figure 1.3, per capita milk consumption decreased from 31.3 gallons per year in 1970 to 21 gallons per year in 2007. More specifically, whole milk consumption dropped noticeably from 25.5 gallons per person per year in 1970 to 6.4 gallons per person per year in 2007. Low-fat and fat-free milk consumption rose from 5.8 gallons in 1970 to 14.3 gallons in 2007. Interestingly, we can assume that consumer may be substituting away from consumption of milk to some other beverage category.



Source: USDA, Economic Research Service (2009)

Figure 1.3: Trend in per capita consumption of milk in the United States: 1970-2007

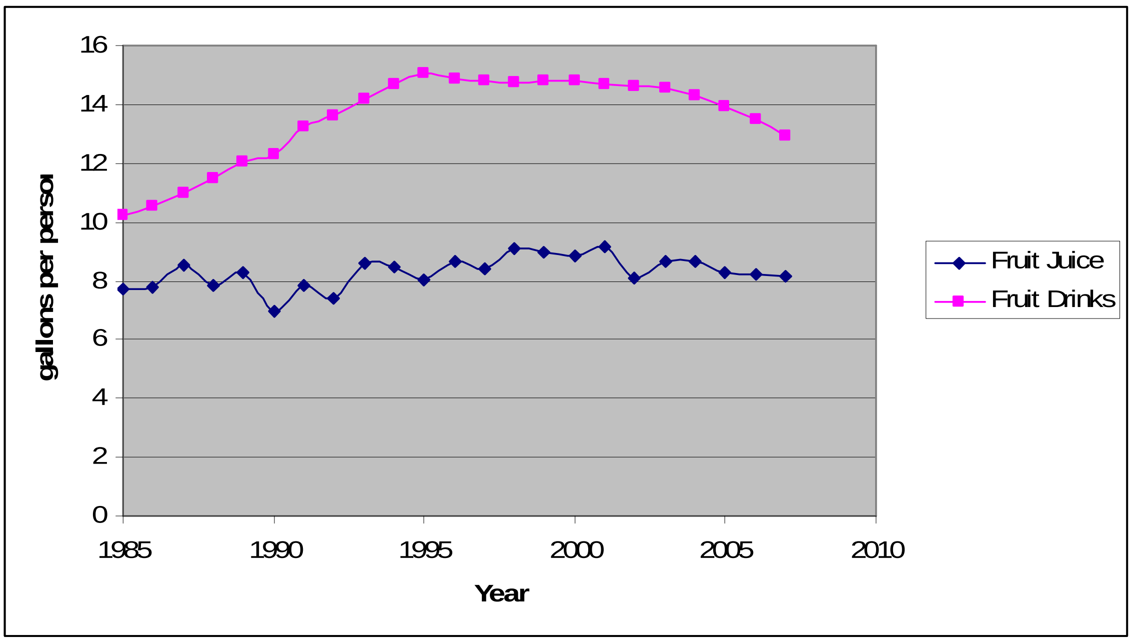
According to Figure 1.4, consumption of carbonated soft drinks increased from 33.6 gallons per person per year in 1980 to 53.8 gallons per person in 1998. Since then, there has been a steady decline in carbonated soft drinks consumption to 48.8 gallons per person in 2007. On the one hand, consumption of diet soft drinks grew steadily, while on the other, regular soft drink consumption declined rapidly after 1998.



Source: USDA, Economic Research Service (2009)

Figure 1.4: Trend in per capita consumption of soft drinks in the United States: 1984-2007

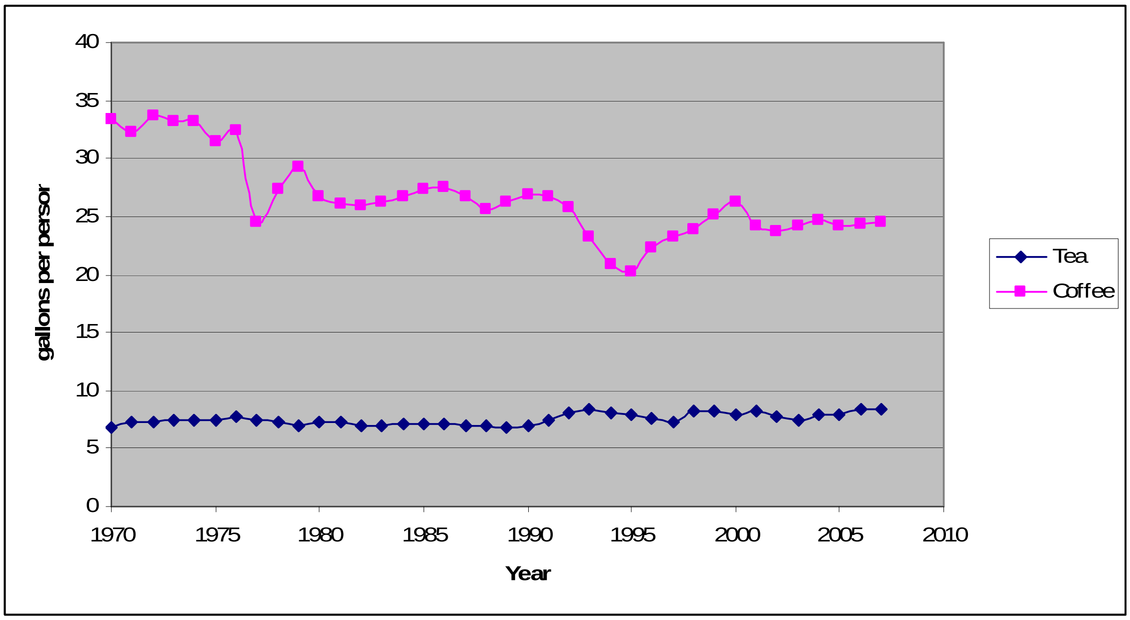
Figure 1.5 shows the trends in per capita consumption of fruit juices and fruit drinks over the period 1985 to 2007. Fruit drinks consumption increased up to 15 gallons per person per year in 1995 but thereafter dropping to 13 gallons per person in 2007. Fruit juice consumption has been more-or-less stable at 8 gallons per person per year during 1985-2007 time period.



Source: USDA, Economic Research Service (2009)

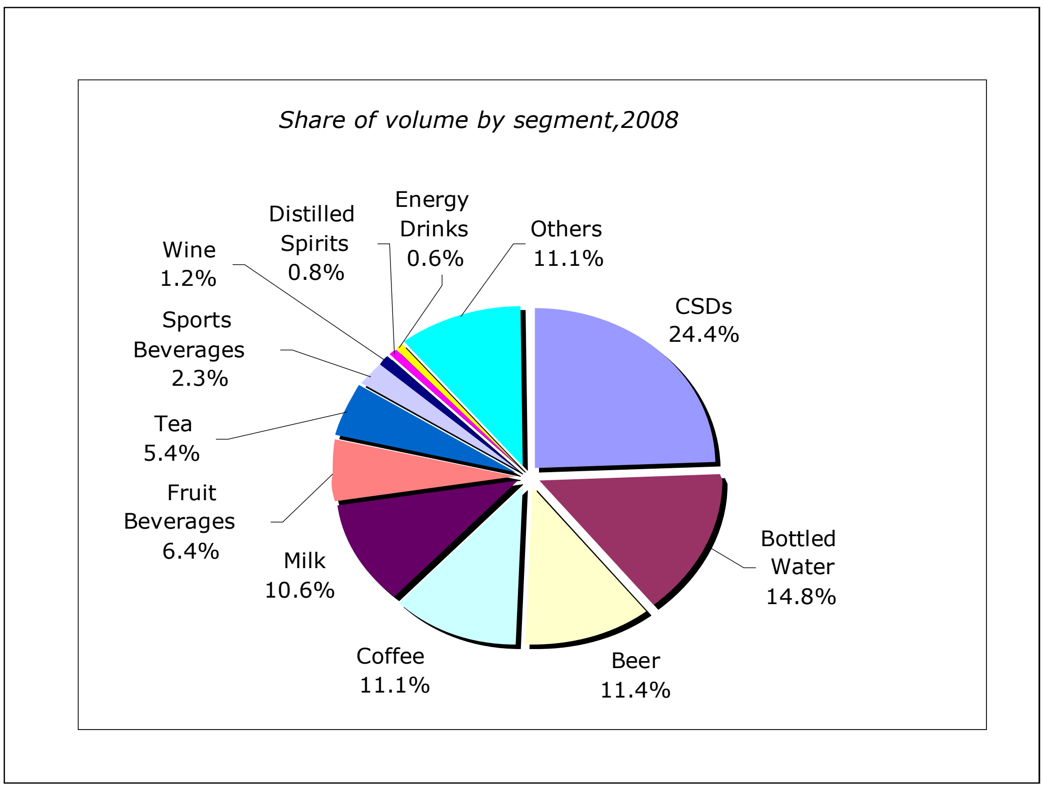
Figure 1.5: Trend in per capita consumption of fruit juice and fruit drinks in the United States: 1985-2007

Figure 1.6 depicts the per capita consumption of tea and coffee over the period, 1970 to 2007. Tea consumption has been quite stable around 6 to 8 gallons per person per year. Coffee consumption was nearly 35 gallons per person per year in 1970, leveling off to 25 gallons per person per year in 2007.



Source: USDA, Economic Research Service (2009)
Figure 1.6: Trend in per capita consumption of tea and coffee in the United States: 1970-2007

As exhibited in Figure 1.7,the Beverage Marketing Corporation reports the share of the volume of both alcoholic and non-alcoholic beverages. Carbonated soft drinks (CSD) are by far the most widely consumed non-alcoholic beverage in the United States accounting for about 25% of the volume share. Bottled water stands second in the volume share taking about 15% of total volume. The other three beverages that take considerable share of the volume are beer (11.4%), coffee (11.1%) and milk (10.6%).



Source: Beverage Marketing Corporation, 2009

Figure 1.7: Share of volume of alcoholic and non-alcoholic beverages in the United States: 2008[2]

[2] CSD=carbonated soft drinks

The Share of the volume by category over the period 2003 to 2008 is exhibited in Table 1.1. Changes in consumer tastes and preferences and the availability of a wide variety of new products in the market may be contributing factors of trends. Also, after changes in the dietary guidelines for Americans put forward by the USDA in 2000 and 2005, changes in the consumption of non-alcoholic beverages are evident (Dharmasena, Capps, and Clauson, 2009).

Table 1.1: U.S Beverage Market: Share of Volume by Category, 2003-2008

Categories	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Carbonated Soft Drinks	27.3%	27.3%	26.8%	26.2%	25.4%	24.4%
Bottled Water	11.2%	12.1%	13.2%	14.4%	15.1%	14.8%
Beer	11.4%	11.3%	11.2%	11.4%	11.4%	11.4%
Coffee	11.3%	11.3%	11.3%	11.3%	11.3%	11.1%
Milk	11.2%	11.0%	10.9%	10.9%	10.7%	10.6%
Fruit Beverages[a]	7.6%	7.4%	7.2%	7.0%	6.6%	6.4%
Tea	5.1%	5.1%	5.1%	5.3%	5.5%	5.4%
Sports Beverages	1.6%	1.8%	2.1%	2.3%	2.4%	2.3%
Wine	1.1%	1.1%	1.1%	1.2%	1.2%	1.2%
Distilled Spirits	0.7%	0.7%	0.7%	0.7%	0.7%	0.8%
Energy Drinks	0.1%	0.2%	0.3%	0.4%	0.6%	0.6%
Subtotal	**88.5%**	**89.2%**	**90.1%**	**91.1%**	**91.0%**	**88.9%**
All Others[b]	11.5%	10.8%	9.9%	8.9%	9.0%	11.1%
TOTAL	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

(r) Revised
a: Includes liquid fruit juice and fruit drinks; excludes powdered fruit drinks and vegetable juices.
b: Includes tap water, vegetable juices, powders and miscellaneous others.
***Source**: Beverage Marketing Corporation; Adams Beverage Group; Distilled Spirits Council of the United States; Florida Department of Citrus; International Dairy Foods Association; U.S. Tea Association*

Several studies pertaining to non-alcoholic beverages have been conducted in the past, but most of these have centered attention on specific beverage items and the impact of selected demographic characteristics on consumption. A heavy concentration of these studies has been placed on milk consumption in the United States. Advertising often was a key focus in previous studies pertaining to milk (e.g. Kinnucan and Forker, 1986 and Kaiser and Roberte, 1996). Some studies also have considered demand interrelationships for several beverages. Examples include Xiao, Kinnucan, and Kaiser (1998) focusing attention on milk, juices, soft drinks, and coffee and tea combined; Heien and Wessels (1988) considering milk, soda, coffee and tea combined, fruit ades, and citrus juices; Richertson (1998) addressing hot drinks, milk, soft drinks, alcohol, and all other food; and Zheng and Kaiser (2008) centering attention on fluid milk, juice, soft drinks, bottled water, coffee and tea combined.

Some studies in the literature also have emphasized substitutability and complementarity effects among non-alcoholic beverages through a formal demand systems approach. Again, only a few other beverage categories have been incorporated into these studies. Certain beverages such as isotonics and diet soft drinks may not have been included in the set of items. Kinnucan (1986), Gould *et al.* (1990), Gould (1996), Kaiser and Reberte (1996), Ueda and Frechette (2002) all have conducted demand systems analyses focusing primarily on milk. Kinnucan et al, (2001) and Yen et al., (2004) again focused on a limited set of non-alcoholic beverages including milk, tea and coffee in a demand systemwide framework. However, two studies in the literature covered a richer set of non-alcoholic beverages in a systemwide framework, notably

Pittman (2004) and Zheng and Kaiser (2008). Pittman (2004) analyzed demand interrelationships using the 1999 ACNielsen Homescan Panel for a disaggregate set of non-alcoholic beverages. Zheng and Kaiser (2008) focused on fluid milk, juice, soft drinks, bottled water, and coffee and tea (combined) using annual time series data for the United States from 1974 through 2005 in estimating impacts of advertising on the demand for non-alcoholic beverages in the United States.

In our analysis, we develop and employ a unique cross-sectional and time-series data set based on ACNielsen Homsescan panels for household purchases of non-alcoholic beverages from 1998 through 2003. Using such data along with a rich delineation of non-alcoholic beverage categories (we employ 10 categories of non-alcoholic beverages), we model economic and demographic drivers of the decision to purchase, as well, once the purchase decision is made, we model the level purchased of a given non-alcoholic beverage. We use both the Heckman two-step procedure as well as a demand systems approach.

This study generates important information not only for government policy makers but also for beverage manufacturers, marketers, advertisers/promoters and managers in grocery stores. Knowledge of economic and demographic drivers, own-price and cross-price sensitivity, and substitutability/complementarity among beverages, are very important to manufactures and promoters and government policy makers within the beverage industry for appropriate strategies in pricing, marketing, product positioning, identifying at-risk populations and designing nutrition and health policy.

Probability Forecast Evaluation Study

Qualitative choice models are widely used in economic modeling when the dependent variable corresponds to discrete outcomes (alternatively, qualitative choice models also are called discrete choice models). Qualitative (discrete) choice models are used to model choices/preferences of decision-makers. Decision-makers can be individual persons, households, or firms. Choice alternatives available might represent competing products, different actions like buy or not buy a product, or any other option or items over which choices must be made (Train,2003).

Among a wide range of qualitative choice models available to model different situations (probit, logit, generalized extreme value, mixed logit, ordered probit, nested logit, multinomial probit and multinomial logit, etc), dichotomous probit and logit models are important to model choices where the dependent variable is set up as a zero-one (0-1) dummy variable (for example, the dependent variable is set equal to 1 for those households who buy a given beverage, say, bottled water, and equal to 0 for those who not buy).

Once appropriately modeled, qualitative choice models determine the probability of the choice decision (that is the probability of purchase or non-purchase). Importantly these probit and logit models are used to identify statistically significant factors that are related to the choice decision (for example economic variables such as price of a beverage concerned and income of the household head, and other demographic variables such as age of household head and region etc).

In addition, with an appropriate decision rule, these models provide predictions of various choices. A key question relates to the accuracy of these predictions. Accuracy of predictions can be measured using traditional metrics such as expectation-prediction success tables, where the percentage of correct (incorrect) predictions are calculated in comparison to the total number of predictions based on a predetermined cut-off probability level as a reference point. The expectation-prediction table is limited in their abilities to correctly classify and evaluate probabilities in the absence of predetermined cut-off probability levels. On the other hand, more informative techniques such as calibration, resolution, the Brier score and the Yates decomposition of Brier score (explained in the chapter labeled Literature Review) can be used to measure accuracy of predictions.

In our study we develop binary probit and logit models to focus on the decision made by a sample of U.S. households to purchase various non-alcoholic beverages. The source of the data for this analysis is the ACNielsen Homescan scanner data for calendar year 2003. We evaluate the probabilities generated through qualitative choice models both within-sample and more importantly, out-of-sample using an array of probability evaluation techniques.

Nutrition Study

Obesity among all walks of life is one of the most urgent and widely emphasized nutrition-related health problems in America today. According to the joint publication, *“A Handbook on Obesity in America”*, by The Endocrine Society and The Hormone

Foundation (2005), 127 million adults in the U.S. are overweight (BMI[3] 25-29.9), 60 million are obese (BMI 30-39.9) and 9 million are extremely obese (BMI 40 or greater than 40). Nayga (2008) reported that recent obesity rates for men and women in the United States are 36.5% and 41.8% respectively.

Overweight/obesity problem is not only an issue with adults but also with children and adolescents. The Centers for Disease Control and Prevention (2007) of U.S. Department of Health and Human Services, reports that from 1980 through 2004, the prevalence of overweight is increasing among children and adolescents in America. The percentage of children aged 2 to 5 years classified as overweight increased from 5% to 13.9% from 1980 to 2004, and the percentage of children aged 6 to 11 years classified as overweight rose from 6.5% to 18.8%. The percentage of adolescents (12 to 19 years) classified as overweight also increased from 5% to 17.4% over this time period.

In addition to environmental and genetic factors, the selection of food and beverages may potentially be a contributing factor to the condition of obesity. With the publication of the 2000 and 2005 USDA Dietary Guidelines for Americans, the role of beverages in the American diet increased in attention. There is a very wide variation in beverages in terms of their energy (caloric) content and nutrient composition, ranging from zero-calorie bottled water to low-calorie diet soft drinks to heavily-caloric coffee drinks. Therefore, excessive consumption of certain beverages is not a good dietary choice due to extra calories they can contribute toward the daily recommended calorie

[3] BMI is the Body Mass Index. It is calculated as a ratio between a person's height (in meters) and weight (in kilograms). The exact formula is as follows: BMI=weight(kilograms)/height (meters squared) or BMI=(weight(pounds)/height(inches squared))*703

requirement designed through a food guide pyramid published by USDA. According to the Dietary Guideline for Americans (2005), daily recommended calorie requirement vary with age, gender and level of physical acticvity. It can vary from 1000 kilo calories per person per day for a child (age 2-3 years) to 3200 kilo calories per person per day for a highly physically active male (age 14-18 years)[4]. Therefore, the beverage choice that individuals make has a potentially important influence on the quality of the diet, and more importantly on the risk of being obese and overweight.

The 2000 Dietary Guidelines gave prominence to the role of soft drinks and other sweetened beverages on the U.S. obesity problem. The 2005 Dietary Guidelines reiterated the need to limit calories from soft drinks. It emphasized even more strongly than previously the need to increase consumption of non-fat and/or low-fat milk in lieu of carbonated soft drinks (Dietary Guidelines for Americans, 2000 and 2005).

Consumption of non-alcoholic beverages also contributes various kinds of nutrients to the diet. Milk is a major source of calcium and vitamin D. According to the U.S. Department of Health and Human Services (2000), calcium and vitamin D are two nutrients that are of public concern. In an analysis of USDA food consumption survey data, Yen and Lin (2002) found that, for each 1-ounce reduction in milk consumption by a child, calcium intake was reduced by 34 milligrams. Juices are prepared from either fruits or vegetables and are good sources of vitamin C. Also, there are calcium-fortified fruit juices available today, such as orange juice. Vitamin C and calcium are two of the

[4] However, 2000 kilo calories per person per day is used as a standard required daily calorie requirement in food nutrition lables. Following the Dietary Guidelines for Americans (2005), daily calorie requirement should be adjusted for age, gender and level of physical activitiy

healthy nutrients that come from consumption of non-alcoholic beverages. Caffeine is another ingredient found in most carbonated soft drinks, coffee, and tea. According to the American Beverage Association (2007), beverage manufacturers have responded positively to the changing needs and interests of consumers by introducing many low-calorie, zero-calorie, calcium fortified, and decaffeinated beverage choices.

Many U.S government programs targeting nutritional enhancement of households, such as the Supplemental Nutrition Assistance Program (formally the Food Stamp Program), National School Lunch Program, School Breakfast Program, and Special Supplemental Food Program for Women, Infants and Children (WIC), are in need of more current information pertaining to non-alcoholic beverage consumption. Profiling of households is important to identify demographic populations potentially at risk in the consumption of non-alcoholic beverages. For example, the WIC program provides vitamin C and calcium-rich beverages such as fruit/vegetable juices and milk to its recipients. Eligibility for such programs are evaluated through a multitude of factors including a poverty threshold (calculated taking into account annual income of the household and household size). Government programs center attention on 100%, 130% or 185% of the poverty thresholds. Ascertaining the impact of USDA Dietary Guidelines (year 2000 Guidelines in our analysis) is important from a public policy standpoint.

Purpose and Objectives of This Research

In this dissertation we will analyze the household demographic and economic drivers of the decision to purchase non-alcoholic beverages and the factors that determine their intake level of non-alcoholic beverages (conditional on the decision to purchase). We also will focus attention on evaluating probabilities of purchase of non-alcoholic beverages. Next we concentrate on the drivers of nutrient and caloric intake from non-alcoholic beverages, identifying households potentially at risk. Finally, we center our attention on interrelationships among non-alcoholic beverages consumed at home and the contribution of habits and/or inventory behavior in consuming non-alcoholic beverages.

The specific categories of non-alcoholic beverages considered in these analyses are: isotonics; regular soft drinks; diet (low-calorie) soft drinks; high-fat milk (whole milk and 2% milk); low-fat milk (1% milk and skim milk); fruit drinks; fruit juices; bottled water; coffee; and tea. In this light, we offer specific objectives of each study in the next sections.

Demographic Study and Demand Systems Study

A thorough and complete analysis of demand for non-alcoholic beverages is necessary primarily due to changes in potential drivers of consumption over time. We will achieve such objectives in two separate types of analyses. We use a cross-sectional data set (Nielsen Homescan scanner panel for 2003) to study factors affecting the probability of purchase and demographic drivers of purchase volume. This analysis will be done to address specific objectives (1) and (2). To accomplish specific objectives (3), (4) and (5), we use a unique time-series data set generated from Nielsen Homescan scanner panels from January 1998 through December 2003. Specific objectives considered in this study are:

(1) to determine the factors affecting the decision to purchase (probability of purchase) non-alcoholic beverages;

(2) once the decision to purchase non-alcoholic beverages is made, to determine the drivers of purchase volume;

(3) using the unique time-series data set, to investigate the demand for ten non-alcoholic beverage categories;

(4) to estimate own-price, cross-price and expenditure elasticities of demand as well as diversion ratios for the aforementioned non-alcoholic beverages; and

(5) to determine the dominance of inventory behavior or habit persistence in non-alcoholic beverage consumption (the periodicity is monthly).

Probability Forecast Evaluation Study

The general objective of the study is to consider and apply methods to evaluate probabilities emanating from qualitative choice models of non-alcoholic beverage consumption in the United States. Specific objectives of the study are, to evaluate within and out-of-sample probabilities generated through the respective models using the following metrics:

(1) expectation/prediction success tables;

(2) probability calibration and resolution graphs (Dawid, 1986);

(3) mean probability score (the Brier score (Brier, 1950)); and

(4) the Yates-partition of the Brier score (Yates, 1988)

The expectation/prediction success table perhaps is the standard method to evaluate the predictive performance of qualitative choice models (Stock and Watson, 2007).Alviola (2009) used the Brier Score and the Yates partition of the Brier score in the investigation of the choices of organic milk and conventional milk. However, this dissertation is the first to apply probability calibration, resolution, the Brier Score, and the accompanying Yates partition of the Brier score in evaluating predictive performance of qualitative choices models pertaining to a detailed delineation of non-alcoholic beverages.

Nutrition Study

After the publication of aforementioned USDA Dietary Guidelines for Americans, when consumers presumably are well-informed about the nutritional contribution of beverages to their diet, their consumption patterns of non-alcoholic beverages ought to change. That is to say, one question of interest is whether or not the 2000 and 2005 USDA Dietary Guidelines for Americans have been effective in making changes in the intake of calories, calcium, caffeine and vitamin C derived from non-alcoholic beverages.

Demographic and price information that affect the intake of above nutritional categories through the consumption of non-alcoholic beverages also are important to properly identifying drivers of nutrient intake and to assist in the targeting of population at risk.

Specific objectives of this study are to:

(1) determine the factors affecting calcium, caffeine, vitamin C and caloric intake from the consumption of non-alcoholic beverages at home for the period 1998 through 2003;

(2) ascertain the impact of the 2000 USDA Dietary Guidelines for Americans on the intake of calcium, caffeine, vitamin C and calories from non-alcoholic beverages consumed at home from 1998 through 2003.

Organization of the Dissertation

This dissertation is organized as follows. In Chapter I, we present background information, problem statements and justifications to each of the study: *the demographic study*, *the demand systems study*, *the probability forecast evaluation study*, and *the nutrition study*. Next we state the purpose and objectives (general and specific) of each of our studies. The extant literature is discussed in Chapter II. We have provided summary information about the authors, data and methodology, results and implications of each reviewed study. Chapter II ends with concluding remarks and an account of the distinct contributions of our study to the literature. Chapter III is devoted to an extensive description on the data and data preparation pertaining to our study.

Chapters IV through VII are devoted to four types of studies we investigate in this dissertation. Methodology, data analysis and discussion pertaining to each study are included under each chapter. We discuss the economic and demographic tendencies in the consumption of non-alcoholic beverages in Chapter IV. Chapter V is devoted to the probability study where probabilities generated through qualitative choice models are evaluated through calibration, resolution, the Brier score and the Yates partition of the Brier score. Demand interrelationships, habits and dynamics in the consumption of non-alcoholic beverages are examined in Chapter VI. Finally, in Chapter VII, we investigate nutritional contributions of non-alcoholic beverages to the U.S. diet. Conclusions, study limitations and future works are discussed in Chapter VIII.

CHAPTER II

LITERATURE REVIEW

In the following section we elaborate the extant literature on each study. We will explain the estimates, methodologies, and data used for each study. In the first section, we offer a discussion on the past literature on demographic information, demand for non-alcoholic beverages in a static and a dynamic setting and influence of habit formation/inventory behavior on consumer demand for goods. Following this discussion we provide details on the literature in the area of probability evaluation. Finally, selected articles concerning the nutrition contribution of non-alcoholic beverages are discussed.

Demographic Study and Demand Systems Study

In the past, the substantial portion of all demand and demographic studies concerning the effects of price, income and selected demographics have centered attention on only a selected number of non-alcoholic beverages. Milk was studied widely over several studies often bringing including the effects of various types of advertising and promotion (Kinnucan and Forker, 1986 and Kaiser and Roberte, 1996). Capps (2003) conducted an expansive review of literature of dairy demand studies. More recent selected articles since 2003 are discussed in this section. However, demographic and demand studies pertaining to some beverages are limited in the literature. For example, we could find only three studies that have taken bottled water into account and one that took into account sports drinks (we call them isotonics). Special attention is given to articles that utilize demand systems.

However, true panel data concerning household information is hard to come by (there are few exceptions). Therefore, in studying demographic drivers of non-alcoholic beverages, most studies use cross-sectional data sets centering attention to a given year. Some studies have used yearly time-series data to study demand for non-alcoholic beverages (for example, Zheng and Kaiser, 2008). There were very few articles that centered attention on inventory behavior and habit formation in modeling demand for non-alcoholic beverages.

Heien (1982) modeled the structure of U.S. food demand using a log-log almost complete system (ACS) (both quantity-dependent and price-dependent form). The systems approach mitigates the effects of multicollinearity while facilitating the measurement of interrelatedness between food groups. In this analysis, fourteen food groups were used out of which only two were beverages, namely, frozen orange juice and milk. The analysis was further modified using the partial adjustment model particularly to test the *habit formation* hypothesis.

Annual time-series data (covering the period 1947 to 1979) of quantities consumed per capita for disaggregated food items were obtained from various issues of Food Consumption, Price and Expenditures Surveys of United States Department of Agriculture (USDA). Divisia price and quantity indexes were computed to develop aggregate food data from individual components. U.S. income and product accounts data were added onto the latter data to generate the workable data set. Quantity and price dependent demand models were estimated using the three-stage least squares estimation procedure. Elasticities and flexibilities were calculated at their respective sample means.

Own-price elasticities of demand for frozen orange juice and milk were -0.535 and -0.539 respectively, indicating inelastic demand. Milk and orange juice were found to be net substitutes; however, this relationship was not significant at the 5% level. Both orange juice and milk also were found to be income inelastic. Results further suggested that habits played a significant role in demand for food, although they were not as large as other studies on aggregate commodities had suggested.

Huang and Rauniker (1983) studied household fluid milk expenditure patterns in the South and in the United States as a whole. In addition to general economic conditions, changes in expenditure patterns on fluid milk are affected by demographic shifts, changes in tastes, preferences and regional discrepancies. Evidence for the latter argument was supported by USDA 1977-78 Nationwide Food Consumption Survey (NFCS) milk consumption data.

Data for empirical implementation came from USDA 1977-78 NFCS data pool, where two-types of expenditure and other data on whole milk and low-fat milk consumption were selected. The Family Life Cycle (FLS) concept was employed to better delineate expenditure patterns of food among household units. Some households in the survey may have not purchased fluid milk during the period. Therefore, the Tobit maximum likelihood procedure was designed to provide a more efficient estimation of parameters.

The income coefficient for low-fat milk was positive and significant for both southern and total the U.S., low-fat milk was a normal good. This argument is slightly different for whole milk, where, the income coefficient was negative for the whole

United States., but positive for the southern region. That is to say, whole milk was a normal good for the southern region; however, whole milk was found to be an inferior good across the United States. Huang and Rauniker (1983) further found that, larger the household, the larger the consumption of whole milk compared to low-fat milk.

Kinnucan and Forker (1986) used monthly data pertaining to New York City for the years 1971 to 1980 to analyze the seasonal response to milk advertising. A log-log demand specification was developed taking natural log of quantity of fluid milk as dependent variable for the above time period. Explanatory variables considered were, seasonal dummies, per capita income, price of milk, price of cola, price of coffee, race and stock of *"goodwill"* to measure current and past advertising effects (Nerlove and Waugh, 1961).

The income elasticity was estimated to be 1.12 and significant. However, the authors concluded that this estimate of income elasticity was too high compared to other similar studies in the literature, where most have found the demand for milk to be income inelastic. Demand for milk was found to be price inelastic (own-price elasticity of demand -0.04). Positive but small cross-price elasticities of milk with coffee and soft drinks indicated that milk and coffee were gross substitutes for milk.

Uri (1986) estimated a demand model in a log-log setting for seven beverages categories. The beverages categories considered were, soft drinks, beer, fruit drinks, drink mixes, spirits, wine and bottled water. Price and quantity data for 1982 were obtained from *Beverage World* (1983). Price represents a unit value where total retail expenditure was divided by total quantity sold for each beverage. Demographic information collected was as follows: age (six age groups), personal income, weather (temperature), number of deaths due to cirrhosis of the liver, and a dummy variable to deal with spirits consumption in Nevada. Weather variable was designed to capture any fluctuation in beverage consumption due to higher and lower than average temperatures (for example, bottled water may be consumed more than alcoholic beverages to quench the thirst). Weather data were obtained from National Oceanic and Atmospheric Administration.

The model was estimated through the maximum likelihood approach to obtain most efficient parameters and test for restrictions in demand theory (homogeneity and symmetry). All beverages, but beer and spirits, showed negative and inelastic own-price elasticity of demand. Here we report numbers with respect to non-alcoholic beverages only. Soft drinks had an own-price elasticity of demand of -0.89, while the own-price elasticity of demand was -0.82 and -0.79 for fruit drinks and bottled water respectively. Income elasticities were all positive and greater than one (indicating that all beverages are luxury goods, a somewhat surprising result). Bottled water consumption was found to be most responsive to temperature changes and to the presence of population in the post-64 years of age category. Almost all beverages were found to be gross substitutes in consumption.

Kinnucan (1986) developed an advertising-sales response model to include demographic factors that affect milk demand specifically concentrating on the New York City market. Age structure and racial composition of a population are primary factors influencing demand for milk.

A log-log model was developed to include natural log of milk quantity consumed as the dependent variable. A host of explanatory variables considered were (all were in log form); New York City annual personal income, New York City retail price of milk, U.S. cola price, U.S. coffee price, monthly generic advertising expenditures, percentage of New York City population under age 20, percentage of New York City population who are non-white, time trend variable and monthly seasonal dummies. Monthly times-series data from January 1971 through June 1980 were gathered for aforementioned variables.

The estimated income elasticity of demand was 0.416 indicating that milk is a normal good. The own-price elasticity of demand was estimated to be -0.095; however it was not statistically significant in this study. Coffee and cola beverages had positive cross-price elasticities, indicating gross substitutes for milk. Furthermore, the study suggested that the age and race had strong negative relationship for fluid milk demand.

Heien and Wessells (1988) centered attention on estimating the demand for dairy products in the United States under the assumption of a two-stage budgeting procedure. A complete demand system for food incorporating demographic effects was estimated. In their analysis cross-sectional data were used from Household Food Consumption Survey (HFCS) of USDA for the period 1977 to 1978. This survey contained data on prices and expenditures for over 1000 food items as well as detailed demographic information of participating households.

An almost ideal demand system (AIDS) of Deaton and Muellbauer (1980) was used with a specific addition to model demographic effects similar to what Capps, Tedford and Havlicek (1985) and Heien and Willett (1986) used in earlier work. Non-beverage and beverage milk products were considered in the analysis. Beverage products used were; milk (whole, skim, chocolate), coffee and tea, sodas (colas, fruit, diet, and carbonated water), fruit ades and citrus juice. Demographic information included in the analysis were proportion of meals eaten at home, number of household members by age and gender, season, region, occupation, tenancy, race, shopping habits, pregnancy status of female household members and value of food stamps. The model was estimated using iterative three-stage least squares estimation procedure under constraints imposed by economic theory.

According to own-price elasticities estimated, milk and sodas were price inelastic (-0.63 and -0.58 respectively). Coffee and tea and citrus juice had elastic own-price elasticities of demand (-1.07 and -1.14 respectively). Soda was a gross complement for milk. Coffee and tea, fruit ades, and citrus juice were found to be gross substitutes for milk. Household members by age and gender, and the proportion of meals eaten at home were highly significant in determining milk consumption.

Gould, Cox and Perali (1990) focused attention on estimating the demand for fluid milk products (whole milk and low-fat milk) in the United States in a systemwide framework. Unlike most previous studies, this study used a time-series dataset incorporating effects of changes in prices and demographic characteristics. This time-series dataset covered the period 1955 to 1985 and also included data from food-away-from-home consumption, in contrast to previous cross-sectional studies that considered only data from food-at-home consumption.

The Almost ideal demand system (AIDS) of Deaton and Muellbauer (1980) was used in the modeling exercise. Five commodities included in the analysis were whole milk, low-fat milk, fruit juices, other non-alcoholic beverages (of coffee, tea, and carbonated beverages), and other food. Different age group proportions, the percentage of population that was non-white and the median number of school years were used as demographic variables in this study. Price and quantity information of various beverages were collected from multiple sources including USDA food consumption, prices and expenditures data, U.S. Bureau of Labor Statistics, Manchester Bunch and Simon and *Dairy Field*. SYSNLIN procedure of SAS was used to estimate the econometric model.

All beverages were found to have inelastic demands (Gould, Cox and Perali (1990), Table 2, page 8). Briefly, the own-price elasticities were, whole milk -0.324, low fat milk -0.437, juices -0.327, and other beverages -0.193. Additionally, all beverages were found to be expenditure inelastic in this study.

Heien and Wessells (1990) estimated an almost ideal demand system model (AIDS model of Deaton and Muellbauer, 1980) for eleven food items (including several non-alcoholic beverages) using a cross-sectional dataset (micro-data) correcting for censoring problem inherent in the data. They used the 1977-1978 Household Food Consumption Survey data of USDA as their data source. Non-alcoholic beverage categories used in the analysis were; milk coffee and tea, and sodas and fruit ades and citrus juices.

A two-stage budgeting model was used. In the first stage, the probability of purchase was generated using a probit model. Inverse Mills Ratio (IMR) was calculated and used as an instrument for zero observations in the second stage demand model. The IMR was found to be significant at 5% level for each food category indicating it was necessary to deal with the censoring problem in the data. Furthermore, they compared the elasticity estimates generated through a model that corrected for censoring problem with one that did not address the censoring issue. Here we report only the elasticity estimates pertaining to non-alcoholic beverages which are generated through the model that appropriately addressed the censoring problem. Coffee and tea and sodas and fruit ades were found to have elastic demands with own-price elasticities of -1.01 and -1.10. The own-price elasticity of demand for milk was estimated to be -0.77 and that for citrus juice was -0.87. Expenditure elasticities were inelastic for all non-alcoholic beverages considered in this study.

Brown, Lee and Seale (1994) focused on estimating demand relationships among juice beverages in the United States using a differential demand systems approach developed by Barten, 1993. Four differential demand systems were nested in the Barten (1993) model. They were the Rotterdam model, a differential version of almost ideal demand system (AIDS) model, and two mixed models (CBS and NBR systems). Weekly retail scanner data (collected by A.C. Nielsen Company) on U.S. juice beverage consumption for the period of December 10, 1988 through November 11, 1992 were used. Specific beverage groups used were as follows; orange juice, grapefruit juice, apple juice, blended juice, juice drinks, juice cocktails and remaining juices.

The nested model was estimated using maximum likelihood method. The data supported the CBS model. Estimated own-price elasticity of demand for orange juice was found to be -0.88 and that for all other beverages were elastic. The own-price elasticity of demand estimated for other beverages are as follows; orange juice -0.88; grapefruit juice -1.88; apple juice -1.9; blended juice -1.99; juice drinks -1.20; juice cocktails -2.66. Apple juice and orange juice expenditure elasticities were estimated to be 0.92 and 0.85 respectively. Grapefruit juice, blended juice, juice drinks and juice cocktails had expenditure elasticity greater than one.

Grapefruit juice, apple juice, blended juices, juice drinks and juice cocktails were found to be net substitutes for orange juice. Similar pattern continued with all the other juices as well (all juices were net substitutes).

Cornick, Cox and Gould (1994) investigated demand for fluid milk in a multivariate Tobit analysis. Weekly cross-sectional household level data on fluid whole milk, skim milk, and reduced-fat milk were extracted from consumer panel dataset maintained by Nielsen Marketing Research for the period March 1991 through March 1992.

Presence of children significantly affected milk expenditures. Furthermore, authors found a positive COLLEGE coefficient (Education level at college level) in the skim and negative coefficient in the whole milk categories. Black households consumed less skim milk and reduced fat milk and more whole milk. Hispanic households also consumed more whole milk and less of skim milk and reduced-fat milk. All regional dummy variables were statistically significant in the whole milk equation. Compared to the pacific region, only households in the East, North and Central region purchased less whole milk and those in the Northeast, Middle Atlantic and south Atlantic regions consumed less reduced fat-milk.

Gould (1996) noted that U.S. fluid milk consumption had changed dramatically since the early 1970s through 1990s. More specifically, there was a decline in whole milk consumption and on increasing trend in consumption of reduced or/and non-fat fluid milks. A three-equation fluid milk demand system that explicitly incorporated substitution possibilities across milk types was used. This data set contained many zeros, which required a censored demand system approach to appropriately handle the sample selection bias problem. Even though it was difficult to implement, the approach developed by Lee and Pitt (1986) was used. This procedure gives latitude for sample selection bias correction while simultaneously capturing cross-commodity censoring impacts. Purchase data (quantity and expenditure) of three types of fluid milks were used along with demographic information from 4,300 households who recorded fluid milk purchases for at-home consumption over a 12-month period. Three types of milks used were, whole milk, 2% milk and other reduced-fat milks. The time frame for the analysis was April 1991 through March 1992. Consumer scanner panel maintained by Nielsen Marketing group was used.

Demographic variables used in the analysis were income as a percent of poverty threshold, percent of household members less than 13-yesrs of age, percent of household members greater than 65-years of age; meal planner characteristics such as non-white and those who completed the college; region of residence. Model estimation was conducted using the maximum likelihood method in MAXLIK within the GAUSS software package.

Results revealed that, household composition, region of residence, ethnicity, income and education significantly impacted fluid milk demand. Own-price elasticities of demand estimated for whole milk, 1% skim milk and 2% skim milk were -0.80, -0.59 and -0.51 respectively. All estimated cross-price elasticities were positive indicative of substitutability in consumption. All expenditure elasticities were significant and very close to one.

Kaiser and Reberte (1996) used a log-log model in estimating demand for fluid milk products. Explanatory variables used were as follows: retail price of whole milk, retail price of low-fat milk and retail price of skim milk; retail price of orange juice; disposable per capita income; a variable measuring consumer concern about dietary fat; quarterly intercept dummies; generic advertising expenditure. Per capita sales of milk products were taken as the dependent variable in each equation. Kaiser and Reberte (1996) noted that a common characteristic of all past studies pertaining to generic fluid milk advertising had been to aggregate all milk products into one single product. However, in their study, they disaggregated fluid milk products into whole, low-fat and skim milk, in studying the impact of generic advertising effects on demand for each type. Using monthly time-series data from the New York City area from January 1986 through December 1992, separate demand functions were estimated for each milk category. Retail price of each milk product was collected from New York Department of

Agriculture and Markets. Retail price of orange juice was collected from Consumer Price Index for the northeastern United States.

All estimated own-price elasticities of demand were in the inelastic range. They were, -0.003 (whole milk), -0.14 (low fat milk), and -0.30 (skim milk). Highly significant income elasticities of demand, ranging from 0.84 through 1.01 were estimated. Fat concern variable was statistically significant in the whole milk demand equation. The advertising elasticities were, 0.16, 0.19 and 0.18 respectively for whole, low-fat and skim milks respectively.

Maynard and Liu (1999) studied the issue of growing concern among U.S. dairy product marketers on dairy product demand elasticities and how they affect their pricing policies. They suggested reasons to expect more elastic demand than previous years. They are, influx of new substitute products, declining breakfast cereal consumption, changing eating patterns across broad sections of society, demographic changes and evolving promotion and advertising strategies. Elasticities estimated over the past 25 years showed a wide variation, because each study was unique in their combination of model specification, market level, product aggregation, study period, time dimension and selection of exogenous variables. Thus, an updated demand analysis on dairy products using several models was provided. As well model specification issues were discussed relating their contribution to varying demand elasticities.

The analysis used weekly national average retail scanner data provided by -Nielsen via International Dairy Foods Association for the period November 1996 through October 1998. Price and quantity data were obtained for white and flavored milk, six categories of cheese, four categories of table spreads, five categories of frozen desserts, carbonated beverages, and orange juice. Personal consumer expenditure data were obtained from Bureau of Economic Analysis. Advertising on dairy products was not considered in this analysis. Seasonality was incorporated into the study as well.

Three types of model specifications used were quantity-dependent log-log model, the linearized almost ideal demand system (LA/AIDS) (Deaton and Muellbauer, 1980) and differential demand systems that nest the Rotterdam model, differential version of LA/AIDS model, NBR model and CBS model (Barten (1993) and Lee, Brown and Seale (1994)).

The own-price elasticity of demand estimated from the log-log specification was -0.54 for white milk, and -1.41 for flavored milk. For the LA/AIDS model, the own-price elasticity estimates were -0.63 for white milk and -1.40 for flavored milk. Estimated NBR own-price elasticity values estimated were -0.78 for white milk and -1.47 for flavored milk. The variation in own-price elasticity of demand estimates offered justification for effect of model specification for elasticity estimates. No information was provided concerning cross-price and expenditure elasticities.

Glaser and Thompson (2000) conducted a study concerning the growing demand for organic milk in the U.S. At this time, organic milk processors entered the market and more mainstream supermarkets were beginning to sell organic products. Natural-product retail supermarkets such as Whole Foods and Wild Oats sold exclusively organic products. Retail sales of organic and conventional beverage milk were estimated using national-level supermarket scanner data. Estimation was done of a demand model to generate own- and cross-price and expenditure elasticities pertaining to organic and conventional beverage milk.

In the econometric estimation of demand systems, data used were from three sources, thus, Spince Information Services (SPINS), -ACNielsen scanner data and Information Resources, Inc. (IRI) data. All milks considered were measured in half-gallons. Three types milk were considered, branded, private label and organic. Each type was categorized into four fat contents; whole milk, 2% milk, 1% milk, and non-fat/skim milk. Four demand systems were estimated for each category of fat content based on the-Almost ideal demand system of Deaton and Muellbauer (1980). All expenditure and uncompensated own-price and cross-price elasticities were reported. Compensated elasticities were not reported.

Except for private label 1% milk, all of other own-price elasticities of demand for branded and private label milks for all fat contents were in the inelastic region. Own-price elasticity of demand for organic milk for all fat types on the other hand was statistically significant and generally in the elastic region. Although the own-price elasticities of organic milk were quite large at their sample means, their absolute value were declining rapidly over the sample period. Cross-price elasticity estimates indicated that organic and branded milks are substitutes in every fat content category except for 1% milk. Furthermore, it is said that substitution between the most expensive milk types, organic and branded, appears plausible because organic price premiums tended to be smaller between the two than the premiums between organic and private-label milks.

Expenditure elasticities calculated for organic milk were quite large. Due to very small budget shares associated with organic milk compared to conventional milk, the nature of the AIDS elasticity formula used to calculate expenditure elasticity gives rise to such numbers.

Schmit, Chung, Dong, Kaiser and Gould (2001) conducted a study on effects of generic dairy advertising on U.S. household demand for milk and cheese. U.S. dairy producers and fluid milk processors contribute large sums of money annually to increase the demand for dairy products and fluid milks through generic advertising, promotion, and product research. Prior research had centered attention on understanding effects of generic advertising on producer returns. However, most of those studies have focused either on national or state level using aggregated national or state level data. This study used a micro-level approach which allows for examination of household heterogeneity and intertemporal linkages, and is more consistent with the theoretical foundations of demand theory.

This study concentrated on estimating demand for milk and cheese products using household level panel data incorporating generic advertising expenditures. Weekly household purchase data and annual household demographic data were gathered from Nielsen Homescan Panel for the period January 1996 through September 1999. Weekly data on national fluid milk and cheese advertising expenditures were merged into the household file; therefore, advertising varies across time and not across households. Then all data were aggregated to monthly level and was in gallons for milk and pounds for cheese. Milk was separated into whole, reduced fat, light and skim milk types.

A Heckman-style two step sample selection model was used to handle the censoring problem inherent in the data. In the first stage, a probit model was estimated to capture the probability of purchase of milk and cheese and the appropriate instrument (Inverse Mills Ratio) to be use in the second stage demand equation was calculated. In the second stage, a demand system model is estimated taking inverse mills ratio as an additional explanatory variable.

First-stage probit estimation results revealed that price was inversely related to the probability of purchase. Income effects had a very low effect on determining the frequency of milk purchases. College-educated households had a low probability of purchase. Purchase probabilities were directly related to the age of the household head, and the presence of working mothers reduced the purchase probability. Generally, whites tend to purchase more milk than non-whites. Advertising positively contributed toward the probability of purchase of milks and cheeses.

Estimation of second stage demand parameters were done using the method of maximum likelihood estimation method. Own-price elasticities of demand were all negative and less than unity (inelastic) for all categories but low fat milk. The overall long-run milk advertising elasticity was 0.25 based on a 39-week lag structure. Finally, the study showed that generic advertising increased the demand for milk consumption.

Kinnucan, Miao, Xiao and Kaiser (2001) conducted a study to model the effects of advertising on U.S. non-alcoholic beverage demand. Unlike past studies that primarily dealt with milk, other dairy products and fruit juices, this study considered more non-alcoholic beverages and modeled the interrelationships among them, paying more attention to advertising aspects. More specifically, "spillover effects" of advertising, i.e. whether advertising for one beverage affects the demand for related beverages, was studied here in an integrated systemwide framework employing the Rotterdam demand system.

Specific non-alcoholic beverages considered were milk, juices, soft drinks, coffee and tea. Annual time-series data covering the period 1970 to 1994 on consumption of fluid milk, fruit juices, soft drinks and coffee and tea were obtained from *Putman and Allshouse*. Price data were obtained from the U.S. Department of Labor's *CPI Detailed Report* (1971-1977). Advertising data were collected from annual issues of *AD $ SUMMARY* published by Leading National Advertisers, Inc. (LNA, 1970 to 1995). Estimates of demand parameters were obtained using Iterative Seemingly Unrelated Regression (ITSUR) routine in *EViews*.

Own-price elasticities were all less than one in absolute value, which suggests that non-alcoholic beverage demand are price inelastic. All income elasticities were between zero and one, suggesting beverages are normal goods. Coffee and tea was the most income responsive (0.39) and milk the least (0.08).Estimated advertising elasticities confirmed the importance of spillover effects.

Age and food-away-from-home *(fafm)* were two demographic variables considered in the study. Results suggested that, changes in the age structure and dining out were relatively unimportant in explaining the observed consumption.

Yen and Lin (2002) centered attention on beverage consumption among U.S. children and adolescents. Surveys conducted by USDA indicated major changes in beverage consumption among U.S. children and adolescents during past two decades. More specifically, soft drink consumption rose while consumption of milk declined. According to authors, high soft drink consumption also might lead to excessive energy intake which may contribute to another growing nutrition related problem in the United States, childhood obesity. Yen and Lin (2002) looked at demographics associated with milk, soft drinks and juice consumption.

This study used a cross-sectional data set from the 1994 to 1996 USDA Continuing Survey of Food Intakes by Individuals (CSFII). Beverage categories used in this analysis were, milk, carbonated soft drinks, fruit drinks and ades, fruit juice and vegetable juice. Socioeconomic and demographic factors included in the sample were: per capita income; age; number of hours spent on television watching; gender; meal planner's educational level; race; ethnicity; and region.

A full information maximum likelihood estimator (FIML) and a quasi-maximum likelihood alternative (QML) were used to estimate a censored system of equations. Full Information maximum likelihood estimation was carried out by Newton's method and QML estimation by the quadratic hill-climbing algorithm (Goldfield *et al*., 1966).

Effect of age was significantly negative on milk consumption but positive on soft drinks. As income increased both soft drinks and juice consumption increased, however milk consumption was not significantly affected. Meal planers education had a positive impact on juice consumption, but did not significantly affecting milk and soft drink consumption. Children consumed more soft drinks and less milk and juices while watching television and on weekends children consumed more soft drinks and less milk and fruit juices. Boys also tended to consume more soft drinks and milk than girls. Black children consumed less milk than their white counterparts. Children living in city and suburban areas consumed more juice and milk than those from rural areas. Southern children consumed less milk compared to those in the West. In comparison to children live in the West, Midwestern children consumed more soft drinks. Northeastern children consumed more juice but less soft drinks compared to children in the West. Furthermore, authors calculated elasticities for each variable using McDonald and Moffitt (1980) method.

Ueda and Frechette (2002) conducted a study on modeling structural change in New York State milk consumption. USDA reported that there were two major trends in U.S. milk consumption; one in 1970s and other in 1990s. According to them, during this period, annual whole milk consumption has decreased dramatically while there was an increasing trend in low-fat and non-fat (skim) milks. Previous analyses on milk demand have indicated that these changes in demand could be due to: increased public concern about cholesterol and animal fat, change in demographic profile, change in substitute prices, increased income and increased education.

In their paper Ueda and Frechette (2002) investigated to see whether there was statistically measurable evidence of structural change in New York State fluid milk demand using a demand system approach. Fat labels printed on cartons itself may have not contributed to structural change, however, that is the only way that consumers could differentiate whole milk from low-fat counterparts. In this study, a structural analysis was performed. In the analysis, milk products were assumed to be weakly separable group.

Barten (1993) non-nested model selection criterion was used to select the best model among four demand systems (Rotterdam, AIDS, CBS and NBR). Then the selected system was re-estimated with a Kalman filter specification (allowing parameters to vary over time) and subsequently compared with a fixed-parameter specification to identify structural change.

Monthly fluid milk data on price and sales for New York State were used in this study. They were secured from New York State Department of Agriculture and Markets *(New York State Statistics, Annual Summary)* for whole milk, 2% milk, 1% milk and skim milk for the period 1991 through 1998 (a total of 96 observations).

Results from nonparametric approach revealed that most probable structural breakpoint occurred around December 1994. However, it was likely that the structural change was gradual throughout the period. This gradual structural change was then modeled using Kalman filter as a part of a parametric specification. In the parametric approach, each of four alternative models was estimated using seemingly unrelated regression (SUR) method. Almost ideal demand system was found to be best fitting data; hence it was used to perform structural analysis. All estimated expenditure elasticities were statistically significant, however, those for low-fat and skim milk were positive and those for whole milk demand were negative. Furthermore, own-price elasticity of demand for whole milk was more than unity. Finally, the authors concluded that both parametric and nonparametric methods confirm the incidence of a structural change in milk demand.

Yen, Lin, Samllwood and Andrews (2004) centered attention on U.S. low-income household demand for non-alcoholic beverages. Beverage consumption patterns in the United States had changed dramatically over the past two and a half decades. For example, on the one hand, per capita consumption of carbonated soft drinks more than doubled from 1970 to 1999 and on the other, milk consumption decreased by a staggering 25% during the same period (Putnam and Allshouse, 1999). A study by Harnack, Stang and Story (1999) using USDA 1994 Continuing Survey of Food Intakes by Individuals data, estimated a discrete-choice model suggesting that soft drinks displaced milk and fruit juices. Yen, Lin, Smallwood and Andrews (2004) investigated the effects of economic factors (prices and expenditures), demographic characteristics, nutrition information and dietary beliefs in beverage consumption.

Data for this study were gathered from the National Food Stamp Program Survey conducted by Mathematica Policy Research, Inc. for the USDA's Food and Nutrition Service division. It covered the period from June 1996 through January 1997. Non-alcoholic beverages included in this study were whole milk, reduced-fat milk (2%, 1%, and skim milk) juice (100% fruits and vegetables), soft drinks and coffee and tea (combined). Beverage quantities were measured in fluid ounces per week. Explanatory variables included were prices of non-alcoholic beverages in cents per fluid ounces, household composition (number of children present), nutrition information variable, dietary beliefs, race and location. A Translog censored demand system (Christensen, Jorgensen, and Lau, 1975) was estimated using a nonlinear extension to Tobit system of Amemiya (1974).

Results from the study showed that, all own-price elasticities were negative and significant at 1% level. More specifically, uncompensated demand for reduced-fat milk consumption was more elastic than its counterparts. Demand for all other beverages was inelastic: whole milk -0.69; juice -0.52; soft drinks -0.80; coffee and tea -0.89. Most of compensated cross-price elasticities were positive, indicative of possible net substitution between beverages. For example, whole milk, reduced fat milk, juice and coffee and tea are all net substitutes for soft drinks. However, they found that, whole milk was a net complement to juice and juice and coffee and tea were net complements to reduced fat milk. Coffee and tea and soft drinks had expenditure elasticities greater than unity. Expenditure elasticities for whole milk, reduced fat milk and juice is 0.80, 0.81, -0.90 respectively. Furthermore, results suggested that nutrition information, and dietary beliefs played an important role in beverage consumption.

Zheng and Kaiser (2008) examined the impact of advertising on the demand for non-alcoholic beverages in the United States. In particular, they centered attention on impacts from cross-commodity advertising, commonly known as *spillover effects*. For example, if an increase in milk advertising increases the demand for milk, at the same time decreases the demand for bottled water due to cross-commodity relationship that milk and bottled water have, policy makers must take such effects into consideration in designing appropriate policy tools. It is important to consider cross-commodity effects, because, per capita consumption of non-alcoholic beverages has shown historically notable trends with respect to changes in consumption, such as, decline in milk and coffee consumption; steady growth in soft drink consumption; a phenomenal growth in bottled water consumption. In the past, effects of advertising on demand for non-alcoholic beverages were studied mostly using single-equation models and very few in a multi-equation setting (Kinnucan, Miao, Xiao and Kaiser, 2001, Yen et al. 2004, and Pittman 2004). However, only Pittman (2004) had taken bottled water into account.

In this study, Zheng and Kaiser used annual time-series data for the United States for 1970 through 2005. Price and quantity data were collected from two government sources: the *CPI Detailed Report* from the U.S. Bureau of Labor Statistics and the *Food Availability (Per Capita) Data System* from the Economic Research Service (ERS) at the USDA. Some other data came from Beverage Marketing Corporation (BMC). Advertising data came from private sources, primarily from *Ad $ Summary* published by Leading National Advertisers, Inc., and *AdView*, an advertising tracking program maintained by Nilesen. The LA/AIDS model was used to fit the time-series data. Five non-alcoholic beverage categories were used in this demand system estimation. They were, fluid milk, juice, soft drinks, bottled water and coffee and tea combined. Other socio-demographic variables used in the study were proportion of U.S population less than 5 years of age and food-away-from-home expenditures as a proportion of food expenditures.

Endogeneity issues related to total expenditure and correction for first-order serial correlation were addressed in the study. A full information maximum likelihood procedure was implemented, imposing theoretical restrictions from demand theory.

Uncompensated own-price, cross-price and expenditure elasticities, compensated own-price and cross-price elasticities and advertising elasticities were generated from the model. All of own-price elasticities generated was negative and less than unity for all beverages: milk -0.154, juice -0.172, soft drinks -0.151, bottled water -0.498, coffee and tea -0.083. Calculated expenditure elasticities were found to be significant only for milk (0.614) and coffee and tea (3.144). About 50% of cross-price elasticities estimated was net complements and others were net substitutes. For example, juice, soft drinks and coffee and tea were net complements for milk and bottled water was a net substitute for milk. Milk, bottled water, and coffee and tea were net complements for juice, while soft drinks were a net substitute for juice. Juice and milk were found to be net complements for coffee/tea.

Elasticity estimates were compared with past studies. Milk advertising produced positive results for milk. , However, it had deleterious effects on coffee and tea demand (due to spillover effects).

Davis, Blayney, Cooper and Yen (2009) estimated demand elasticities for fluid milk products in the United States using a censored translog demand system. Demand for fluid milk products have been studied in the past using different data sets and a wide variety of methodological tools. In this paper, authors use more recent data set (Nielsen scanner data for the year 2005) to update and compare/contrast fluid milk demand elasticity estimates. Again, they face the censoring problem inherent in such data sets (not all households purchase fluid milk products every time they visit a grocery store, hence they record a zero expenditure for fluid milk for that visit). They used a similar tool used in Yen, Lin, Samllwood and Andrews (2004) to model such a censored sample.

Nielsen Homescan scanner data on expenditures and quantities of milk consumed and demographic information for 7997 households in year 2005 was used in this modeling exercise. The categories of fluid milk used were whole milk, reduced fat milk, flavored whole milk, flavored reduced fat milk, buttermilk, canned milk and other milks. Prices (or unit values) were reported for all products after accounting for any coupon or promotion that might have been in effect. Demographic variables selected were as follows; central and southern regions of the U.S., non-Hispanic whites, female college graduates, children present in home, size of household and married individuals.

In their study they found that, while demographic information was important in modeling exercise, the major drivers of fluid milk demand were price and income. All compensated own-price elasticities were negative and significant at 1% level. Reduced fat milk was demand inelastic (-0.52), while all other milk types showed an elastic demand; whole milk -1.31, flavored whole milk -2.16, flavored reduced fat milk -1.16, buttermilk -1.50, canned milk -1.42 and other milks -2.32. Whole milk was a net substitute for reduced fat milk, flavored reduced fat milk, and buttermilk. Reduced fat milk was a net substitute for flavored reduced fat milk and buttermilk. Canned milk was a net substitute for whole milk, reduced fat milk, flavored whole milk, flavored reduced fat milk, and buttermilk. Whole milk was a net complement for flavored whole milk. Estimated expenditure elasticities were all positive and significant at 1% level. Reduced fat milk had expenditure elasticity greater than unity (1.07). All other milks had inelastic expenditure elasticities; whole milk 0.93, flavored whole milk 0.80, flavored reduced fat milk 0.91, buttermilk 0.46, canned milk 0.44 and other milks 0.88.

Above, we have discussed past literature from 1983 through 2009 that dealt with estimating demand for non-alcoholic beverages. It is very clear that most studies were centering attention to dairy and dairy products in estimating socio-economic-demographic factors affecting demand and/or exploring the effect of advertising on demand. A minority of studies brought in more non-alcoholic beverages into the picture than fluid milk (such as juice, soft drinks, bottled water, coffee and tea), there again mostly concentrating on advertising effects. Again, very few studies brought in demographic variables into their models. The major challenge in bringing in demographics and trying to do a cross-sectional analysis is the censoring problem inherent in such data sets. In most cases two-step procedures were conducted to handle the censoring problem.

Cross-sectional data were mainly obtained from USDA surveys such as Continuing Survey of Food Intakes by Individuals (CSFII) for several years and National Food Stamp Survey Data. Some regional and state-wide data came from New York State Department of Agriculture and Florida Department of Agriculture. More recent consumer level scanner data mostly came from Nielsen Homescan scanner panels (for various years) and Information resources Inc. (IRI) panel data. Most of the time series data were obtained from government sources such as U.S. Bureau of Labor Statistics, USDA Economic Research Service and U.S. Department of Commerce. Some other time series data were obtained from Beverage Marketing Corporation (BMC).

A wide array of models was used in estimating demand for non-alcoholic beverages. Most of earlier studies used single-equation models (mostly log-log specification), however, more recent studies employed the multi-equation demand systems approach. Popular demand systems used were, Translog, Rotterdam, AIDS and LA/AIDS and Barten Synthetic specification (nesting Rotterdam, AIDS, NBR and CBS models). Estimated own-price, cross-price (uncompensated and compensated) and expenditure elasticities were comparable to some degree across the studies. They could have been affected by several reasons, such as, level of data aggregation/disaggregation (for example treat milk as one category or disaggregated categories such as whole milk and reduced fat milk), model specification (variables and functional form), and time frequency of data (yearly, monthly, and weekly).

As we discussed so far, consumer demand for beverages can be affected by an array of socio-economic-demographic characteristics. Furthermore, habits that consumer has in purchase decisions or inventory decision on a product may affect the demand for a given beverage. For example, some consumers may purchase coffee no matter what due to inherent habit of consuming coffee (this phenomenon is known as "*habit persistence*" or "*addictive behavior*" in literature). However, habits do not develop overnight and may take a longer time span to develop. "*Inventory behavior*" is a different situation where some consumers may purchase large volumes of products say during promotion times and store them for future consumption. Such type of inventory behavior takes place in a short time span (say a week).

There are not very many studies in the literature that looked into habit persistence and/or inventory behavior aspects in consumer demand modeling. In particular we could not find any study that dealt with respect to modeling demand for (non-alcoholic) beverages incorporating habit persistence and inventory behavior. However, methodological developments have taken place since the early part of twentieth century after pioneering work in the area of distributed lags done by Irving Fisher (Nerlove, 1972). Throughout the literature, researchers have tried to model consumer habit formation in demand estimation through the incorporation of a *lag* of the dependent variable (quantity or expenditure share) in the system. This approach is now very popular in estimating demand in a systemwide framework while addressing the habitual behavior through a modification done to the intercept coefficient of a demand system (see Chen and Veeman, 1991 for a good discussion on how to add in the lag of the dependent variable to intercept coefficient of almost ideal demand system (AIDS) of Deaton and Muellbauer, 1980). The other school of thought had a lag of the dependent variable (quantity of the good in question) introduced in a slightly different fashion. Houthakker and Taylor, 1970 developed this latter specification through an introduction of a *state* or *stock* variable in the structural equation which lead to a subsequent lag of a dependent variable in the reduced form equation (more details will be discussed in the methodology section of this dissertation). Furthermore, habit persistence is also called "*psychological stock*" and inventory behavior is alternatively termed "*physical stock*" in the literature. Model developed by Houthakker and Taylor, 1970 is convenient since it not only can model habitual behavior but also inventory behavior. In this section of the literature review, we discuss the methodological development in modeling habits and/or inventory behavior and some empirical applications available thus far.

Habit formation and inventory/stock effect in consumer demand analysis has a noteworthy history. In their attempt to model such behavior, researchers have used a lagged dependent variable in their models. Such introduction of a lag effect made models *dynamic*. Dynamic models give extra pieces of information such as the ability to measure short-run and long-run behavior of a policy instrument, in comparison to static models that could provide only a snapshot view (short-run). For example, if one brings in a lag of period one quantity variable to the set of right hand side variables, to make almost ideal demand system (AIDS model) the habit persistence version, it not only allows to model habit persistence, but also makes the AIDS model dynamic.

Early studies on lags and habit persistence were done by Duesenberry (1949), Brown (1952), and Farrell (1952) following the pioneering work on distributed lags worked out by Fisher (1930).

Duesenberry (1949) in his book “Income, Saving and Consumer Behavior” on pages 24-25 gives an interesting explanation to habit forming behavior. He stated that the mechanism which connects the consumption decision of individuals is not the rational planning but of learning and habit forming behavior. Furthermore, he said that, at any moment a consumer already has a well established set of consumption habits and most of this is due to a genetic process which begins in childhood.

For example, if we suppose an individual suffers a 50% reduction in income and realize that it is going to be permanent. Interesting behavioral reaction by the individual would be that he will continue to act the same way as he did before his income was reduced and incur similar expenditures in satisfying his needs. No sooner he is into such behavior that he would begin to realize that his assets are depleting. At that point either he has to completely stop purchasing some items or substitute with cheaper items for those that he desire to purchase. This happens after he uncomfortably regretted on what he did. Eventually he will reach a new consumption pattern such that he will not, in retrospect, regret for his expenditures. In doing so, he would establish a new set of habits for current situation. In closing Duesenberry (1949) lists four interesting elements in consumption habit formation process. They are as follows: it is a basic physical or social need which can be satisfied by acquisition of goods and services; it is a real or imaginary experimental behavior; it is the results of such behavior where in some cases individual may regret on expenditures he made; and it is learning that a certain pattern (habitual behavior) is successful where no expenditures are further regretted.

Brown (1952) stated that lagged (or past) values of some variables involved exert an important influence on current behavior of consumer in his decision making. This lead to the development of what he called *"hysteresis"* or habit persistence theory. His works were primarily centered on the consumption function where current consumption is a function of current income. As opposed to the famous Modigliani-Duesenberry hypothesis[5] of consumption behavior, Brown (1952) stated that it was not the past income that is important in understanding the habit persistence, but the previous real

[5] Modigliani-Duesenberry hypothesis, in very simple form, states the following. The current consumption is a function of current income and past income (not past consumption), because consumers are slow to adjust to current income changes due to some sort of inertia in their reactions to these changes. The inertia is due to consumers' memories of the highest previous level of disposable income which they have attained in the past (Brown, 1952).

consumption actually experienced was the key variables that must be on the right hand side of the consumption function. The reason for this latter argument was that the habits associated with level of consumption previously enjoyed become “impressed” on human physiological and psychological systems and this produces and inertia or “hysteresis” in consumer behavior. Immediate question that one might ask would be, how many lags should we have in the model or in other words, what is the appropriate time *(t)* that real consumption should be lagged? Intuition may tell us that, the strongest influence on level of current consumption comes from what happened in the immediate past (and not the distant past). Therefore, the effect on current consumption behavior by past behavior is strongest when t is small and gradually dies away as t becomes larger in a continuous fashion (Brown, 1952). At the end Brown (1952) concluded that, all that is required is only one period lag of the consumption variable to appropriately model the habit forming behavior (because as each new consumption vector occurs, it becomes the most recent, and hence the strongest habit forming experience).

Farrell (1952) performed the first empirical analysis on irreversible demand functions that had trends/habits embedded in it. Nevertheless, Marshall (1936) mentioned the possibility of irreversible demand functions and later Haavelmo (1944) discussed the problem theoretically. The question is what an irreversible demand (function) is? For example, let us assume a man who smokes faces a drop in tobacco prices or rise in his income. As a result, he will take up more smoking or better (worse) yet he will form a habit, and will not, when price or income return to its former level, cut his consumption to its former level (in reality he may cut back some, however, it is not sufficient to get back to his former level due to his addictive behavior/habit). This is the irreversibility that he would show in his behavior.

Farrell (1952) estimated an irreversible demand function using British data from the period 1870-1938 for four commodity groups; beer, spirits, tobacco and tea. In the function that he used he had per capita consumption on the left-hand-side and on the right-hand-side he included per capita real income, price, one period lag per capita consumption, one period lag per capita real income and one period lag price. It should be noted that Farrell (1952) used only one period lag on those variables that he used in the right-hand-side of the irreversible demand function. That was done following the same argument put forward by Brown (1952). For spirits where the trend is negative, it could be argued that the habit forming properties of spirit drinking lead to a positive irreversibility effect.

Above models developed by Duesenberry (1949), Brown (1952) and Farrell (1952), were extended further by Koyck (1954), Nerlove (1958), and Stone and Rowe (1957) using distributed lag and partial adjustment hypotheses. Consumer inertia in decision making was a key element in those earlier models.

Koyck (1954) worked extensively in developing relationships of say, current consumption to past consumption behavior. In doing so, he developed distributed lag models[6] to handle similar situations. In his book, *Distributed Lags and Investment Analysis (pp 8)* he states that "not every consumer may react the same way for a price reduction of a good. In most cases, psychological inertia keeps consumer from reacting

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[6] Quoting from Koyck *"generally the lag in the reactions of a number of subjects will be distributed over a period of time." Then it will be a "distributed lag".*

instantaneously and readjusting his behavior to a new situation. This is due a habit that consumer has developed over the years and it is well represented by lagged reactions."

Stone and Rowe (1957) developed a simple dynamic demand theory where consumption and net investment are distinguished from one another. In addition, they also differentiated between actual and equilibrium levels of consumption. Primarily they concentrated in demand estimation in durable and semi-durable goods. Amount of physical stock of a durable good that one holds is important in determining its future demand (this is called the effect of inventory on demand). Durable goods are designed to last more than one time period, or can be stored for a longer time period than non-durable goods. In very broad sense, food is generally a non-durable good while clothing a durable one. However, some foods can be stored for a longer time period compared to others. For instance, milk has relatively short shelf life (non-durable) compared to carbonated soft drinks (say colas that are relatively durable). Therefore, the *time* that a good can be stored before being consumed relates to the durability of that good. In this light, demand for durable goods can be modeled slightly differently than that of non-durable. According to Stone and Rowe (1957), modeling demand for durable goods has the property of *"stock-at-hand"* that needs to be taken care of. This reference is called the *"physical stock"* or *"inventory behavior"* in demand analysis.

Further, authors developed a dynamic theory of demand incorporating opening stock and current consumption of a durable good. Opening stock was calculated from the knowledge of past purchases, the rate of depreciation, and the manner in which purchases were assumed to be spread throughout the period (Stone and Rowe, 1957). At the end an important aspect of theory was the distinction between the opening stock and the equilibrium stock of the good. The model was applied to British data from 1930 to 1955 for clothing and other household durable goods.

Stone (1954), Pollak and Wales (1969) and Pollak (1970) were influential in bringing in habit persistence into complete system of demand relations. Stone (1954) introduced linear expenditure system, a complete system of demand relations[7] and applied that to analyze demand patterns in the United Kingdom over the years 1920-1938. He used data from six commodity groups that he defined for the entire economy. They are as follows: meat, fish, dairy products and fish; fruits and vegetables; drinks and tobacco; household running expenses such as rent, fuel and light, non-durable household goods and domestic service; durable goods such as clothing, household durables, vehicles, and communication services; all other consumers' good and services. Notice that, even though dairy products were in the list of goods Stone considered, it is not clear if he had beverage milk in that sub category. Interestingly, description of data does not give any indication as to whether if Stone had any information about beverages in his study.

[7] A system of demand functions that satisfy theoretical restrictions of demand theory i.e. adding-up, homogeneity, symmetry and negative semi-definite Slutsky substitution matrix is called a *"complete system of demand relations (functions).''* This is only true if individual level demand functions are specified. However, more often than not, we have "market" or "aggregate" level demand functions that use market or aggregate level data (say for example annual observations on prices and per capita consumption). Unfortunately, a complete set of market demand functions need not be theoretically plausible even though it is true at the individual level (Pollak and Wales, 1969). Nevertheless, for the purpose of research strategy, we have to assume that at the market level we work with a representative consumer for the whole category of goods considered, and demand functions derived for such a consumer are theoretically coherent (satisfies homogeneity, adding-up, symmetry and negative semi-definite Slutsky substitution matrix).

Gorman (1967) developed a theoretical framework to model tastes, habits and choices. Choices, tastes and habits are interrelated. According to his argument, *"choices depend on tastes and tastes depend on past choices"*, leads to habit formation in the long-run. Starting from a consumer utility function which depend on levels of goods consumed and taste parameters, he derives to show what is required by utility functions and habits in order to satisfy the long-run habit forming behavior.

Pollak and Wales (1969) estimated the linear expenditure system put forward by Stone (1954) centering attention to its dynamic and stochastic structure. The static version of the demand function that is used to generate linear expenditure system of demand functions can be written as follows:

$$(2.1) \qquad x_{it} = b_i - \frac{a_i}{p_i}\sum_{k=1}^{n} p_k b_k + \frac{a_i}{p_i}\mu$$

In equation 2.1, x_{it} is per capita quantity consumed, p_i is price of the good being considered, μ is the income, and a_i and b_i are unknown parameters to estimated.

To make the linear expenditure system dynamic, authors introduced two possible routes. Method one: since b_i enter demand function linearly, they made b_i dynamic (changing b_i s over time or b_{it}). The new demand function with varying *b*'s was as follows:

$$(2.2) \qquad x_{it} = b_{it} - \frac{a_i}{p_{it}}\sum_{k=1}^{n} p_{kt} b_{kt} + \frac{a_i}{p_{it}}\mu_t$$

Authors state that the easiest way to make *b*'s to vary was to assume that b_{it} was a linear function of time, hence the following specification for b_{it} :

(2.3) $b_{it} = b_i^* + \beta_i t$

However, they further state that, even though they estimated linear expenditure system with such dynamic specification, it is not very satisfactory because it gave so little insight into the structure of the economic system. Furthermore, quoting from authors, *"…such specification implies that taste change would not continue unabated (i.e., the necessary quantities would continue to increase) even if prices and income remained constant over a long period of time…."* Therefore, an alternative dynamic specification was proposed which eventually superseded the method one explained in above equation 2.3. This latter specification directly dealt with the mechanism underlying *changes in tastes*. It was based on the habit formation/persistence concept in consumer demand. Habit formation was introduced to the demand specification allowing *b*'s to depend on past consumption. The most fundamental habit forming model was based on the supposition that b_{it} was a linear function of consumption of the *i*th good in period *t-1*, i.e.:

(2.4) $b_{it} = b_i^* + \beta_i x_{it-1}$

Furthermore, authors give an extensive account on the stochastic specification of linear expenditure system. Annual prices and per capita consumption information for four broad categories of goods, namely, food, clothing, shelter and miscellaneous goods for the U.S. economy for the period 1948 to 1965 was used in generating estimates using linear expenditure system assuming four different dynamic specifications for b_{it}. They were constant $b_{it} = b_i$, linear time trend $b_{it} = b_i^* + \beta_i t$, proportional habit formation, $b_{it} = \beta_i x_{it-1}$, and linear lagged consumption habit formation model $b_{it} = b_i^* + \beta_i x_{it-1}$.

Pollak (1970) expanded on his work he previously did on dynamic linear expenditure system in Pollak and Wales (1969) into more general form. Past consumption patterns are important determents of current consumption relations, hence introduction of past consumption levels in the demand function makes it conveniently dynamic. As a result, shot-run and long-run consumer behavior can be understood through such demand relations. He elaborated on three reasons why long-run and short-run demand functions may differ (in the absence consumer durable goods). Briefly, they are as follows: (1) fixed commitments consumer may have (mortgage payment on a home loan) would keep him from responding to changes in price and income, hence delaying in achieving long-run equilibrium; (2) opportunity cost of time in learning and adjusting into a new situation can be very high if consumers are ignorant of past consumption possibilities; (3) consumer goods considered may be habit forming.

In his paper Pollak (1970), formulated a dynamic model of consumer behavior based on habit formation using a special class of demand functions derived from the "modified Bergson family" of utility functions. Pollak (1970) listed five different specifications of above utility functions. Demand functions were generated for every utility function and made them dynamic. Long-run demand functions are associated with the habit-formation model discussed above. It is a *"steady-state"* or *"long-run equilibrium"* that defines the long-run utility and hence demand functions. These long-run demand functions were not derived by maximizing a long-run utility function, rather defined as steady states or equilibrium values corresponding to the short-run demand functions.

Houthakker and Taylor (1970) in their book entitled *"Consumer Demand in the United States: Analysis and Projections"*, developed a theoretical model to account for habit persistence and inventory behavior in consumer demand analysis and applied their model to 83 different types of items (agricultural commodities and other household goods) using U.S. data from 1929 through 1970. The model they developed is called "the state adjustment model". This model has two equations, a short-run demand function which mapps prices, income/expenditure and stock of a good to its quantity demanded and a second stock depreciation equation which corresponds to short-run demand function, where $q(t)$ is the quantity demanded at time *t*, $s(t)$ is the stock or inventory of the good at time *t*, and $x(t)$ is the income at time *t*:

(2.5) $q(t) = \alpha + \beta s(t) + \gamma x(t)$

the stock depreciation equation, where $\dot{s}(t)$ is the stock depreciation rate (physical of psychological stock) at time t, and $q(t)$ and $s(t)$ defined as above. The constant depreciation rate is δ:

(2.6) $\dot{s}(t) = q(t) - \delta s(t)$

Using equations 2.5 and 2.6, a reduced form estimable equation can be derived (please see the methodology section of this dissertation for this derivation). The reduced form equation for a single good problem is as follows (we have derived this for a multi-good situation in this dissertation):

(2.7) $q_t = A_0 + A_1 q_{t-1} + A_2 \Delta x_t + A_3 x_{t-1} + A_4 \Delta p_t + A_5 p_{t-1} + \varepsilon_t$

Terms in equation 2.7 can be described as follows: q_t is the quantity demanded at time *t*; q_{t-1} is the quantity demanded at time lag one period; $\Delta x_t = x_t - x_{t-1}$ is the first differenced value of income/expenditure; x_{t-1} is the one period lag value of income; $\Delta p_t = p_t - p_{t-1}$ is the first differenced value for price of the good being considered; p_{t-1} is the price lag one period value; and ε_t is the independently and identically distributed random error. Once equation 2.7 is estimated, using relationships explained in the methodology section, structural parameters can be recovered. Also, using a local set of coordinates, we can calculate both compensated and uncompensated elasticity estimates for each commodity. Furthermore, short-run and long-run derivatives were calculated. Short-run and long-run derivatives were used to calculate short-run and long-run elasticities, respectively. Sign of β in the primal equation 2.5 helped them determine the inventory behavior or habit persistence behavior of consumers in consuming 83 different types of goods. They concluded that habit formation quite clearly predominates in the United States consumption.

It should be noted that, Winder (1971) explained an alternative route (without using calculus) to derive the dynamic model starting from equation 2.5 and equation 2.6 compared to the method explained in Houthakker and Taylor (1970). This also will be demonstrated in the methodology section of this dissertation. Moreover, Winder (1971) showed the relationship of Houthakker and Taylor (1970) model to a familiar Stock-

Adjustment Model (see Winder pages 370-371 for a derivation of Stock Adjustment Model and its relationship with Houthakker and Taylor (1970)).

Phlips (1972) and Spinnewyn (1981) did a slightly different twist to modeling consumer demand with habit formation incorporated. They introduced multi-period utility models where not only past consumption affected current behavior, but also effects of current consumption on future consumption behavior. In other words, habit formation was mapped into two time dimensions.

Just as Stone (1954) and Pollak and Wales (1969) and Pollak (1970), did start their empirical work, Phlips (1972) also started out with the Klein and Rubin (1947) utility function[8] in developing the linear expenditure system. Pollak and Wales (1969) used four alternative forms to model b_{it} (see Pollak and Wales 1969, page 621, table 1). However, Phlips (1972) used a different approach to model b_{it} whereby b_{it} now was a function of current values of state variables representing stocks of durable goods or habits. Furthermore, short-run behavior was shown a partial adjustment to long-run equilibrium, as a result permitting estimation of a reaction coefficient for each commodity.

[8] Klein and Rubin (1947) developed the linear expenditure system (starting from a specific utility function) in an attempt to develop a true cost of living index. Samuelson (1947) and Geary (1950) explained the economic interpretation of the linear expenditure system and showed that it is based on the following utility function: $U_i = \sum_{i=1}^{n} a_i \log(x_i - b_i)$ where x_i's are quantities and a_i and b_i are parameters such that, $a_i > 0$, $x_i - b_i > 0$, and $\sum_{i=1}^{n} a_i = 1$. The demand function derived starting from above utility function is as follows: $x_{it} = b_i - \frac{a_i}{p_i}\sum_{k=1}^{n} p_k b_k + \frac{a_i}{p_i}\mu$ where μ is total income or expenditure and p_i is price.

New relationship between the state variable s_{it} and b_{it} can be defined as follows:

(2.8) $$b_{it} = \theta_{it} + \alpha_{it} s_{it}$$

where s_{it} stand for current values of certain state variables. b_{it} and θ_{it} are estimable parameters. Sign of α_{it} is related to habit formation and inventory behavior. When commodity *i* is a durable good (when habit formation was not present) α_{it} is negative. He further calculated long-run and short-run demand functions.

Data from eleven U.S. commodity groups for the period 1929 to 1967 (leaving out the World War II period, 1942 to 1945) were used to estimate uncompensated and compensated elasticities (own-price, cross-price and income). Food and beverages was one of the categories considered. Compensated short-run (long run) own-price elasticity and income elasticities were -0.11 and 0.74 (-0.23 and 0.58) respectively.

Taylor and Weiserbs (1972) estimated an additive quadratic model (AQM) and popularly known linear expenditure system (LES). Below we show the two estimating equations. Equation 2.9 shows the AQM and 2.10 shows the LES:

(2.9) $$q_{it} = K_{i0} + K_{i1} q_{it-1} + K_{i2} \lambda_t P_{it} + K_{i3} \lambda_{t-1} P_{it-1} + u_t$$

(2.10) $$q_{it} = K_{i0} + K_{i1} q_{it-1} + K_{i2} (\lambda_t P_{it})^{-1} + K_{i3} (\lambda_{t-1} P_{it-1})^{-1} + u_t$$

where $i = 1,....,n$. In above equations q_i refers to the expenditure share on the *i*th commodity, P_i the price of the *i*th commodity, and λ_t the marginal utility of total expenditure corresponding to total consumption expenditure as the budget constraint (even though λ_t varies with time *(t)*, it is constant across commodities *(i)*).

They used U.S. data on eleven commodity groups from 1929 to 1968 (annual data) extracted from the Office of Business Economics in the *July Survey of Current Business*. Short-run and long-run elasticities were calculated for both models. They observed that λ_t s of two models move very close to each other (except for few occasions). In addition to calculating elasticities, authors performed a forecasting exercise to find that LES forecasts are comparatively better than AQM generated forecasts.

Lluch (1974) develops a theoretical model using dynamic optimization/calculus of variation techniques to explain the consumer allocation problem in the presence of habit formation effects. In most cases, consumer does not recognize the effect of current expenditure allocation on future utility (consumer is said to be myopic about above situation). In this paper, Lluch (1974) develops an intertemporal formulation of the consumer problem that allows for simultaneous treatment of the consumption-saving and the expenditure allocation decisions while taking habit persistence into account. Author develops the theoretical framework starting from two utility functions, thus, Klein-Rubin utility (Klein and Rubin, 1948) and quadratic utility functions. It also should be noted that durability issues of goods is not taken into consideration in deriving above framework.

Manser (1976) analyzed elasticities for U.S. demand for food using a host of non-additive utility functions allowing for habit formation/persistence. Annual time-series data for four major types of food: meats, produce, cereal and bakery products and miscellaneous foods, were gathered from various government sources (USDA, U.S.

Bureau of labor statistics) for years 1948-1972. Following expenditure functions were estimated and own-price and expenditure elasticities were generated for each good. Functions estimated were, static indirect translog, indirect translog with habit formation, additive indirect translog with habit formation, additive indirect translog static, indirect translog with linear Engle curves with habit formation, indirect translog with linear Engle curves static, Klein-Rubin with habit formation, and Klein-Rubin static.

Results find that, the own-price elasticities for the functional forms, which allow for habit formation, were not uniformly smaller than those for the static forms. All substitution elasticities implied by each habit formation model are same (or smaller) than those for respective static model.

Lin (1974) proposed an alternative method to deal with the identification problem inherent in Houthakker and Taylor (1970) state adjustment model. Houthakker and Taylor (1970) explained the identification problem associated with δ, the constant stock depreciation rate. With the introduction of price variable to the right hand side of the primal equation and/or reduced form equation of Houthakker and Taylor (1970) state adjustment model, they observed that two forms of reduced-form and structural parameters could be derived, hence δ is overidentified. Method that Houthakker and Taylor (1970) suggested to get around of that problem depended on an iterative procedure. It was pointed out where the procedure did not guarantee of convergence. However, Lin (1974) suggested another approach which does not depend on iterative procedures (he called it a functional approach). Lin (1974) demonstrated his procedure numerically to find that it superseded Houthakker and Taylor (1970) iterative procedure.

More on this overidentification problem will be discussed in the Methodology section of this dissertation.

Sexauer (1977) make an important contribution to the habit formation and inventory behavior in consumer demand analysis. Main argument in his thesis was to highlight the importance of short-run effects of possible exogenous developments and policy instruments as opposed to long-run, on the pattern of consumer expenditure. A lot of studies concentrated on using annual time-series data (at least in the 1970s) in their empirical work. Drawing intra-year policy implications about consumer behavior from studies based on annual data can be misleading. Recall from Houthakker and Taylor (1970) when they said consumption habits are far more important than household stocks on the pattern of consumer demand. In the contrary, study by Sexauer (1977) took a different approach to above conclusion made by Houthakker and Taylor (1970). According to him, the habits as opposed to inventories are not an absolute, but depend on "*time dimension*" considered. Houthakker and Taylor (1970) however, overlooked the possible importance of their model on the nature of the time dimension of the data. Furthermore, this investigation by Sexauer (1977) shows that short-run consumer behavior is influenced more by consumer inventories than habits.

To understand the effect of time dimension on the influence of habits or inventory behavior on consumption expenditures, Sexauer (1977) did his work taking four time frequencies into account. They were, annual, semiannual, quarterly, and monthly. At the end he concluded that the importance of habit formation relative to inventory behavior in an economy decrease as the time period analyzed deceases.

The important contribution of Sexauer (1977) was his explanation on the "*dual nature of* β" Most commodities are subject to both a habit-formation effect and a stock-adjustment effect. As a result, an observed β is a combination of both effects. Let β_H and β_I be *betas* associated with habit formation and inventory adjustment respectively. Houthakker and Taylor (1970) explained only a net effect, the dominance of habit formation or inventory behavior over the other, but did not explain anything about specific sizes of β_H or β_I .The coefficient associated with β_H arises from habit effect and that of β_I from inventory behavior.

The sign and change of sign that *betas* take depends on the commodity and time period that services can be extracted from a particular commodity. For nondurable goods[9] with annual data the *betas* should change sign from positive to negative as time period considered approaches zero. In other words, inventory adjustment becomes dominant over habits as time period shrinks.

Modifying Houthakker and Taylor (1970) demand model, Sexauer (1977) brought in two betas discussed in the above section into the demand equation as follows (two state variables, one for each effect). Also, the coefficient of each state variable now must be a function of time period of observation:

(2.11) $$q(t,\tau) = \alpha(\tau) + \beta_H(\tau)s_H(t,\tau) + \beta_I(\tau)s_I(t,\tau)$$

[9] Distinguishing characteristic of a durable commodity is that, once purchased, services can be rendered over time for a longer period rather than consumption of the commodity itself at a point in time. Commodity with latter characteristic is a nondurable good (Nerlove, 1958). Almost any commodity can be taken as a durable good, if the time period considered is short enough. During that short time period, the good under consideration may render services over time, hence a durable good. Sexauer (1977) states that, for an annual period, an automobile is a durable good, however a loaf of bread is not. On the contrary a loaf of bread can be a durable good for a family who does shopping once a week and purchase bread and store them in pantry for the consumption over a week period.

where τ be the length of the period of observation, $\beta_H(\tau) > 0$ be habit formation, $\beta_I(\tau) < 0$ be inventory adjustment and for most of the commodities, $\frac{\partial \beta_I(\tau)}{\partial \tau} > 0$ and $\frac{\partial \beta_H(\tau)}{\partial \tau}$ is indeterminate.

The stock depreciation equation of Houthakker and Taylor (1970) also have to be modified to suit to equation 2.11 Since the observed δ, the stock depreciation coefficient is an amalgam in the Houthakker and Taylor (1970) which communicates only the net effect, it has to be modified to account for both habit and inventory depreciation. Finally, the new stock depreciation equation can be specified as follows:

$$\text{(2.12)} \qquad \frac{\partial s(t,\tau)}{\partial t} = q(t,\tau) - [\delta_H(\tau)s_H(t,\tau) + \delta_I(\tau)s_I(t,\tau)]$$

where τ be the length of the period of observation, $\delta_H(\tau) > 0$ be habit formation, $\delta_I(\tau) > 0$ be inventory adjustment and for most of the commodities both of above relations are positive. Even though the new model postulated above is theoretically sound, it has difficulties in estimation due to identification issues associated with the model (parameters are under-identified). Therefore, Sexauer (1977) uses the Houthakker and Taylor (1970) model for his estimation work.

Annual, semiannual, quarterly and monthly data were gathered for 16 commodity groups for U.S. from a variety of sources. They varied from electricity to cars to furniture to food and beverages (please see the table 1 of Sexauer (1977), page 137 for a complete listing of commodities used in this study). Calculated beta coefficient, changed on average from 0.2973 for annual, to 0.0757 for semiannual, to -0.3419 for quarterly, to

-0.7136 for monthly. Therefore, the effect habit formation dominates with annual data, however, its influence become significantly less the semiannual data. Inventory adjustment dominates over habits with quarterly data and that influence became stronger with monthly data.

Pope, Green and Eales (1980) conducted a study to test for homogeneity and habit formation in a flexible demand specification of U.S. meat consumption. They identified three common problems facing an empirical analyst of demand relations. They were the choice of functional form for econometric estimation; decision to inflate or deflate prices; the representation of changing preferences. They attempt to cover the last of three problems discussed above, in this study.

They modeled habit formation in a flexible demand specification (Box-Cox transformations are applied here, Box and Cox, 1964, and Zarembka, 1974). U.S. data on meats (beef, pork, poultry and fish) for the years 1950 to 1975 were used in the analysis, emphasizing short-run effects. Three habit-version demand specifications are considered in Pope, Green and Eales (1980). First was to add a time trend variable to take care of the changes in tastes. Second, transformed lagged consumption variable is added to equation 2 of Pope, Green and Eales (1980), page 778 going in accordance with Houthakker and Taylor (1970) to take care of habits. Third, as shown in Phlips (1974), the quantity demanded of *i*th commodity is assumed to be a function of the psychological stock of habits, prices and income and lagged values of quantity, price and income were introduced to equation 2 of Pope, Green and Eales (1980), page 778. Based on likelihood ratio tests, it was found that state adjustment model of Houthakker and Taylor (1970) to be superior over static and partial adjustment model.

Spinnewyn, (1981) discussed consumer demand under rational habit formation. That is to say, for a rational consumer, past habits determines current consumption levels and future habits will be determined through the current consumption behavior. In doing so, the author extended the Houthakker and Taylor (1970) type model into a multi-period utility model. Such models were first developed by Lluch (1974) and Phlips (1974). In this paper, the author explains a simplified way of solving inter-temporal models with habit formation. If preferences are expressed in terms of uncommitted consumption stocks, this study show that models with habit formation can be made formally equivalent to models without habit formation, simply by redefining the cost of consumption and wealth concept. Majority of the paper was devoted to above derivation and related concepts.

Wohlgenant and Hahn (1982) focused on the nature of dynamic adjustment in monthly consumer demands for meats. Again, this article concentrates on meat demand which is not the current theme of this dissertation. However, we are discussing this paper due to its contribution toward the methodology that authors used to model dynamic adjustment; Houthakker and Taylor (1970) which is a key method used in this dissertation. This paper by Wohlgenant and Hahn (1982) estimated monthly consumer demands for meats in the U.S. and examined the role of inventory behavior and habit persistence on estimated short-run demand elasticities.

Wohlgenant and Hahn (1982) type demand equations were estimated with monthly data over the period January 1965 through June 1979. To handle the seasonality effect, eleven monthly seasonal dummies were included in the model. Data for three meat types were gathered; beef, pork and chicken. Two types of models; unrestricted and restricted, were estimated and results were reported.

Results showed that beef and pork were substitutes; however, the relationship with chicken was not clear. Monthly inventory behavior predominated for both beef and pork. For pork, stock adjustment coefficient was highly significant, indicating inventory adjustment as an important feature for short-run consumer behavior. Houthakker and Taylor (1970) model (or state adjustment model) was compared with Nerlovian Partial Adjustment Model (another model that could handle dynamic effects of consumer demand) to find that former beats the latter. Authors conclude by saying that, demand is more price elastic within a given month over a longer period, if inventory behavior had predominated habit persistence.

Blanciforti and Green (1983) estimated almost ideal demand system (AIDS) incorporating habit effects in the same way it was done by Pollak and Wales (1969) to linear expenditure system. Advantage of making AIDS model dynamic is that, temporal relationships between price and income elasticity estimates can be examined.

Almost ideal demand system in the budget share form is given by:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln(\frac{x}{P}) \tag{2.13}$$

where P is the Translog price aggregator term (price index) given by:

(2.14) $$\ln P = \alpha_0 + \sum_k \alpha_k \ln p_k + \frac{1}{2}\sum_j \sum_k \gamma_{kj} \ln p_k \ln p_j$$

and p_j is the price of *j*th good and *x* is the income (Deaton and Muellbauer, 1980). Following specification added in lieu of α_i in 2.13 makes the AIDS model dynamic as well as prepare it to handle habits in consumption. It makes α_i to be a linear function of previous consumption levels:

(2.15) $$\alpha_i = \alpha_i^* + \alpha_i^{**} q_{it-1}$$

where q_{it-1} is the lagged quantity of the good (or quantity of the good consumed in the previous period). For estimation purposes, the Translog price index was replaced by the Stone's price index (which is free from estimable parameters). Stone's price index is given by:

(2.16) $$\ln P^* = \sum w_k \ln p_k$$

where w_k is the budget share of the *k*th good.

Annual U.S. time-series data for the years 1948 to 1978 were used to estimate demand systems. They used eleven aggregate commodity groups. They are food, alcohol and tobacco, clothing, housing, utilities, transportation, medical care, durable goods, other non-durable goods, other services and other miscellaneous goods.

Results indicated that, ten of the eleven habit coefficients, α_i^{**}, are positive indicating habit forming behavior. The only exception was automobile parts which had a negative habit coefficient, indicating non-habit forming behavior. Also, they found that, although not reported in their paper, estimated structural parameters and elasticities were different between static and dynamic models for food groups. They concluded that, almost ideal demand system incorporating habits and allowing for autocorrelation appears to be more viable system to model consumer behavior.

Anderson and Blundell (1983) centered attention to testing restrictions in a flexible dynamic demand system using Canadian data. In particular, this paper develops a vector time-series model of expenditure shares in the context of a singular dynamic demand system. The model allows for both short-run and long-run behavior. It is assumed that consumers are unlikely to adjust for equilibrium in every time period. Three possible reasons for such behavior are adjustment costs, incorrect representations and misinterpreted real price changes, and habit persistence. The autoregressive, partial adjustment model and habit persistence models were tested to find out the best model that explained the data.

Annual time-series data on five categories of non-durable goods from Canada for the time period 1947-1979 was used in this study. Five groups of products considered were, food, clothing, energy, transport and communications and recreation.

Income elasticities were unity or very close to unity for most cases. Own-price elasticities were over estimated in the static model while cross-price elasticities were underestimated. Data rejected static, simple autoregressive and partial adjustment models. It also was found that consumers are more responsive to long-run price changes.

Yanagida and Tyson (1984) analyzed the factors affecting U.S. shrimp consumption, primarily centering attention to the nature of dynamic changes in monthly demand models for shrimp. Monthly data for U.S. for the time period 1976-1981 were used in the analysis. Shrimp consumption per capita was regressed on retail real price for shrimp, per capita real personal income, per capita shrimp consumption lagged one month, consumer price index for all goods less food, and 0/1 dummy variable to capture seasonality. The coefficient of the lagged quantity provides a measure of habit formation in current consumption. If the above coefficient is zero, there is no inventory effect or habit formation. A positive coefficient implies habit formation, whereas a negative coefficient is associated with inventory adjustment. A second demand equation was estimated and compared to the first one. In the second equation, other than the variables we had before, a new variable named change in stocks (to capture inventory adjustment) was included in the analysis. Change in stock was measured as a first differenced relation of shrimp stocks. Both models were estimated in log-log functional form, insuring constant price elasticities. Estimated long-run price elasticity was more elastic than the short-run price elasticity, indicating predominance of habit effects.

Weissenberger (1986) constructed and estimated a system of dynamic demand equations under the rational expectations assumption about anticipated wealth. Author goes into an elaborative derivation, in particular making familiar almost ideal demand system (AIDS) intertemporally dynamic. Indirectly, he brings in the habit formation in consumption idea, where past consumption affect current expenditure decisions and current consumption decisions influence future habits. Empirical work has been carried out taking annual time-series data from eight commodities. They are; food, drink and tobacco, fuel and light, clothing, other goods, other services, durable housing goods, cars and motorcycles. Compensated and uncompensated price-elasticities and expenditure elasticities were estimated for all eight goods.

Becker and Murphy (1988) concentrated on developing a theory of rational addiction. Rationality stands for a consistent plan to maximize utility over time. They also brought in the concept of addiction, which related to habit forming behavior. Addiction is a very strong desire to consume some good where a very strong past consumption of the good affects the current consumption. This is also called habit formation. Article explained more about rational addiction and time-to-time relating it to habit forming behavior in consumer demand.

Capps and Nayga (1990) revisited the problem of effect of length of time on measured demand elasticities using Houthakker and Taylor (1970) state adjustment model. In considering the effect of time, there are two opposing forces that affect the elasticity of demand. They are storage activities and product substitution. Short-term elasticities (week or month) are generally greater than longer-term elasticities due to storage possibility. Role of inventory behavior and habit persistence also depend on the time dimension. This argument was reinforced by Sexauer (1977) after the pioneering work by Houthakker and Taylor (1970), which actually overlooked the effect of time dimension on habit and inventory behavior. This paper by Capps and Nayga (1990) focused on effect of the length of time on demand for fresh beef products (disaggregated beef products such as brisket, chuck, ground, loin, rib and round).

Monthly, bi-weekly and weekly time-series observations were developed from point-of-sale scanner database for the period September 1986 through November 1988.

There were 113 weekly, 56 bi-weekly and 25 monthly observations used in this analysis. Six beef product commodities (listed above) were modeled in a systemwide Houthakker and Taylor (1970) framework. Total expenditures in lieu of income were used in this analysis (original Houthakker and Taylor (1970) model used income in their modeling for U.S. economy). A Non-linear routine in SHAZAM (iterative seemingly unrelated regression) in a systemwide framework was used to estimate the system using maximum likelihood estimation. Model estimates were fixed for serial correlation problem in the data.

Results from above estimated model are as follows. All the own-price elasticities were negative and all expenditure elasticities were positive. With weekly data, inventory behavior predominated over habits. Also, short-run price and expenditure elasticities were larger in weekly data compared to data with other time dimensions.

Chen and Veeman (1991) investigated habit formation and structural change for demand for meat in Canada using an almost ideal demand system. They made the AIDS model dynamic by incorporating lag one period of the quantity variable on the right hand side of the AIDS model (in doing so they introduced the model specification to handle the habit forming behavior similar to work done by Blanciforti and Green (1983)).

Canadian data for meats (beef, pork, chicken and turkey), from first quarter of 1967 to forth quarter of 1987 were used in this study. The non-linear maximum likelihood procedure of SHAZAM was used for estimation. Both static and dynamic versions and restricted versions of both models with parameter restrictions implied by consumer theory were estimated.

Results indicated that, for the models in which homogeneity and symmetry are restricted, static model is rejected in favor of dynamic AIDS model at 5% level of significance. Preference for the dynamic model was with a low level of significance (only 15% level) when the theoretical restrictions were relaxed. Estimates from AIDS model incorporating habit persistence indicated that the demand for chicken is more expenditure elastic than for beef and pork.

Thus far, all studies used annual, quarterly, monthly, bi-weekly and weekly time-series data to investigate the habit formation hypothesis in consumer demand analysis. Heien and Durham (1991) tested the habit formation hypothesis in demand analysis, for the first time in the literature, using a household level cross-sectional dataset. Even though adding a lagged variable to the right hand side of a demand model (AIDS models, linear expenditure models, more general Box-Cox transformation models, log-log models, etc) was considered *ad-hoc* in the literature, it is very widely used in the literature to model habit formation and consumer demand. In this paper, it was conjectured that habit effects are over stated due to the fact that almost all studies used time indexed data.

Empirical estimates from both single equation models and complete demand systems show that habits in consumer demand analysis played a very vital role. Heien and Durham (1991) further stated that, use of time-series data to model habit forming models could give rise to several problems. First, the possible high correlation between the dependent variable and lagged dependent variable could give rise to erroneous statistical properties, hence wrong policy recommendations. Second, the possible presence of high levels of multi-collinearity amongst right-hand-side variables in the time-series data used for the model. Third, (common rule for both time-series and cross sectional data) is the possible estimation bias imparted by the lagged dependent variable. Omission of important variables which are correlated with lagged consumption to overstate the effects of lagged consumption and as a consequence increase habit effects.

The object of Heien and Durham (1991) was to test the linear habit formation hypothesis on individual household level microdata. Due to absence of price data, authors could not estimate a complete system of demand equations. However, a Quadratic Expenditure System (QES) was estimated assuming that all consumers face a single price (in other words, price was normalized to unity in this QES). Through a method developed by Pollak and Wales (1981), called translation, demographic variables were incorporated into the above price normalized QES. Use of cross-sectional data at household level gives rise to an additional problem at the estimation stage. It is the censoring issue associated with the dependent variable (or a truncated dependent variable). To circumvent that problem, decision to consume is modeled a dichotomous choice problem, where in the first stage, a probit regression is computed which determines the probability of purchase of the good by a given household. Then an Inverse Mills Ratio is calculated using probability density and cumulative probability density values extracted from probit estimation. Then, calculated inverse mills ratio is used an instrument in the second stage demand equation.

The data panel contained information from 5000 households in the U.S and it was conducted by the Bureau of Labor Statistics as their Consumer Expenditure Survey:

Interview Survey. Data covered the time period from third quarter of 1980 through fourth quarter of 1981. Demographic variables used in this study were, number of males over fifteen years, number of females over fifteen years, number of males two to fifteen, number of females two to fifteen, and number of children under two, region of country (north, south, central, west), and for the quarters. For the comparison purposes, authors estimated another model with time-series data to cover 16 categories of goods. They were obtained from the Personal Consumption Expenditures, U.S. National Income and Products Accounts to cover the period 1960-1986. It should be noted that, since time-series approach contains market level data, there is no censoring issue, and hence Mill's ratio approach is not required.

They concluded their paper giving reasons for the overstatement of habit effects in time series data. They are, collinearity problems, simultaneity, autocorrelation, and potential omitted variables. Furthermore, they stated that *"habit effects from time-series data differ substantially from those based on cross-section data"*.

Okunade (1992) examined functional forms and habit effects in the U.S. demand for coffee. According to our knowledge, this was one of the first studies that concentrated directly on non-alcoholic beverage demand and habit formation. According to Shapiro, Dolan and Quelch (1985), coffee is the leading hot beverage consumed by about 60% of the U.S population. Changes occurring in the U.S. population composition mix may be a good reason for such amounts of coffee consumption and trends. Moreover, U.S. is the largest importer of coffee from Brazil, Colombia, Bolivia and host of other coffee exporting countries.

This study was considered as a multidimensional extension of previous research done on the U.S. demand for coffee. One of the objectives was to test the compatibility of the habit formation framework with U.S. coffee consumption. This study adopted a single-equation demand modeling framework incorporating dynamic forces of habit formation in a flexible Box-Cox demand model. According to Phlips (1974, page 149), a dynamic specification provides a more realistic description about empirical consumer behavior. Annual time-series data for the period 1957 to 1987 were gathered for consumption of coffee per capita, quantity lagged one-time period, real price of coffee, real price of orange juice, real per capita disposable income, and real price of sugar. The flexible Box-Cox model with habits found to be reinforcing with an earlier finding of Houthakker and Taylor (1970). Habit coefficient is statistically significant implying that habits are reinforced by recent consumption experience.

The long-run price elasticity of demand was -0.339. The cross-price elasticity with respect to sugar was -0.138. The substitution between coffee and other beverages was weak or did not exist. In the conclusion, it was indicated that U.S. per capita consumption of coffee is strongly influenced by habits. Coffee demand was more inelastic in the presence of habit effects, than in model specifications with-out the habit effects.

Price and Gislason (2001) conducted a study to identify habit in Japanese food consumption. A convention among economists is that consumer takes some time (more than a single time period) before he responds to changes in price and income and make a full quantity adjustment. This is also called inertia among consumers. More specifically, Japanese consumers are highly traditional and would take more time to adjust for a change in economic condition. Author compared and contrasted the difference between the use of dynamic AIDS model and Houthakker and Taylor model (1970) in modeling consumer habit formation. Their argument was, AIDS model is more suited for a static study and with the dynamic structure introduced, is difficult to estimate the AIDS model with lagged variables in comparison to Houthakker and Taylor model (1970).

A Japanese data set obtained from Statistics Bureau, Annual Report on the Family Income and Expenditure Survey, Prime Minister's office was used for the 29-year period from 1963 to 1991. Prices, quantities and expenditures at retail level were used for five commodities. Goods considered were, meat, sea food, cereals, vegetables and fruits. Houthakker and Taylor (1970) state adjustment model was used to model possible habit effects in the consumption of above goods. One problem of using such time-series data set was the presence of structural change during the period. Therefore, they had to control for structural change by doing a sequential Chow test. In this model, a dummy variables was subsequently to take care of structural change.

Results indicated that, direct price elasticities ranged from about -2.872 or sea food to -0.618 for cereal. Total expenditure elasticities and they ranged from 2.713 for meat [10].No restrictions were placed on estimating Houthakker and Taylor (1970).

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[10] It should also be noted that elasticities are affected by the length of the time period or adjustment period concerned (Manderscheid,1964). Consumer response to a price change could take following paths. One, he may stock-up due to a price promotion in the market and consume the good in a later time, thereby responding quickly to a price change (drop). Two, a consumer may not change his behavior so quickly (hesitant to change the consumption pattern) in the short-run, however, after some time, he may respond to the price promotion.

Heien (2001) centered attention to habit formation, seasonality, and time aggregation in studying consumer demand analysis. Habitual behavior was entertained in the past literature mostly via introduction of a lag (lag of consumption) of some sort.

Traditional arguments concerning habit did not emphasize on seasonal effects such as availability (strawberries during summer), special holidays (turkey at Thanksgiving), weather (summer vacations), etc. Seasonality is often associated with above facts; however habit forming related to recurring desires and their influence on present consumption. This paper by Heien (2001) primarily tried to distinguish between seasonality affect and habit forming behavior.

The employed model specification is as follows:

$$q_{it} = \alpha + \beta q_{(i-1)t} + \gamma X_{it} + \rho_1 D1_{it} + \rho_2 D2_{it} + \rho_3 D3_{it} + \sigma q_{(1-4)t} \tag{2.17}$$

where *t* denotes the year and subscript *i* denotes the quarter. Seasonal dummies were *D1, D2, D3*. The quantity consume was *q* at time *t* for quarter *i*. *X* is vector of other variables such as prices and income. Specification of 2.17 distinguished between an immediate habit effect $(q_{(i-1)t})$, and constant seasonal effects (ρ_i), and a seasonal effect changing with consumption a year ago for a given quarter $(q_{i,t-1})$.

It was stated that effects of habit forming and seasonality were in fact not separated in previous work done by early researchers and this work by Heien (2001) separated the impact coming from seasonality through introduction of seasonal dummies into the regression equation. Now, what was left after that separation was the contribution coming from habit effect. Above hypothesis/statement were tested using two sources of data: one, nondurables and services (data from U.S. Department of

Commerce, Bureau of Economic Analysis) and the other for meats (data from USDA, ERS). Both of above data sets were not seasonally adjusted to begin with. Two models were estimated. First, model in above equation 2.17 was estimated using quarterly data and second, they were aggregated to generate an annual data set and same model was fitted to annual data. Finally, magnitude of habit effect was compared in between the model with quarterly data against the one with annual data. Heien (2001) concluded that, seasonality had been neglected in consumer demand analysis, and as a result much of the habitual effects actually could be explained as hidden in seasonality variable.

Probability Forecast Evaluation Study

This section is organized as follows. First we give a brief account about qualitative choice models. Second, we talk about subjective and objective probabilities followed by an account on proper scoring rules in evaluating probabilities. Third, we offer an elaborative account on different techniques used to evaluate probabilities.

Qualitative Choice Models

Qualitative choice models are widely used in economic modeling of choices, when the dependent variable concerned is qualitative (discrete) in nature. The qualitative dependent variables can be classified into two categories. They are dichotomous (binary) and polychotomous dependent variables (Kennedy, 2003). If the dependent variable is set up as a zero-one (0-1) dummy variable (only two choice categories), they are classified under dichotomous dependent variable models. Binary probit and logit models are examples for aforementioned category.

If categorical dependent variable is categorized into many choice categories, they are called polychotomous dependent variable models. An example for a polychotomous dependent variable can be a situation where a commuter is presented with three choices of commuting to work, thus, by subway, by bus or by private car (Kennedy, 2003). Multinomial probit and multinomial logit models are used to measure such choice behaviors.

In this study we concentrate on binary probit and logit models. When a binary decision is regressed on explanatory variables (quantitative economic variables such as price and income, and qualitative demographic variables such as education level, region) we would expect to have predicted values for dependent variable to fall between the interval 0 and 1. This further suggests that the predicted value of the dependent variable could be explained as a probability that a decision making unit (say, a household) making a choice (say, purchase a non-alcoholic beverage), given all the other factors used as explanatory variables. Regression of a zero-one dummy variable directly on a group of explanatory variables using ordinary least squares leads to the *linear probability model*. However, linear probability model has an inherent drawback where the predicted probabilities could fall outside the range of 0 and 1 causing difficulties to the analyst to interpret the outcomes. Therefore, what is needed is some means of squeezing the estimated probabilities inside the 0-1 interval without actually creating probability estimates of 0 or 1 (Kennedy, 2003). The two most popular forms used in this respect are logit and probit models. The logit model uses a logistic distribution in generating probabilities while probit model uses a standard normal distribution.

Following we offer a shot technical note on logit and probit models (for more details please refer to a standard econometrics textbook such as (Greene, 2003). A dichotomous dependent variable can be regressed on a host of explanatory variables to obtain an index value for each observation, i.e. Z_i where $Z_i = X_i'\beta$. In this equation, X represents the explanatory variables and associated regression coefficients are represented by β. The logistic cumulative distribution function $F_L(Z_i)$ is represented as follows:

$$(2.18) \qquad P_i = F_L(Z_i) = \frac{e^{Z_i}}{(1+e^{Z_i})}$$

where $-\infty < Z_i < \infty$.

The associated probability generated through assuming that index variable has a logistic distribution is P_i. This guarantees that the calculated probabilities fall into the zero-one interval.

On the other hand, if we generate probabilities using index variables formulated above and applying them to an integral of standard normal density function (integrating a probability density function give rise to a cumulative distribution function ($F_P(Z_i)$), we get probabilities associated with a probit model. Mathematically, probabilities associated with probit model are:

$$(2.19) \qquad P_i = F_P(Z_i) = \int_{-\infty}^{Z_i} \frac{1}{\sqrt{2\pi}} e^{Z_i^2/2}\, dz$$

where $-\infty < Z_i < \infty$. It is guaranteed that these probabilities are in the zero-one interval.

Subjective Probabilities Versus Objective Probabilities

The entire calculus of probability can be derived both using axioms on sets and axioms on human behavior. A Russian mathematician, Andrey Kolmogorov gets credit for developing Kolmogorov probability axioms that are based off of concepts such as axioms of Borel Sets and *zigma*-algebra (Cassella and Berger, 2001). On the other hand, the work of Bruno deFinetti (deFinetti 1970a and deFinetti 1970b) and Leonard Savage (Savage, 1954) on probabilities took another path in deriving the calculus of probability, which is based on axioms on human behavior. This latter school is called the subjective probability school. From the subjectivist point of view, a probability is a degree of belief in a proposition (Lichtenstein et al., 1982). Subjective probabilities are generated within human mind (through expert knowledge/judgment of one or more forecasters for a given situation and/or a model that a probability forecaster has in his/her mind). Subjective probability forecasting have been used extensively in the field of weather forecasting .According to deFinetti (1970a), subjective probability is the only meaningful interpretation of the word probability.

On the other hand, probabilities are generated through models developed using objective information, such as data on various variables. These do not depend on forecaster's judgment (Murphy and Winkler, 1984). Probabilities that are generated through econometric modeling (regression based forecasting) fall into the category of objective probabilities. More specifically, econometric models such as logit and probit models give out probabilities that are well behaved within the boundaries of calculus of probability, i.e. for example, if P_i is the model generated probability, $0 \leq P_i \leq 1$condition is satisfied. In this study we are interested in objective probabilities that are generated through probit and logit models.

Proper Scoring Rules

As far as subjective probabilities are concerned, there are two important aspects that have to be taken into account when a forecaster issues probabilities for an event. They are probability assessment and probability evaluation. Foremost, the question is how one should make sure that a forecaster issues forecast probabilities that agree with what they actually think the probability for the event to occur (or not-to-occur) would be. Put it differently, are the issued probabilities honest? This is a question of motivation of a forecaster to issue probabilities that correspond to his/her true beliefs and not to "*hedge*" on issued probabilities (a probability that does not correspond to his/her true beliefs is offered) (Murphy and Epstein, 1967). The device used to motivate and assess the probabilities that correspond to ones true beliefs is called a *scoring rule*. Scoring rule is any algorithm that assigns a payoff for a probability assessment, where the payoff depends only on the assessor's stated probability distribution and the event that actually occurred (Jensen and Peterson, 1973). Much of the earlier theoretical work on personal probability elicitation and scoring rules were done by deFinetti (1970b) and Savage (1954) and Savage (1971). (There is a large body of literature that discusses the scoring rules primarily to motivate and assess probabilities issued in weather forecasting. For example see Murphy and Winkler (1971)). Others will be cited throughout this section.

The motivating scoring rule must be a *proper scoring rule.* That is to say, a forecaster can maximize the expected value of a scoring rule only when he/she issues probabilities that correspond to his/her true beliefs (or in other words when the true density is chosen) (Hendrickson and Buehler, 1971). Any proper scoring rule remains proper through a linear transformation, provided that the multiplicative constant is positive (Jensen and Peterson, 1973). That is to say, it is possible to generate an infinite number of proper scoring rules. However, such positive transformation could change the range of the possible scores that in turn change the flatness/steepness of the scoring function (three most popular scoring functions are discussed below). Any deviation from this would not allow him to maximize the scoring rule value, which would penalize him according to a penalty function. Formalization of above concept of a *proper scoring rule* for elicitation of discrete probability distributions is discussed below. Families of proper scoring rules for elicitation of continuous probability distributions are developed and discussed in Matheson and Winkler (1976). In our work, we use scoring rules that are associated with discrete probability distributions.

Consider a forecaster assigns a set of *p* probabilities $(p_1, \cdots, p_N)$, where $p_n \geq 0$ and $\sum_n p_n = 1$ where $(n = 1, \cdots, N)$ for *N* mutually exclusive and exhaustive states of concern. Suppose the forecaster's true beliefs concerning the states are expressed by the set of *r* probabilities $(r_1, \cdots, r_N)$, where $r_n \geq 0$ and $\sum_n r_n = 1$ where $(n = 1, \cdots, N)$. Then, in maximizing the expected value of the scoring rule value, forecaster will make his probabilities correspond with his true beliefs, i.e. he/she will set:

(2.20) $\qquad p_n = r_n$ for all *n*, $(n = 1, \cdots, N)$

Literature on proper scoring rules has evolved around three major scoring rules, namely; (a) logarithmic scoring rule (b) quadratic scoring rule and (c) spherical scoring rule. Our objective is not to give a comprehensive account on proper scoring rules, however, we expect to give a brief explanation on proper scoring rules. In our work, we use a variant of quadratic scoring rule (probability score or the Brier Score (Brier, 1950)) to evaluate probabilities that are generated using probit and logit models. Since we are concerned with a prediction *p* and an observation *d* (for derivation and notational simplicity we consider an observation as a binary choice, such as making a purchase and not-making a purchase, where when making a purchase we set *d=1* and for not-making a purchase we set *d=0*). The following account on above three types of proper scoring rules is extracted from Winkler and Murphy (1968) and Murphy and Winkler (1970).

<u>Logarithmic Scoring Rule</u>

Logarithmic scoring rule *L(p,d)* is defined as:

(2.21) $$L(p,d) = \ln(dp'),$$

where *d* is a row vector of dummy variables (0,1) and *p* is column vector of probabilities. In summation notation, it also can be defined as following:

(2.22) $$L(p,d) = \ln(\sum_{i=1}^{N} d_i p_i),$$

where $(i = 1, \cdots, N)$. If outcome E_j occurs for the *j*th event, i.e. *d=1*:

(2.23) $$L_j(p,d) = \ln\ p_j$$

(note that logarithmic scoring rule can take into account probabilities associated with events that actually occurred). Then the assessor's expected score is *E(L)*, where:

(2.24) $$E(L) = \sum_j r_j \ln p_j$$

Maximizing the expected score (*E(L))*, subject to coherence, i.e. $\sum_{i=1}^{N} p_i = 1$ we can write the following Lagrange optimization problem (note that λ is a Lagrange multiplier):

(2.25) $$E(L) + \lambda(1 - \sum_{i=1}^{N} p_i) = \sum_{i=1}^{N} r_i \ln p_i + \lambda(1 - \sum_{i=1}^{N} p_i)$$

Differentiating equation 2.25 with respect to p_i and setting the first order condition to zero gives us the following:

(2.26) $$\lambda \sum_{i=1}^{N} p_i = \sum_{i=1}^{N} r_i$$

Equation 2.26 implies that $\lambda = 1$ for $p_i = r_i$, which states that stated probability p_i equals to the true probability that assessor has in mind r_i. In other words, logarithmic scoring rule is a proper scoring rule.

<u>*Quadratic Scoring Rule*</u>

Quadratic scoring rule *Q(p,d)* is defined as:

(2.27) $$Q(p,d) = [1 - (p-d)(p-d)']$$

where $(p-d)$ is a row vector and $(p-d)'$ is column vector. In summation notation, it also can be defined as following:

(2.28) $$Q(p,d) = [1 - \sum_{i=1}^{N} (p_i - d_i)^2]$$

where $(i = 1, \cdots, N)$. If outcome E_j occurs for the *j*th event, i.e. $d_j = 1$,and $d_i = 0$ for all $i \neq j$. Then:

(2.29) $$Q_j(p,d) = (2p_j - \sum_{i=1}^{N} p_i^2)$$

Then the assessor's expected score is *E(Q)*, where:

(2.30) $$E(Q) = \sum_{j=1}^{N} r_j (2p_j - \sum_{i=1}^{N} p_i^2)$$

Maximizing the expected score (*E(Q)*), subject to coherence, i.e. $\sum_{i=1}^{N} p_i = 1$ we can write the following Lagrange optimization problem (note that λ is a Lagrange multiplier):

(2.31) $$E(Q) + \lambda(1 - \sum_{i=1}^{N} p_i) = \sum_{j=1}^{N} r_j (2p_j - \sum_{i=1}^{N} p_i^2) + \lambda(1 - \sum_{i=1}^{N} p_i)$$

Differentiating 2.31 with respect to p_j and solving the first order condition shows that $p_i = r_i$, hence quadratic scoring rule is a proper scoring rule. Murphy (1978) further generalizes the concept of the quadratic scoring rule and gives and account on a family of quadratic scoring rules. According to Murphy (1978), the general form of the quadratic probability score $GQ(p,d)$ is as follows:

(2.32) $$GQ(p,d) = [1 - (p-d)C(p-d)']$$

In above 2.32, C is a nxn symmetric and positive definite matrix of weights. $Q(p,d)$ is obtained from $GQ(p,d)$ when C is taken as an identity matrix.

The Brier score (or the probability score, *PS*), which is used extensively in this paper is a linear function of the quadratic scoring rule (Winkler and Murphy, 1968). In particular (*BS* stands for the Brier Score):

(2.33) $$BS = \frac{1}{N}[1 - Q(p,d)]$$

Spherical Scoring Rule

The spherical scoring rule *S(p,d)* is defined as:

(2.34) $$S(p,d) = \frac{dp'}{(pp')^{1/2}}$$

In equation 2.34, *d* is a row vector of dummy (0,1) variables and *p* is a row of probabilities issued. Note that prime denotes a column vector. Equation 2.34 can be expressed in summation notation as follows:

(2.35) $$S(p,d) = \frac{\sum_{i=1}^{N} p_i d_i}{(\sum_{i=1}^{N} p_i^2)^{1/2}}$$

Winkler and Murphy (1968) show that maximizing expected value of *S(p,d)* subject to coherence give rise to the condition where $r_i = p_i$, hence proving that spherical scoring rule is a proper scoring rule.

As explained above, proper scoring rules can be used to motivate people to provide good probability assessments (they also can be used to evaluate subjective or objective probabilities as explained in the section 2.2.4 below).

Bessler and Moore (1979) used scoring rules to assess probabilities of agricultural forecasts. They found that truncated logarithmic rule to be convenient to use and reasonably accurate. It was truncated to show the minimum probability at say, 0.01 and add a positive sum so that assessors maximize at positive wealth value when logarithmic scoring rule was used.

Nelson and Bessler (1989) showed the use of proper scoring rules as a motivational device using an experiment. In here, one group of subjects was rewarded under a proper scoring rule as a control and another group was rewarded under an improper rule as a treatment. Subsequently, results from two rules were compared. An interactive computer program was used to elicit subjects' with probability assessments of future events. After a probability forecast was entered into the computer, the actual outcome was revealed and each subject received a monetary reward which reflected the accuracy of his forecast according to the scoring rule being used.

Winkler (1994) motivated the idea of an asymmetric proper scoring rule, more specifically the *quadratic asymmetric proper scoring rule*. Specific rules encountered so far in the literature used a symmetric scoring rule, symmetric in the sense that the expected score for a perfectly-calibrated probability assessor (or model generated probabilities) is minimized at a probability of one-half (Winkler, 1994). Derivation of quadratic asymmetric scoring rules and their graphical exposition can be found in Winkler (1994).

Probability Forecast Evaluation: Theoretical Developments and Applications

On the one hand, we elaborated on the use of (proper) scoring rules in assessing probabilities and eliciting honest forecasts that correspond to forecaster's true beliefs (Murphy and Winkler, 1970). On the other hand, (proper) scoring rules can also be used as an evaluation device for probabilities issued either subjectively (like in weather forecasting work) or objectively (with the use of an econometric model). In the task of evaluation of probabilities, scoring rules need not necessarily be *proper* scoring rules

(Murphy and Winkler, 1970). The reason for preceding argument is that, evaluation is a posteriori task (*ex-post* task), which is a task that takes place in the presence of complete knowledge of the true state (Murphy and Winkler, 1970). However, Winkler (1969) has indicated that game theoretic problems may arise if the assessor is rewarded (or penalized) and evaluated with different scoring rules (Murphy and Winkler, 1970). These problems can be eliminated if the same scoring rule is used in both the assessment and the evaluation (Murphy and Winkler, 1970). In our study, since we are not interested in probability assessment, rather evaluation, we would not have such problems explained above. However, we are using a variant of the quadratic probability score (the Brier Score as shown in equation 2.16), which is a proper scoring rule.

In evaluating probabilities generated through an econometric model or expert knowledge of a person, the primary focus is on the *substantive "goodness"* of probabilities. Substantive goodness is the subject matter expertise that the assessor or the model has in generating probabilities (Winkler and Murphy, 1968 and Bessler, 2005) (On the other hand, *normative "goodness"* of probabilities refers to the ability of the model or person to issue probabilities which meet the coherence conditions of Kolmogorov or deFinetti (Bessler, 2005)).

According to Murphy and Winkler (1970), there were two viewpoints of probability evaluation. They are *inferential viewpoint* and *decision-theoretic viewpoint*. As far as the inferential viewpoint is concerned, the most important attribute of the probabilities is the *validity*. Validity is defined as the association between probability statements and the actual outcomes (Murphy and Winkler (1970). In other words, it is the association between *ex-ante* (before-the-fact) forecast probabilities and *ex-post* (after-the-fact) observed relative frequencies (Murphy and Winkler, 1984 and Winkler, 1996). On the other hand, from a decision-theoretic viewpoint, scoring rules may be related to a decision maker's utilities or expected utilities if the decision maker uses the assessed probabilities in an actual decision situation (Murphy and Winkler (1970). In our work we use a similar viewpoint parallel with inferential viewpoint (validity and other extensions to that as discussed below).

The Brier score (Brier, 1950), which is a variant of the quadratic probability score (equation 2.16 shows the Brier score is a linear function of the quadratic probability score) is the first known example of a strictly proper scoring rule (i.e. a scoring rule that discourages hedging on the part of the forecaster) (Murphy and Winkler (1984). Expanding equation 2.33 using the quadratic probability score formula will result is the following formula:

(2.36) $$BS = \frac{1}{N}\{1-[1-\sum_{i=1}^{N}(p_i - d_i)^2]\}$$

(2.37) $$BS = \frac{1}{N}\sum_{i=1}^{N}(p_i - d_i)^2$$

Equation 2.37 shows a simple form of the Brier score where only one side of the probability partition is taken into account. For example, if we consider a two sided event (two mutually exclusive and exhaustive events) such as purchase and non-purchase of a beverage, for which we issue probabilities and if we use only one side of the probabilities issued for the event (one out of two mutually exclusive and exhaustive events), say, purchase of a beverage, in evaluating probabilities, we opt to use formula 2.37. Brier (1950) gives a more general formula for evaluating probabilities generated through a r sided event (i.e. r mutually exclusive and exhaustive events).Brier (1950) calls it a *verification formula*. Borrowing from Brier's (1950) original notation, suppose that each of *n* occasions an event can occur in only one of r possible classes or categories and on one such occasion, i ,the forecast probabilities are $f_{i1}, f_{i2}, \cdots, f_{ir}$, that the event will occur in classes $1,2,\cdots,r$, respectively. The r classes are chosen to be mutually exclusive and exhaustive so that $\sum_{j=1}^{r} f_{ij} = 1$ for $i = 1,2,3,\cdots,n$. Then the *verification score* (mean probability score *(PS)* or Brier score *(BS)* are used interchangeably for verification score) can be depicted as follows:

(2.38) $$BS = \frac{1}{n}\sum_{j=1}^{r}\sum_{i=1}^{n}(f_{ij} - E_{ij})^2$$

In the equation 2.38, E_{ij} takes the value *1* or *0* depending on the event occurred in class j or not. The Brier score has a minimum value of zero for perfect forecasting, i.e. issue probability 1 (100%) for event that occurred after the fact and issue probability zero (0%) for event that did not occur after the fact. The upper limit for the Brier score is equal to the number of mutually exclusive and exhaustive events (r) that is taken into consideration. For example, for $r = 2$ situation such as a purchase decision (purchase and did not purchase), the upper limit of the Brier score is 2, i.e. $0 \le BS \le 2$. Furthermore, for $r = 3$ situation such as a quality index (low quality, medium quality and high quality), the upper limit of the Brier score is 3, i.e. $0 \le BS \le 3$. It is worth stating that, when there are only two mutually exclusive and exhaustive events ($r = 2$) (two sided event), such as a purchase decision above, the upper limit of the Brier Score calculated is as twice as much as high, compared to the Brier Score when only one side of that event is considered. Brier (1950 has an example showing above scenario using weather forecasting (rain forecasting). In our study dealing with beverage purchase decisions, we have two mutually exclusive and exhaustive events (purchase or not-to-purchase). In evaluating probabilities generated from qualitative choice models on beverage purchase decisions, we use only one side of the event, hence the upper limit of the Brier Score for our study is 1, i.e. $0 \leq BS \leq 1$.

Brier (1950) further stated the importance of measuring the degree of relationship between stated (forecast) probabilities and the relative frequency of the event's occurrence. Moreover, he also emphasized the importance of correlation between the forecast and observed probabilities, even though he did not offer a formal description of it.

Sanders (1963) showed through experiments done in their synoptic laboratory at Massachusetts Institute of Technology (MIT), that the use of the Brier score has been found completely satisfactory as a method of evaluating probabilities. He further stated that, there are two important evaluation attributes embedded in the Brier score. They are *validity*, which measures relationship between the probabilities issued and realized relative frequencies and *sharpness*, which measures the nearness to certainty. With the evolution of literature in this area, it is important to note that the term *calibration* and *resolution* was used to express the concept of *validity* and *sharpness* respectively.

Sanders (1963) depicted that mean probability score (the Brier score) can be partitioned into *reliability* and *resolution* as follows:

(2.39) $$BS = \frac{1}{M}\sum_{f=1}^{F} M_f (p^f - \bar{d}^f)^2 + \frac{1}{M}\sum_{f=1}^{F} M_f \bar{d}^f (1 - \bar{d}^f)$$

where $\bar{d}^f = \frac{1}{M_f}\sum_{m=1}^{M} d_m$

In equation 2.39, p is the probability issued and d is the associated outcome index variable (also elaborated in Murphy and Epstein, 1967). Sanders (1963) then considers that the probability p_m, where $(m = 1, \cdots, M)$ assumes only F distinct values. Thus, the collection of M predictions is divided into F sub-collections, where, M_f is the number of predictions in the collection for which $p_m = p^f$ (Murphy and Epstein, 1967). First and second term of the right hand side of equation 2.39 measures reliability and resolution, respectively. According to Murphy and Epstein, (1967), reliability component is also named "*bias in-the-small*".

Epstein and Murphy (1965) translated the *validity* and *sharpness* attributes of probabilities embedded in the Brier score into a geometrical framework of probabilities earlier developed by deFinetti (1962). They showed that the Brier score and deFinetti's score based on probability triangles are essentially equivalent.

Berlsford and Jones (1967) used a logit model to generate minimum temperature forecasts and the Brier score to evaluate forecast probabilities generated. It is important to note that the Brier score is essentially the mean squared error of forecasts. They found that logit model generated probability forecasts gave out low mean squared errors compared other models used in their study. They did not decompose the mean squared error into *validity* and *sharpness* measures.

Murphy and Epstein (1967) talked about the evaluation of probabilistic predictions using the Brier score and reliability and resolution (partitioned probability score or Brier score by Sanders (1963)). More specifically, the verification process concerned with perfection of predictions, i.e. the association between predictions and observations (later termed *calibration* in our work) is studied using an artificially constructed example in meteorology.

Even though the probability score developed by Brier (Brier, 1950) is very suitable in evaluating probabilities, it cannot be used to evaluate probability forecasts of ordered variables, such as say, predictions on four temperature classes: $T \leq 0F$, $0F < T \leq 20F$, $20F < T \leq 40F$, $,T > 40F$. If two forecasts were *(0.1,0.3,0.5,0.1)* and *(0.5,0.3,0.1,0.1)* and the last category, $,T > 40F$, were observed, Brier score assigns same score for both forecasts (Epstein, 1969). However, according to Epstein, (1969), most would agree that the former was a somewhat better forecast. Furthermore, this conclusion was based on the fact that temperature categories 3 and 4 are closer to one another than that of 1 and 4. This is the notion of *distance* Epstein (1969) used to generate a new version of the Brier score called Ranked Probability Score (RPS). Please refer to Epstein (1969) and Murphy (1970) for further derivations of the ranked probability score. Murphy (1969), further showed that ranked probability score is also a proper scoring rule.

Murphy (1972a), built up on Sanders (1963) work on reliability and resolution partition of the Brier score. More specifically, Sanders (1963) partition was considered to be a *scalar* quantity, i.e. in which each probability is considered to be a separate forecast (Sanders, 1963, p.192)[11] and Murphy (1972a). However, Murphy (1972a) says that in reality, a probability forecast may consist of a set of two or more probabilities. Therefore, a need is highlighted by Murphy (1972a) to work on a vector partition of the Brier score to accommodate multiple probability events. Murphy (1972a) discussed only a two-state situation and is expanded into an *N*-state situation in another paper (Murphy, 1972b).

Following account on scalar and vector partitions of probability score for two-state and *N*-state situations are borrowed from Murphy (1972a) and Murphy (1972b). Let the probability score for a collection of *M* scalar forecasts p_m is *PS(p,d)*:

(2.40) $$PS(p,d) = \frac{1}{M}\sum_{m=1}^{M}(p_m - d_m)^2$$

where $(m = 1,....,M)$.

For a subset of M^s probability forecasts for which $p_m = p^s$, the PS is $PS^s(p,d)$:

(2.41) $$PS^s(p,d) = \frac{1}{M^s}\sum_{m=1}^{M^s}(p^s - d_m^s)^2$$

[11] Borrowing from Murphy (1972), Sanders (1963), states that “we have chosen to consider each individual probability statement as a separate forecast.” However, in two-state, i.e. precipitation and no-precipitation, situations, Sanders (1963) actually considers only the probabilities assigned to one of the two states.

Partitioning 2.41 into reliability and resolution, and given that, $\bar{d}^{s} = \frac{1}{M_s}\sum_{m=1}^{M^s} d_m^s$ we get the following decomposition of the probability score into reliability and resolution:

(2.42) $$PS(p,d) = \frac{1}{M}\sum_{s=1}^{S} M^s (p^s - d^s)^2 + \frac{1}{M}\sum_{s=1}^{S} M^s \bar{d}^s (1-\bar{d}^s)$$

Equation 2.42 depicts the scalar partition of the probability score for a two-state situation. The first term in the right hand side of 2.25 is the reliability (or bias-in-small) and the second term reflects the resolution.

Similarly, the probability score for a collection of *K* (=*M/2*), (we have a two state situation), vector forecasts $p_k = (p_{1k,} p_{2k})$ where $(k = 1,......, K)$ is *PS(**p**,**d**)* where:

(2.43) $$PS(p,d) = \frac{1}{K}\sum_{k=1}^{K}\sum_{n=1}^{2}(p_{nk} - d_{nk})^2$$

In vector notation, we have the following:

(2.44) $$PS(p,d) = \frac{1}{K}\sum_{k=1}^{K}(p_k - d_k)(p_k - d_k)'$$

where a prime denotes a column vector.

For a subset of K^t forecasts for which $p_k = p^t$ the probability score would be:

(2.45) $$PS^t(p,d) = \frac{1}{K^t}\sum_{k=1}^{K^t}(p^t - d_k^t)(p^t - d_k^t)'$$

Partitioning 2.45 into reliability and resolution gives us the following:

(2.46) $$PS(p,d) = \frac{1}{K}\sum_{t=1}^{T} K^t (p^t - \bar{d}^t)(p^t - \bar{d}^t)' + \frac{1}{K}\sum K^t \bar{d}^t (u - \bar{d}^t)'$$

Equation 2.46 above shows the vector partition of the probability score. The first term on the right hand side is the reliability and the second term represents the resolution attribute.

Murphy (1972a) and Murphy (1972b) further find that reliability of the forecasts according to scalar partition is, in general greater than their reliability according to vector partition. Additionally, the resolution of the forecasts according to scalar partition is, in general lesser than their resolution according to vector partition.

The *N*-state situation is an extension of 2-state situation and details were elaborated in Murphy (1972b).

Building on work on Sanders (1963), Murphy (1972a) and Murphy (1972b), on partitions of the Brier score, Murphy (1973) developed a new vector partition of the probability score. As reported in Murphy (1973) page 596, the new vector partition of the probability score can be written as follows (note that we have done some changes to notation so that it is consistent with the notation in this dissertation):

(2.47) $$PS(p,d) = PS(\bar{d},d) + \frac{1}{K}\sum_{t=1}^{T} K^t (p^t - \bar{d}^t)(p^t - \bar{d}^t)' - \frac{1}{K}\sum_{t=1}^{T} K^t (\bar{d}^t - \bar{d})(\bar{d}^t - \bar{d})'$$

According to Murphy (1973), the first term of the right hand side of equation 2.47 represents the probability score that would be obtained if each forecast $p_k\,(k = 1,....,K)$ were replaced by the sample relative frequencies for the collection of K forecasts, $\bar{d}$. This term measures *uncertainty* inherent in the events. Second term of the equation 2.47 is identical to the first term in the equation 2.46 and it represents the *reliability* of the collection of K forecasts. The smaller this term, the grater the reliability and the smaller the probability score. The third term on the right hand side of equation 2.47 does not exactly match with the second term of the equation 2.46 which represents the *resolution* attribute. However, in the absence of proper terminology, Murphy (1973) used the same attribute name as second term of equation 2.46.

Murphy and Winkler (1977) used reliability diagrams (see Murphy and Winkler (1977) page 42-43) and the Brier score to evaluate subjective probability forecasts of precipitation and temperature in the United States. Reliability is same as calibration, i.e. measures the degree of correspondence between forecast probabilities and observed relative frequencies. In a reliability diagram (or a calibration chart), we have forecast probabilities on the horizontal axis and realized relative frequencies on the vertical axis (this will be elaborated later in this dissertation). The 45 degree line that goes through the origin in the positive quadrant represents the perfect reliability (calibration) line. Murphy and Winkler (1977) concluded that, weather forecasters can quantify the uncertainty inherent in their forecasts using reliability diagrams.

Yates (1982) developed a new decomposition for the mean probability score (the Brier score). First, he gave a good review of the development of various decompositions of probability score, such as Sanders (1963), Murphy (1972a), Murphy (1972b) and Murphy (1973). The major focus of these earlier papers was to explain the concept of reliability (calibration) and sharpness (resolution) attributes of probabilities and most of them were tested or analyzed using data from meteorological science. In contrast to earlier decompositions, Yates (1982) developed a *covariance decomposition* of the Brier score. The most basic form of the covariance decomposition of the mean probability score $(\overline{PS})$ (the Brier score) is given as follows (Yates, 1982):

(2.48) $$\overline{PS}(f,d) = S_f^2 + S_d^2 + (\bar{f} - \bar{d})^2 - 2S_{fd}$$

where S_f^2 and S_d^2 are the variances of the forecast probability and outcome index, respectively. Covariance between the forecast probability and outcome index is S_{fd} .The overall mean probability forecast and mean outcome index is $\bar{f}$ and $\bar{d}$ respectively. Yates (1982) further stated that, equation 2.48 is a well-known method of expressing a mean squared difference of two variables (recall that the Brier score is a mean squared difference between two variables, i.e. forecast probability and outcome index).

Yates, (1982) explained a more transparent and useful form of equation 2.48 as follows:

(2.49) $$\overline{PS}(f,d) = \bar{d}(1-\bar{d}) + \Delta S_f^2 + S_{f,\min}^2 + (\bar{f} - \bar{d})^2 - 2S_{fd}$$

where variance of the outcome index is $S_d^2 = \bar{d}(1-\bar{d})$, and variance of forecast probability is $S_f^2 = \Delta S_f^2 - S_{f,\min}^2$, where $S_{f,\min}^2 = (\bar{f}_1 - \bar{f}_0)\bar{d}(1-\bar{d})$. In equation 2.49 above, $\bar{f}_1$ and $\bar{f}_0$ are, respectively, mean forecast probabilities of events that actually occurred and events that actually did not occur. Yates (1982), page 141, figure 2 provides an excellent diagram connecting the relationships between Sanders, Murphy and covariance decomposition of the mean probability score. Yates (1982) explained the concept of a covariance graph that shows the bias, mean and distribution of forecast probabilities of events that actually occurred and what actually did not occur. Yates

(1988) extended the covariance decomposition of the mean probability score into multiple events. He brought in illustrations from medical diagnosis and grade projections by university instructors to show the multiple event probabilities issued and their associated mean probability scores. More elaborative description about the Yates decomposition of mean probability score is given in the Chapter V.

Drawing illustrations from professional oddsmaker's predictions of baseball game outcomes, meteorologist's precipitation forecasts and physician's diagnosis of pneumonia, Yates and Curley (1985) demonstrated the ability of covariance decomposition of mean probability score to highlight important attributes of probability forecasts. They further developed covariance graphs i.e. forecast probabilities are on *y*-axis and outcome index on *x*-axis for each case above to show the importance of resolution attribute of forecast probabilities.

Seidenfeld (1985) gave a detailed account on calibration and quadratic scoring rules as a method to successfully evaluate forecast probabilities. He explained the calibration curve with special emphasis on underconfident, well calibrated, overconfident and mixed confident cases.

Blattenberger and Lad (1985) developed a graphical representation of the calibration, resolution (they called it refinement) and the Brier score in a three dimensional picture to show their relative importance. They used the Murphy decomposition of the mean probability score to extract calibration and resolution components.

Murphy (1986) introduced a new decomposition of the Brier score, which was based on conditional distributions of forecast probabilities given observed events. This new decomposition consists of a term involving the variances of the conditional distributions and another term related to the mean errors of forecasts, which involves the squared differences between the means of the conditional distributions and the respective mean observations (latter are necessarily zero or one) (Murphy, 1986). The algebraic representation of the new decomposition is as follows:

(2.50) $$BS = 2[\bar{d}_1 Var(f_1) + \bar{d}_0 Var(f_0)] + 2[\bar{d}_1(\bar{f}_1 - 1)^2 + \bar{d}_0(\bar{f}_0 - 0)^2]$$

where f_1 and f_0 are conditional distributions, where the former is associated with forecast probabilities of events that occurred and latter is associated with forecast probabilities that did not occur. Refer to Murphy (1986) page 2672 for a detailed derivation of equation 2.50.

In two-event situations (such as purchase or non-purchase of a non-alcoholic beverage), calibration curve (or the reliability diagram) provides a good geometrical framework for evaluating calibration attribute of probability forecasts. However, Hsu and Murphy (1986) developed an *attributes diagram* in which the accuracy, resolution, skill as well as the reliability all can be pictured in one diagram. The interpretation and use of the *attributes diagram* is illustrated by bringing in samples of probabilistic quantitative precipitation forecasts.

Kling and Bessler (1989) estimated and evaluated probability distributions on future observations of time-series for interest rates, money, prices and output for U.S. They further demonstrated and applied sequential method for recalibrating (or debiasing) predictive distributions based on previously issued distributions and outcomes. Next, recalibrated distributions were tested for calibration. Results from the analysis indicated that calibration hypothesis[12] cannot be rejected for most of the time-series and forecast horizons when the recalibration procedure is applied. They further find that, traditional point forecasts can be improved (in a mean-square error sense) when forecasts are derived from recalibrated distributions. Authors conclude that, almost 80% of the cases that they investigated, recalibration resulted in lower root mean-squared errors.

Zellner, Hong and Min (1991) used two variants of an autoregressive leading indicator (ARLI) models to forecast turning-points in growth rates of 18 countries' annual real income for the years 1974-1986. Probabilities of "upturns" and "downturns" (turning points) of the different economies' were calculated using Bayesian predictive densities. Various versions of ARLI models were estimated in a pooling and a non-pooling environment and optimal turning point forecasts were obtained. They also used the Brier score to evaluate the above probability forecasts (lower the Brier score, the better the forecast of turning points as upturns and downturns).

Taking a different perspective to probability forecast evaluation, Murphy (1995) explained the application of coefficient of correlation and determination as measures of forecast evaluation. Furthermore, decompositions of familiar quadratic measures of accuracy are used to explore differences between these quadratic measures and coefficient of correlation and coefficient of determination.

[12] Calibration hypothesis states that a model is well calibrated if, for an issued probability of *f* for an event before the event occurs, the realized relative frequency after the fact is also *f*.

Arkes et al., (1995) used the Brier score and its covariance decomposition to evaluate prognostic estimates. This is the first attempt of the use of mean probability score and its covariance decomposition to evaluate medical judgment. Prognostic estimates of physicians, their patients and the patients' decision making surrogates were analyzed using above techniques. Major decompositions such as bias, slope and scatter were displayed on covariance graphs for each of above groups. Results show that, physicians have the best overall estimation performance and their bias and scatter are not always superior to those of other two groups.

Kramer (1997) developed a theoretical structure to evaluate credit scores, which is based on the Brier score. No empirical work is reported here.

Covey (1999) used the Brier score and the Yates decomposition of the Brier score to evaluate bankers' probability forecasts related to three possible future trends in farmland values which was obtained from a quarterly survey of the Midwestern agricultural bankers conducted in by the Federal Reserve Bank of Chicago. The results suggest that bankers generate better probability forecasts of quarterly trends in the value of good farmland values than obtained from a naïve or equally likely outcome uniform model (Covey, 1999). Bankers had a high resolution power, meaning they could discriminate information regarding the occurrence and nonoccurrence of the three possible trends.

Hora (2004) explained a new method to measure calibration attribute of probability forecasts. Traditionally, one method for measuring calibration for continuous quantities is to count the number of times value fall into intervals having specified probabilities (for example, counting the number of times values fall into each of the percentiles, say, four quartiles). However, according to Hora (2004), preceding approach did not fully utilize the information available, because the calibration within the quartile was not measured. Moreover, Hora (2004) further stated that, unless assessments were constrained to have specified probability intervals, there would be too many intervals of different probabilities to make meaningful judgments about calibration.

Bessler and Ruffley (2004) used the Brier score and a covariance partition of it due to Yates (1982) to study the probabilistic forecasts of a vector autoregression on stock market returns. Calibration measures and the Brier score and its partition were used for model assessment. The partitions indicated that the ordinary least square version of the model did not forecast stock market returns well. Furthermore, model was well calibrated; however, it showed little ability to sort the events that occur into groups from events that do not occur (poor resolution power). Yates partition of the Brier score picked up on the resolution concept; however, calibration matrices did not.

Lahiri and Wang (2005) examined the value of probability forecasts of real gross domestic product of United States, using calibration, resolution, the relative operating characteristics (ROC charts) and alternative variance decompositions. They find that, even though quadratic probability score and calibration tests suggests the forecasts of all five regions to be useful, the other approaches clearly indicated the long-term forecasts having no skill relatively to a naïve baseline forecast.

Casillas-Olvera and Bessler (2006) studied probability forecasts of inflation and gross domestic product by monetary authorities using the Brier score and Yates-partition of the Brier score. The Brier score and Yates-partition values were calculated for monetary policy committee and other forecast category for macroeconomic variables such as inflation and gross domestic product. A graphical approach illustrating each forecaster's ability to discriminate between events that occur and events that do not occur was also presented here.

It is worth to note that King and Bessler (1989), Zellner et al. (1991), Bessler and Ruffley (2004) and Casillas-Olvera and Bessler (2006) were the only studies so far that have used optimal scoring rules (such as Brier score and Yates-partition of the Brier score) to evaluate probability forecasts from econometric models. This dissertation is the first such attempt to evaluate probability forecasts developed from qualitative choice models (probit and logit) using optimal scoring rules such as the Brier score and the Yates-partition of the Brier score for non-alcoholic beverages.

Nutrition Study

In this section, we initially discuss daily nutritional needs of individuals, and we review past studies conducted dealing with nutritional contributions of non-alcoholic beverages to the U.S. diet.

Dietary Role of Non-alcoholic Beverages

Daily intake of calories, calcium and vitamin C can vary with gender, age and nutritional need of an individual. For example, active 2 to 3 year olds may require up to 1400 kilocalories per day regardless of their gender. An active male who is in the age category of 31-50 may require up to 3000 kilocalories per day. On average, calorie requirements are relatively lower for active females than active males by about 500 kilocalories per day. However, pregnant and lactating mothers need extra calories to sustain their special status (Center for Nutrition Policy Promotion, 2005). However, on average, a normal healthy adult who does not have a special body condition requires about 2000 kilocalories per day.

Daily calcium requirement grows with the age. On average a healthy adult needs about 1000mg (one gram) of calcium per day (U.S. Department of Health and Human Services, 2004). Vitamin C also is a vital nutrient that is necessary in the daily diet. On average, an adult should get about 155mg of vitamin C per day to maintain a healthy body (Center for Nutrition Policy Promotion, 2005).

Unlike calcium and vitamin C, caffeine is an ingredient that should be consumed in moderation. According to the Surgeon General, excessive consumption of caffeine may interfere with calcium absorption (U.S. Department of Health and Human Services, 2004). Excess amounts of caffeine also may have deleterious effects on pregnancies, leading to miscarriages and impairment in the development of the fetal nervous system.

Past Studies and Government Policy Actions

We now turn attention to past studies done on contributions of non-alcoholic beverages to the U.S diet and related government policy actions.

Harnack et al., (1999) studied nutritional consequences of soft drink consumption among U.S. children and adolescents. This study was limited to U.S. children aged 2 to 18 years during calendar years 1994 and 1995. The source of data for this analysis was the USDA Continuing Surveys of Food Intakes by Individuals (CSFII). Caloric intake was found to be positively related to soft drink consumption, while milk and fruit juice consumption was negatively associated with soft drink consumption.

According to Gortmaker et al. (1993), adolescent and young adulthood obesity/overweight problems not only contributed to health-related risks but also these problems have a deleterious effect on self-esteem and on educational attainment. They also found that adolescents were more likely to consume soft drinks than preschool- and school-aged children. White children consumed more soft drinks than black children, and boys consumed more soft drinks than girls. It was recommended that “dietetic professionals should inquire about soft drinks consumption when counseling children and ask parents to limit the amount of soft drinks brought into homes.

Gartner and Greer (2003) centered attention on the decline in milk consumption in America and the associated vitamin D deficiency among children.

French et al. (2003) investigated the trends between 1977/78 and 1994/95 in the prevalence, amounts and sources of soft drink consumption among U.S. children and adolescents (6 to 17 years of age) using data from three national surveys. They found that the prevalence of the soft drink consumption increased by 48% over this time period. Mean intake of soft drinks more than doubled from 5 fl oz to 12 fl oz per day. Further, French et al, (2003) found that larger proportions of soft drinks were consumed at home compared to vending machines, restaurants and school cafeteria.

Ahuja and Perloff (2001) examined the caffeine intake of U.S. children 9 years and under using data from USDA Continuing Survey of Food Intake by Individuals (CSFII) for the period 1994-96 and 1998. According to them, most widely consumed caffeine rich foods were coffee, tea, carbonated soft drinks and chocolate. It was found that more children actually obtained caffeine from consuming chocolate than from consuming carbonated soft drinks; 44% of children consumed chocolate in comparison to 20% who drank carbonated beverages containing caffeine. Furthermore, it was found that white children consumed more caffeine than the black children.

Chanmugam et al. (2003) studied fat and energy (calories) intake by U.S. households during the period 1989-1991 and 1994-1996 using CSFII data. They found that one of most important changes was the drop in whole milk consumption and an increase in the consumption of reduced-fat milk and carbonated soft drinks. Furthermore, they found that the higher caloric intake was due to excessive consumption of carbonated soft drinks. This research reinforced the findings of a similar study by Guthrie and Morton (2000). The latter was done to identify food sources of added sweeteners in the U.S. diet. Guthrie and Morton (2000) used 1994-1996 CSFII data in their investigation. They found that during the period 1994-1996 Americans aged 2 years and older obtained 16% of their total caloric intake from consumption of added sweeteners. One third of this intake came from consumption of regular soft drinks. Furthermore, Guthrie and Morton (2000) found that the percent contribution to added sweeteners intake from the consumption of soft drinks increased throughout the childhood and adolescence and peaked during the ages from 18 to 34 years for both men and women. The intake subsequently decreased steadily for older adults.

Capps et al. (2005) was the most comprehensive study done investigating the nutritional contribution of non-alcoholic beverages to the U.S. diet. The focus of their research was the nutrient availability from non-alcoholic beverages purchased for at-home consumption. Previous studies used data from the CSFII focusing on food and beverage intake based on individual recall over the two nonconsecutive days (within a 3-week period). Capps et al. (2005) used a scanner data set with demographics, namely the 1999 Nielsen Homescan scanner data panel. The focus was on household purchases over an entire year recorded by at-home scanning technology provided by Nielsen. The Homescan scanner panel offered a potentially richer and more recent database for their study than the CSFII. According their findings, daily calorie intake derived from non-alcoholic beverages was mainly determined by employment status and education level attained by the household head as well as race, region and presence of children. Available calcium and vitamin C intake derived from non-alcoholic beverages was lower for poverty households compared to non-poverty households. Caffeine availability derived from non-alcoholic beverages was lower for Blacks, Orientals (Asians) and other races compared to Whites. Using the daily values of the Nutrition Facts portion of the food label as a reference, this study found that for calendar year 1999, non-alcoholic beverages purchased for at-home consumption provided 10% of daily value for calories, 20% of the daily value for calcium, and 70% of daily value for vitamin C, on per-person basis.

The aforementioned research by Capps et al., (2005) used scanner data with demographics attached for calendar year 1999 only. In this study, we use similar scanner data but for six calendar years: 1998, 1999, 2000, 2001, 2002 and 2003. With these data, we are able to consider patterns in nutrient intake derived from non-alcoholic beverage consumption over several years. In addition we are in a position to talk about the effectiveness of USDA dietary guidelines[13] on beverage consumption set forth in year 2000.

Concluding Remarks

In preceding paragraphs, we carried out an extensive discussion on literature review in three main topic areas studied in this dissertation. First, we reviewed past studies in the area of factors affecting demand for non-alcoholic beverages in the U.S. Factors considered were demographic factors, income, price, habits and/or inventory behavior etc.

Let us first look into various type of data and data sources used in past studies. There were two major sources of data; data from government sources and data from private sources. Most of earlier work on consumer demand was done using highly aggregated time-indexed data (time-series data) on various variables. These time-series (or macro level data) mainly came from U.S. government sources like, Unites States Department of Agriculture/ Economic Research Service (USDA\ERS), Unites States Department of Commerce/Bureau of Economic Analysis, Federal Reserve Banks, New York Department of Agriculture, Florida Department of Agriculture, U.S. Bureau of Labor Statistics, etc. Most of data came from above government sources had price and quantity consumption (disappearance data) information on variety of goods. United States government cross-sectional data mainly came from USDA/ERS Continuing

[13] USDA published dietary guidelines for Americans with special emphasis on the consumption of carbonated soft drinks in year 2000. In year 2005, the dietary guidelines placed more emphasis on milk consumption.

Survey of Food Intake by Individuals (CSFII) that was carried out in several years. On top of total expenditure and quantity data, these data sets were rich in demographic information.

Most of private data came from (still continue to come) Nielsen Point-of-sale and Nielsen HomeScan scanner panels, Information Resources, Inc. (IRI) and Beverage Marketing Corporation (BMC). Household level data are very diverse and not aggregated. Nielsen Point-of-sale data are obtained from scanner machines located within stores. Nielsen HomeScan scanner data are obtained from scanner devises that a representative consumer have at home. He/she had to rescan what they purchase. They also provide demographic information time-to-time. In particular, non-alcoholic beverages in this literature review were based on macro level annual, quarterly, monthly, weekly time-series data or cross-sectional data including demographic information. Not all studies included demographic information.

The most widely studied beverage category was fluid milk. Many models concentrated in estimating demand for milk (as a single generic category) and other milk base products like cheese. Some studies disaggregated milk into whole milk, low fat milk and non fat milk/skim milk. There were couple of studies exclusively looked at impact of generic milk advertising on milk demand. Other non-alcoholic beverages considered included carbonated soft drinks (sodas), fruit juices and drinks, coffee, tea and bottled water. None included diet soft drinks, isotonics (sports drinks) and energy drinks. Moreover, breakdowns of other items such as regular and decaffeinated coffee and regular and decaffeinated tea, orange juice, citrus juice, apple juice, could be added into the list. Data availability and objectives of individual research focus must have been the reason as to why some beverages were included (or excluded) for analyses.

Typically, a select number of demographics were placed into the models, again depending on the interest, data availability and focus of research. The most common factors that we could find in literature were age of population/household, race (black, white etc), gender, education level, region (South, West, Midwest, East), percentage of food intake away-from-home, and different age categories in the population. Most of those demographic categories were not found in one study.

Different kinds of econometric approaches were used to model demand for beverages. Some studies used single equation approach in modeling demand for different beverage categories, while others used a systemwide approach using a variety of model specifications available in the literature. Many of those studies which emphasize on systemwide approach use a seemingly unrelated regression (SUR) approach due to many of desirable properties of such a method. First, use of a demand system allows imposition of theoretical restrictions from demand theory directly onto the system. Therefore, on top homogeneity restriction (could be included in single equation setting too), we could impose symmetry, and adding-up taking cross equation relationships into account. This could increase the efficiency of estimation. Second, the information get stored in variance-covariance matrix generated from a system of equations is richer than the one we get from a single equation model. From the former, one could obtain the information about contemporaneously correlated error terms from across the equations, which could be used to increase the efficiency of estimates. Other than econometric gains, from a policy standpoint, a systemwide analysis is preferred, because it allows a discussion of cross commodity interrelationships, that one could have gotten from a single good equation model. Iterative seemingly unrelated regression (ITSUR), full information maximum likelihood (FIML) were some of estimation techniques used in those systemwide modeling.

On top of many positive gains of using a cross-sectional data set, the downside is, more often than not, one could find a nonparticipating household or an individual in purchasing/using some good. That creates “zero observation problem” or popularly known as censoring problem. These censored data points are information; therefore, one cannot throw them away for the purpose of estimation or a bias in estimates could be created. Past literature have handled this problem using a two-step budgeting procedure such as Heckman sample selection procedure to circumvent such zero observation problem.

These studies used several of commonly accepted demand models (systems) in their analysis. The Linear Expenditure System (LES) of (Stone, 1954), Quadratic Expenditure System (QES), Rotterdam model of (Theil, 1965) and Barten (1964), Translog demand system of (Christensen, Jorgenson, and Lau, 1975), Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980), Linear Approximated Almost Ideal Demand System of (LA/AIDS) of Deaton and Muellbauer (1980), Synthetic demand model of Barten (1993) were the most widely used models of the literature.

Most of studies in the literature were based on classical demand theory and, as a result, only price and income determinants were included. However, some others were based on more generalized theories of demand (such as household production theory) and therefore, included other variables such as advertising, health and other factors in addition to price and income (Bryant and Davis, 2003).

Bryant and Davis (2003) looked into the magnitude of impact on the estimates in the demand systems when one of the following is changed: (i) functional form; (ii) local set of coordinates used in elasticity calculation; (iii) presence of alternative (non-economic) variables. Their study included four functional forms, thus, the Rotterdam model, the first-differenced AIDS model, the Central Bureau of Statistics model (CBS), and the National Bureau of Research model (NBR). Non-economic variables included advertising; health information; woman's labor force participation; and four possible combinations of theoretical restrictions. They estimated 576 possible combinations of demand systems and following conclusions were drawn. More important aspects that influenced the variation of elasticity estimates were local set of coordinates where the elasticities were evaluated and theoretical restrictions imposed; less important aspects that could influence the elasticity estimates were functional form and presence of non-economic variables.

Nutritional studies concerning non-alcoholic beverage consumption were mainly concentrating on selected beverages, namely, carbonated soft drinks (sodas), milk (different fat contents), fruit drinks (fruit ades) and fruit juices. Most looked at very specific age or income groups. For example, consumption of milk and sodas by children was the theme for many works done in the past. Therefore, it may be of use to summarize nutritional intakes for a household while looking across the entire bandwidth of non-alcoholic beverages. Capps et al., (2005) provided a comprehensive study dealing with the nutritional contribution of non-alcoholic beverages, carried out using 1999 Nielsen HomeScan scanner data. Past literature, emphasized that fact that it is not a healthy choice for children to consume a lot of carbonated soft drinks, but low or non-fat milk to combat the growing childhood obesity problem.

Available literature in the area of influence of habit formation and inventory behavior in consumer demand analysis was very rich and diverse. Much of the works were done on habit formation and related aspects and a little on the area of inventory behavior of consumer. Developing from work done by Koyck (1954) on distributed lags, habits were modeled into demand functions/systems through a lagged dependent (quantity consumed) variable, where past consumption behavior influenced the current consumption expenditure/behavior. This type of modeling gave researcher the latitude to investigate habit forming behavior in consumer demand and also it made the demand function/system dynamic. With such introduction, researchers were able to derive short-run and long-run consumer responses (elasticities) in their demand modeling. Such dynamic models incorporating habits were done augmenting following familiar models: AIDS, Translog, LES, QES, Log-log models, and more flexible Box-Cox transformation models.

Houthakker and Taylor (1970) had a novel approach where they modeled habit persistence and inventory behavior using a stock adjustment equation. It contained the information about current consumption and rate of depreciation of stock at hand in determining demand for a good. Sexauer (1977) made above Houthakker and Taylor (1970) model richer bringing in the influence of time deciding if the good under consideration was a durable good or not (nondurable). Durability/non-durability is decided depending on the way a good could release services to the consumer once purchased.

Most of habit forming/inventory behavior studies concentrated only about the effect of past consumption behavior on current consumption patterns/behavior. However, habit forming is not that all. Consumers' current consumption also substantially affects their future consumption/behavior. Therefore, some researchers in the past incorporated both sides of the story of habit formation (looking forward and backward), and developed intertemporal dynamic models using dynamic optimization/calculus of variation methods.

Literature on probability forecasting and more importantly, forecast evaluation goes back to most of the work done in the area of weather forecasting literature. It is evident if one looks at the evolution of such work (most of probability forecasting and evaluation work has been published in *Monthly Weather Review* and *Journal of Applied Meteorology*). However, later it branched out into applied economics and applied econometrics works since economists started to use such probability forecasting and evaluation work. Since this dissertation centers attention to probability forecast evaluation, we discussed past literature in the area of methodology development in forecast evaluation.

Calibration is one of the methods that have been very widely used to evaluate probability forecasts. It measures the relationship between the ex ante issued probabilities for an event to occur and ex-post realized relative frequency. If one is perfectly calibrated, above two values must be same. Literature has evolved to measure the discrepancy between above two measures of probability. Probability calibration graph is one visual measure that researchers have uses extensively. The other method to measure calibration is to use a goodness of fit statistic that is distributed *chi-squared* with J-1 degrees of freedom, where J is the nonoverlapping subintervals that exhaust the unit interval (more on this will be discussed in the Methodology section of this dissertation).

Resolution is another method that researchers have used to evaluate probabilities. This deals with proper sorting of realized probabilities looking at the events that occurred and did not occur. Ideally probability evaluator would like to see high probabilities associated with events that did occur and low probabilities associated with events that did not occur, which is perfect sorting. This also can be explained if one regress realized probability on a zero-one dummy and record the intercept and slope coefficient. We would like to have intercept coefficient statistically not different from zero and slope coefficient statistically not different from one.

Proper scoring rule is a condition that is required to issue *"honest"* probabilities and not a condition required to evaluate probabilities. Probabilities are said to be honest if a forecaster issues probabilities for an event that is in agreement with what he truly thinks it is, those probabilities are said to be honest. However, the Brier score (Brier,

1950) is a proper scoring rule researchers have used to evaluate probabilities. Various decompositions to the Brier score have been offered in the literature (see Sanders (1963), Murphy (1972a) and (1972b), and Yates (1982)). Attempts were done to decompose the Brier score into various components for better understanding of realized probabilities. Yate's partition of Brier score into its variance, minimum variance, scatter, bias and covariance is used in this dissertation.

Distinct Contributions of This Dissertation to the Literature

There are four major sections/sub topics to this dissertation. One will look at socio-economic-demographic factors affecting consumption of non-alcoholic beverages by a U.S household. This is a cross-sectional study done using data from 2003 Nielsen HomeScan scanner panels. Most of studies done in the past did not include a finer classification of non-alcoholic beverages. Our study fills in that gap by introducing 10 finely classified non-alcoholic beverages, namely, isotonics (sports beverages), regular soft drinks, diet soft drinks, high fat milk, low fat milk, fruit drinks, fruit juices, bottled water, coffee and tea.

Second our study utilizes a unique time-series data set constructed using data from Nielsen Homescan scanner panels for calendar years, 1998 through 2003. For a given beverage, we have aggregated across households for each year on monthly basis to generate 72 monthly observations of quantity (in gallons) and total expenditure information (in dollars). This data set does not suffer from censoring problem inherent in cross sectional data that house such detailed information about purchases and demographics. To our knowledge, this is the first time that such a dataset is created from

Nielsen HomeScan scanner panels and used in estimating a demand system. We have used quadratic almost ideal demand system (QUAIDS) (Banks, Blundell and Lewbel, 1997) allowing for more flexible Engle curves than AIDS and LA/AIDS models used in the past. Therefore, this is the first attempt to model a richer delineation of non-alcoholic beverages using QUAIDS model. We also use Barten's synthetic model (Barten, 1993) to bring in more dynamic flavor into the demand system estimation, and again, this is the first attempt in the literature that a rich delineation of non-alcoholic beverages were modeled using Barten's synthetic demand system.

We also have used the above time-series data set in trying to understand habit formation and inventory behavior in a dynamic setting using Houthakker and Taylor (1970) state adjustment model. Through such modeling, one could identify effects of habits and/or inventories on demand for non-alcoholic beverages. According to our knowledge, no one in the past have attempted use Houthakker and Taylor (1970) model to understand psychological stocks (habits) or physical stocks (inventories) in determining demand for non-alcoholic beverages. We not only could derive short-run effects, but also long-run behavior on consuming non-alcoholic beverages through such a modeling exercise. This is a unique contribution to habits modeling in demand literature.

We have evaluated probabilities generated from probit and logit models that we used to model the purchase decision in the first step of Heckman two-step procedure. Calibration, quite extensively, and resolution to some degree, have been used in the probability evaluation literature in the past. However, Brier score and Yates partition of

Brier score (co-variance decomposition of Brier score) have been used in limited occasions to evaluate probabilities. Again, according to our knowledge, this is the fist time in the literature that one has used covariance decomposition of the Brier score to evaluated probabilities generated through probit and logit models.

We could find only two studies in the past that looked at nutritional contribution of non-alcoholic beverages to the U.S. diet (Pittman 2004 and Capps et al., 2005). However, they used 1999 Nielsen HomeScan scanner panel (a cross-sectional dataset). In our study, we use even richer data set covering calendar years 1998 through 2003 in understanding the nutritional contribution of non-alcoholic beverages. Using such a dataset, not only we could look at pattern of nutrition intake derived from consumption of non-alcoholic beverages by U.S. households over the years, but also could ascertain the impact of year 2000 USDA Dietary Guidelines for Americans. This nutrition study lines up with a methodological input to the literature in attempting to understand nutritional contribution from consumption of non-alcoholic beverages.

CHAPTER III

DATA

We devote Chapter III for a thorough explanation on data used in all chapters of this dissertation. We use Nielsen HomeScan scanner data for household purchases of non-alcoholic beverages along with demographic information for each year. First we offer special features of the dataset we use (primarily the raw dataset). Next, we give a detailed account on data selection and development for each study in this dissertation.

Data Markets Description

The source of the data for this analysis is the Nielsen HomeScan scanner data for calendar years 1998 through 2003. These data sets are unique in that they are similar to a survey. Moreover, these are household level scanner data with corresponding demographic information.

These data are taken from a sample of households that are within 53 markets (cities and rural markets) and 4 census regions in the United States. Table 3.1 shows the percentage of households surveyed in each city and rural markets for calendar years 1998 through 2003. According to Table 3.1, on average, about 85% of households represented city markets and about 15% of households were from rural markets. Major city markets were Chicago, Los Angeles, New York, San Francisco, Atlanta, Philadelphia, Baltimore, Washington DC and San Antonio.

Table 3.1: Percentage of Households Surveyed in Each City and Rural Markets: 1998 through 2003

Market	Percent of Households Surveyed					
	1998	**1999**	**2000**	**2001**	**2002**	**2003**
Boston	1.05	1.11	0.73	0.72	0.6	0.56
Chicago	**8.83**	**9.03**	**7.91**	**7.35**	**7.35**	**7.3**
Houston	0.36	0.38	0.47	0.41	0.38	0.67
Indianapolis	1.08	1.08	0.94	0.7	0.58	0.47
Jacksonville	0.23	0.17	0.14	0.27	0.19	0.2
Kansas City	0.67	0.66	0.59	0.53	0.51	0.5
Los Angeles	**10.53**	**9.6**	**8.46**	**7.92**	**8.19**	**7.88**
Suburban New York	**4.4**	**4.64**	**4.1**	**3.88**	**3.68**	**3.81**
Urban New York	**3.07**	**3.16**	**2.92**	**2.7**	**2.93**	**2.91**
Non-urban New York	**1.67**	**2.39**	**2.14**	**2.02**	**1.75**	**1.64**
Orlando	0.46	0.41	0.26	0.56	0.48	0.55
San Fransisco	**0.38**	**0.47**	**3.32**	**6.49**	**6.52**	**7.24**
Seattle	0.39	0.59	0.55	0.49	0.43	0.42
Atlanta	**11.77**	**11.77**	**10.62**	**9.33**	**9.52**	**9.44**
Cincinnati	0.9	0.73	0.74	0.73	0.67	0.56
Cleveland	0.8	0.88	0.79	0.7	0.73	0.64
Dallas	0.28	0.31	0.33	0.6	0.56	0.72
Denver	0.54	0.67	0.52	0.5	0.44	0.34
Detriot	1.3	1.03	1.08	0.97	0.99	0.88
Miami	0.46	0.48	0.5	0.62	0.55	0.85
Milwaukee	0.41	0.5	0.44	0.56	0.48	0.45
Minneapolis	0.31	0.48	0.5	0.43	0.4	0.27
Nashville	0.15	0.13	0.12	0.22	0.35	0.33
Philadelphia	**1.21**	**1.42**	**6.96**	**7.34**	**8.32**	**8.33**
Pittsburgh	1.14	1.25	0.92	1.01	0.87	0.86
Portland, Oregon	1.16	0.92	0.82	0.69	0.6	0.54
San Diego	0.33	0.44	0.36	0.34	0.3	0.24
St. Louis	0.7	0.77	0.94	0.78	0.81	0.67
Tampa	0.43	0.64	0.56	0.92	0.81	0.88
Baltimore	**3.73**	**3.64**	**3.42**	**3**	**2.89**	**2.84**
Birmingham	0.21	0.2	0.26	0.43	0.48	0.38
Buffalo-Rochester	0.83	0.92	0.61	0.6	0.48	0.46
Hartford-New Haven	0.78	1	0.82	0.76	0.62	0.45
Little Rock	0.13	0.11	0.12	0.21	0.12	0.21
Memphis	0.08	0.08	0.11	0.28	0.23	0.2
New Orleans-Mobile	0.08	0.11	0.11	0.5	0.55	0.62

Table 3.1 Continued

Market	**Percent of Households Surveyed**					
Oklahoma City-Tulsa	0.18	0.06	0.12	0.35	0.28	0.39
Phoenix	0.69	1.36	1.44	1.19	1.12	1.06
Raleigh-Durham	0.1	0.16	0.17	0.53	0.67	0.69
Salt Lake City	1.7	1.39	1.24	0.98	0.93	0.82
Columbus	0.46	0.47	0.47	0.41	0.32	0.31
Washington DC	**8.01**	**7.68**	**6.77**	**6.43**	**6.66**	**6.31**
Albany	0.47	0.44	0.33	0.22	0.22	0.14
Charlotte	0.36	0.45	0.5	0.49	0.52	0.5
Des Moines	0.49	0.42	0.36	0.31	0.34	0.31
Grand Rapids	0.93	0.77	0.62	0.56	0.59	0.45
Louisville	0.16	0.11	0.18	0.32	0.34	0.38
Omaha	0.51	0.5	0.44	0.32	0.31	0.24
Richmond	0.28	0.2	0.32	0.59	0.47	0.56
Sacramento	0.34	0.33	0.38	0.29	0.23	0.17
San Antonio	**6.74**	**6.42**	**5.9**	**5.46**	**6.76**	**8.54**
Syracuse	1.32	1.2	1	0.78	0.74	0.64
City Markets	83.59	84.13	84.42	84.79	85.86	86.82
Rural Markets	16.41	15.87	15.58	15.21	14.14	13.18

The survey covered 4 regions of the 48 contiguous states of the United States, the East, Midwest (Central), South and West respectively. The percentage of the households surveyed in each region in Nielsen HomeSacn scanner panel data for calendar years 1998 through 2003 is comparable to the regional representation of surveyed U.S. households by U.S. Bureau of Census in the year 2000. In Table 3.2 we show the percentage of households surveyed by the U.S. Bureau of Census in year 2000 and Nielsen HomeScan scanner data for calendar years 1998 through 2003. The six-year average value of percentage of households surveyed by Nielsen is: East 21.16; West 21.22; Midwest 22.41; and South 35.20.

Table 3.2: Percentage of Households Surveyed by U.S. Bureau of Census in 2000 and ACNielsen HomeScan from 1998 through 2003

	ACNielsen HomeScan						U.S. Bureau of Census
Region	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2000**
East	19.33	20.65	22.00	21.77	21.86	21.36	20.00
West	20.45	19.93	21.96	22.19	21.63	21.17	22.00
Midwest	26.00	25.59	23.37	20.83	20.07	18.62	24.00
South	34.22	33.83	32.66	35.20	36.43	38.85	34.00

Demographics Description

Each household is provided with a scanner machine in which they can re-scan and record all items that they purchased in different retail trade locations throughout a given time period. Panelists record the total expenditure and quantity of all items they purchased in that household followed by a periodic input of demographic information about the household. Following Table 3.3 summarizes the demographic information available in the Nielsen Homescan data (panelist descriptives and respective raw categories identified). It should be emphasized that we did not use all of the demographic variables in Table 3.3 in our analysis. The female head of the household is considered the household head in making decisions regarding food at-home purchase, and preparation. Therefore, three demographic characteristics concerning the female head of household is recorded; age, employment, and education status. When the female head is not present in the household, the aforementioned characteristics of the male head were recorded.

Table 3.3: Demographic Characteristics of ACNielsen Panelist Households: Panelist Descriptives and Categories Recorded

Panelist Descriptives	Categories
Household size	Single Member
	Two Members
	Three Members
	Four Members
	Five Members
	Six Members
	Seven Members
	Eight Members
	Nine+ Members
Household income per year	Under $5000
	$5000-$7999
	$8000-$9999
	$10,000-$11,999
	$12,000-$14,999
	$15,000-$19,999
	$20,000-$24,999
	$25,000-$29,999
	$30,000-$34,999
	$35,000-$39,999
	$40,000-$44,999
	$45,000-$49,999
	$50,000-$59,999
	$60,000-$69,999
	$70,000-$99,999
	$100,000 & Over
Age of female head	Under 25 Years
	25-29 Years
	30-34 Years
	35-39 Years
	40-44 Years
	45-49 Years
	50-54 Years
	55-64 Years
	65+ Years
	No Female Head

Table 3.3 Continued

Panelist Descriptives	Categories
Age of male head	Under 25 Years 25-29 Years 30-34 Years 35-39 Years 40-44 Years 45-49 Years 50-54 Years 55-64 Years 65+ Years No Male Head
Age and presence of children	Under 6 only 6-12 only 13-17 only Under 6 & 6-12 Under 6 & 13-17 6-12 & 13-17 Under 6 & 6-12 & 13-17 No Children Under 18
Male head employment	Under 30 hours 30-34 hours 35+ hours Not Employed for Pay No Male Head
Female head employment	Under 30 hours 30-34 hours 35+ hours Not Employed for Pay No Female Head
Male head education	Grade School Some High School Graduated High School Some College Graduated College Post College Grad No Male Head or Unknown

Table 3.3 Continued

Panelist Descriptives	**Categories**
Female head education	Grade School
	Some High School
	Graduated High School
	Some College
	Graduated College
	Post College Grad
	No Female Head or Unknown
Marital status	Married
	Widowed
	Divorced/Separated
	Single
	Unkown
Male head occupation	Professional
	Prop,Managers,Officials
	Clerical
	Sales
	Craftsman/Foreman(Skilled)
	Operative(Semi-Skilled)
	Military
	Service Workers&Private HH Workers
	Farm Owners, Managers,Foreman&Laborers
	Students Employed <30 hours
	Laborers
	Retired, Unemployed
Female head occupation	Professional
	Prop,Managers,Officials
	Clerical
	Sales
	Craftsman/Foreman(Skilled)
	Operative(Semi-Skilled)
	Military
	Service Workers&Private HH Workers
	Farm Owners, Managers,Foreman&Laborers
	Students Employed <30 hours
	Laborers
	Retired, Unemployed

Table 3.3 Continued

Panelist Descriptives	Categories
Household composition	Married FH Living with Others Related MH Living with Others Related Female Living Alone Female Living with Non-Related Male Living Alone Male Living with Non-Related
Race	White Black Oriental Other
Hispanic origin	Yes No
Region	East Central South West

According to Table 3.3, household size was categorized into 9 categories; single member through 9 or more members. Household income was categorized into 16 classes, based on annual income received by a household. Household income ranged from households with less than $5,000 per year through households that earned more than $100,000 per year. Age of the male and female head was grouped into 10 categories, ranging from a classification with under 25 years of age to a classification with over 64 years. Age and presence of children variable communicated two types of information. One is presence of children and if present, the age of children. Based on this information, one may delineate households with pre-school children, pre-adolescent children, and adolescent children. Male and female head employment status was categorized depending on the number of hours worked ranging from less than 30 hours per week to 35 hours or more per week. Not employed for pay was the category where the household head was not employed. Female and male head education was classified into seven classes. They included some grade school, some high school, some college etc. Marital status was classified into five classes. They were married, widowed, divorced/separated, single and unknown. Occupation of male and female head had 12 sub-classes. They ranged from unemployed to professional occupations. White, Black, Oriental/Asian and Other were four categories used to classify race. Hispanic origin too was taken into account. As mentioned previously, four regions of the continental U.S. were considered namely, i.e. South, East, West and Midwest.

Purchase Data Description

Nielsen HomeScan scanner data include purchases of all consumer items bought by a household during a specified period of time. However, for our analysis, we used nationally representative purchase data only for food items. In Table 3.4 we show the total number of households that were available for each calendar year (1998 through 2003). For our analysis, we used purchase data (total expenditure and quantity) and demographic information from households that had such information every month for 12 months. Column 3 of the Table 3.4 shows the total number of households in each year that had purchase and demographic data for all 12 months.

Table 3.4: Number of Households Available and Used in the Study for Each Calendar Year: 1998 through 2003

Year	Total number of households available	Total number of households with 12 months purchases
1998	7624	6116
1999	7124	6397
2000	7523	6600
2001	8216	7142
2002	8685	7439
2003	8833	7642

The household level food purchase data were divided into four product type groups. There were dry grocery, dairy, frozen goods and random weights. In our analysis, we concentrated on beverage products from dry grocery, dairy and frozen categories. Each of three groups considered contained numerous product modules. A product module is a unique number given to each product category to clearly identify the grocery product (in this case the beverage category). In the original data set, these product modules were further subdivided into brand, size, flavor, form, formula, container, style, type and variety. Every product module contained several of unique products identified by universal product codes (UPC). For example, product module 1040 is assigned for orange juice and it contained 417 brands identified by a unique UPC code for each brand (see Pittman, 2004, Chapter II).

Data sorting based on product modules was done by Pittman (2004) in his dissertation for calendar year 1999. We used the same procedure to filter our data for calendar years 1998, 1999, 2000, 2001, 2002, and 2003. We are interested in 10 types of non-alcoholic beverages. We also had to aggregate/disaggregate product modules to find the correct quantity and expenditure information for each beverage category for our analysis. Ten types of non-alcoholic beverages considered in this study are: isotonics (sports drinks), regular soft drinks, diet soft drinks, high-fat milk (whole milk and 2% milk), low-fat milk (1% milk and skim milk), fruit drinks, fruit juices, bottled water, coffee and tea.

Data Selection

In this section we explain the data selection procedure carried out to perform each part of our study. We elaborate on demographic and economic information contained in each dataset (for each year from 1998 through 2003) and offer some summary statistics for each dataset. We redefine some of demographic categories to suit our objectives and analysis in this dissertation; as a result they are somewhat different from the classification we provided in Table 3.3. Demographic categories that we use in our analysis are as follows (we use these categories in all sections of our study): age, employment status and education status of household head; region; race; presence of a Hispanic household; age and presence of children; household head male only, female only or both; poverty status based on 185% poverty level. In Table 3.5 we provide all categories of each demographic variable used.

The variable *“age of the household head”* primarily contains the age of the female household head. However, in situations where a female household head was not present, age of male household head was included in creating the variable. A similar exercise was carried out in creating *“employment status of the household head*” and “*education status of household head*” variables. No change in the variables was done for *“region”*, *“race”*, *“age and presence of children”* and *“Hispanic status”*.

Gender of the household head was a new variable created to reflect the gender of the household decision-making unit. There were some households with only a female household head and others with only a male household head. In some situations we had both male and female representation in the household.

To arrive at poverty 185% variable, USDA 100% poverty guidelines (calculated taking income and household size into account) were adjusted (inflated) by another 85% (to make it 185% now), so that more people could be categorized as in poverty under new poverty line. We have used Poverty 185% variable in lieu of two variables we could observe in the primary data group. They are household income and size (these two variables are taken into account when calculating an appropriate poverty line). In our analysis, households who are below 185% poverty are considered poor.

Table 3.5: Demographic Characteristics Used in Our Study: 1998 though 2003

Demographic Characteristic	Categories
Age of household head	Less than 25 years 25-29 years 30-34 years 35-44 years 45-54 years 55-64 years More than 64 years
Employment status of household head	Household head employed full time Household head employed part time Household head not employed
Education status of household head	Educated less than high school Educated high school level Educated undergraduate level Educated at post college level
Region	Central (Midwest) South West East
Race	Black Asian (Oriental) White Other
Hispanic status	Hispanic Yes Hispanic No
Age and presence of children	Less than 6-year-olds 6-12-year-olds 13-17-year-olds Less than 6-year-olds & 6-12-year-olds Less than 6-year-olds & 13-17-year-olds 6-12 and 13-17 year-olds Less than 6-olds No children
Gender of household head	Household head male only Household head female only Households with both male and female
Poverty status	Above poverty line of 185% poverty Below poverty line of 185% poverty

Summary Statistics

In the following sections we discuss summary statistics of demographic and economic information for each year and on a six-year average basis. All relevant information is summarized in Table 3.6 below.

According to age of household categories we find that a notable proportion of household heads fall into the age category 45-54 years (about 28% of the sample). This situation is evident across all years. Also, about 52% of the sampled households are in the age category 35-54 years.

Information on employment status of the household head reveals that about 66% of household heads are employed either full time or part time for a pay. It is again consistent across years 1998 through 2003. About 62% of household heads have an undergraduate degree and only a small percentage of household heads are educated at below high school level (only about 3.5%).

The racial composition on a six-year average basis shows that the sample was predominantly White (about 82%) and those who are classified as Black takes the second highest position (about 11%). However, looking at the yearly percentage values, one can see that there was only 7.6% black participation in 1998 and it grew to almost 13% by year 2003. On the other hand, composition of whites dropped from about 87% in 1998 to 77% in 2003.

Non-Hispanics accounted for the majority of the sample (about 90%). About 65% of the sample had both male and female household heads at home. There were about 25% of households where the female was the only head of the household.

Table 3.6: Summery Statistics of Demographic Information: 1998 through 2003

	Demographic Category	Percentage of Households						
		1998	1999	2000	2001	2002	2003	6-year Average
Age of Household	<25 years	1.05	0.98	0.85	0.56	0.48	0.29	0.70
	25-29 years	4.60	4.56	3.62	3.39	3.08	2.42	3.61
	30-34 years	10.00	8.49	8.02	7.42	7.37	6.17	7.91
	35-44 years	27.86	24.87	23.87	23.80	22.86	21.18	24.07
	45-54 years	27.45	28.73	28.72	27.96	27.55	27.60	28.00
	55-64 years	17.12	18.37	15.38	16.58	17.68	19.10	17.37
	>64 years	11.94	13.99	15.38	16.58	17.68	19.10	15.78
Employment status of Household	Full time	51.29	50.23	49.40	47.68	47.03	45.42	48.51
	Part time	18.61	17.74	16.87	17.50	16.91	16.43	17.34
	Not for full pay	30.10	32.03	33.73	34.82	36.06	38.15	34.15
Education status of Household	<high school	2.42	3.30	3.24	3.82	3.80	3.53	3.35
	High school	21.50	22.26	25.09	24.96	24.28	24.24	23.72
	Undergraduate	63.98	62.33	60.42	60.35	61.06	61.25	61.57
	Post college	12.10	12.12	11.24	10.87	10.85	10.97	11.36
Region	East	19.33	20.65	22.00	21.77	21.86	21.36	21.16
	West	20.45	19.93	21.96	22.19	21.63	21.17	21.22
	Midwest	26.00	25.59	23.37	20.83	20.07	18.62	22.41
	South	34.22	33.83	32.66	35.20	36.43	38.85	35.20

Table 3.6 Continued

	Demographic Category	Percentage of Households						
Race	**Black**	7.65	9.58	10.82	12.64	13.62	12.99	11.22
	Asian	1.32	1.30	1.38	2.53	2.73	2.87	2.02
	White	87.10	84.96	83.01	81.21	77.98	77.71	82.00
	Other	3.92	4.16	4.79	3.61	5.67	6.44	4.77
Hispanic	**Yes**	6.85	7.38	6.32	6.82	6.95	8.02	7.06
	No	93.15	92.62	93.68	93.18	93.05	91.98	92.94
Gender of Household head	**Female**	20.75	22.75	24.46	24.92	25.91	27.56	24.39
	Male	9.01	9.14	10.74	10.94	10.96	10.59	10.23
	both female & male	70.24	68.11	64.80	64.14	63.14	61.85	65.38
Age and presence of children	**<6 years**	5.54	4.83	4.38	4.47	3.44	3.55	4.37
	6-12 years	7.70	7.11	7.20	7.42	7.22	6.13	7.13
	13-17 years	9.70	8.93	8.20	7.28	7.39	7.17	8.11
	<6, 6-12 years	4.87	3.94	3.62	3.99	3.79	2.93	3.86
	<6, 13-17 years	0.67	0.70	0.65	0.69	0.52	0.54	0.63
	6-12 & 13-17 years	5.16	5.16	4.47	4.27	4.89	4.40	4.73
	<6, 6-12 & 13-17 years	0.80	0.88	0.65	0.78	1.05	0.94	0.85
	no child <18	65.11	68.45	70.83	71.10	71.69	74.34	70.25
poverty status	**< 185% poverty**	11.63	12.62	12.79	14.37	13.65	13.38	13.07
	> 185% poverty	88.37	87.38	87.21	85.63	86.35	86.62	86.93

On a six-year average basis, about 70% of the households in the sample did not have a child (individual below 18 years of age) living with them. About 15 % of households on average had a child aged between 6 through 17 years. The composition of the age and presence of children did not change much over the six-year period. On average, about 13% of households were below the USDA designated 185% poverty line.

Table 3.7 shows the average real price of each beverage over the years. It should be noted that price of beverages in this study is really the unit value calculated dividing total expenditure by quantity. These prices are adjusted for inflation using the consumer price index (CPI) for the particular year in question; therefore, they are real prices per gallon of each non-alcoholic beverage concerned. Isotonics were the most expensive and coffee the least on a six-year average basis. Isotonics stood at $2.62 per gallon while coffee was $0.85 per gallon. Second most expensive beverage was fruit juice ($2.55 per gallon). Milks (high fat and low/non fat were $1.90 per gallon on six-year average basis. Consumers paid $1.48 per gallon for both regular and diet soft drinks on average. A gallon of bottled water, on average, was $1.26 over the six-year period.

Table 3.7: Average Real Prices of Non-Alcoholic Beverages, 1998 through 2003 Dollars per Gallon, Inflation Adjusted Using CPI

Beverage Category	1998	1999	2000	2001	2002	2003	6-year Average
Isotonics	$2.87	$2.71	$2.66	$2.61	$2.45	$2.39	$2.62
Regular Soft Drinks	$1.52	$1.50	$1.49	$1.46	$1.47	$1.45	$1.48
Diet Soft Drinks	$1.55	$1.49	$1.48	$1.44	$1.46	$1.47	$1.48
High fat milk	$1.87	$1.92	$1.90	$1.92	$1.85	$1.84	$1.88
Low fat milk	$1.86	$1.92	$1.93	$1.93	$1.87	$1.85	$1.89
Fruit drinks	$2.23	$2.22	$2.19	$2.14	$2.06	$2.08	$2.15
Fruit juices	$2.58	$2.63	$2.60	$2.51	$2.51	$2.47	$2.55
Bottled water	$1.31	$1.22	$1.30	$1.28	$1.28	$1.20	$1.26
Coffee	$0.79	$0.89	$0.87	$0.79	$0.88	$0.86	$0.85
Tea	$1.15	$1.14	$1.15	$1.21	$1.22	$1.20	$1.18

Data Preparation for Demographic Study

In this study, we used only Nielsen HomeScan scanner data for calendar year 2003. First we selected households that had purchase data records for all 12 months of 2003 (in this case quantity and total expenditure data for non-alcoholic beverages). As such we had 7642 households out of 8833 which had purchases of non-alcoholic beverages for 12 months of year 2003. For those households, we aggregated non-alcoholic beverage total expenditure and quantity data for all non-alcoholic beverages concerned across 12 months to generate per household per year dollar and a volume value respectively. Total expenditure is calculated in dollars and the volume is in gallons.

It should be emphasized that we converted all non-alcoholic beverage data into a common comparable volume measure; gallons, so that we can compare across beverages easily. The conversion formulae were taken from Pittman (2004). At the end, we get total expenditure (in dollars) and quantity (in gallons) data for selected non-alcoholic beverages per household per year. It is an obvious fact that some households may have not purchased a given non-alcoholic beverage during 2003, resulting in a zero for quantity and hence total expenditure for that beverage for that household during 2003. This non-purchase has a direct consequence in calculating price for that particular beverage concerned, because price or unit value is calculated taking the ratio of total expenditure to quantity. Further, this zero observation problem is called *"a censoring problem in data"* and special two-stage budgeting procedures were employed to circumvent such zeros.

We brought in demographic information on top of total expenditure and volume data for each of 7642 households to generate the complete data set ready for analysis. Demographic information included was: age, education and employment status of the household head; region; race; Hispanic status; age and presence of children; gender of household head; poverty status based on 185% poverty line. Specific non-alcoholic beverages considered were, isotonics (sports beverage), regular soft drinks, diet soft drinks, high fat milk, low fat milk, fruit drinks, fruit juices, bottled water, coffee and tea.

Data Preparation for Probability Study

In this particular part of study, we use the same data set we created above for *"Demographic Study"* with a few additions. In the probability study, we use probit and logit models to assess the decision to purchase a given non-alcoholic beverage, eventually generating the probability of purchase. The dependent variable for this part of analysis is a zero-one dummy variable on the action of purchase or non-purchase of a given non-alcoholic beverage. After generating data for 7642 households as in above section 3.4.2, we generated a dummy variable associated with the quantity of purchase. For example, if the quantity of purchase of isotonics is a positive value in gallons, the dummy variable would be given the value of one and if the household did not purchase any isotonics that dummy variable would be given the value of zero for that observation. This operation would generate a zero-one type of variable for all households considered.

Along with demographic variables included in above section 3.4.2, we brought in a price variable to the right-hand side of all probit and logit models. Due to non-purchase record for some households for some beverages, we could not calculate a unit value (or a price) for that particular household. In that event, we calculated a weighted average price considering all non-alcoholic beverages considered (taking total expenditure and volume data from frozen, dry and dairy categories of non-alcoholic beverage types) and included that on right-hand side of all probit and logit models along with demographic variables.

Data Preparation for Nutrition Study

Nutrition study spans across all calendar years considered, 1998 through 2003. We used all demographic variable information characterized in aforementioned probability study along with added nutrition information derived from consumption of non-alcoholic beverages. However, due to non-purchase and hence missing price information for some non-alcoholic beverages for some households, we had to drop such households from the nutrition study analysis. Table 3.8 we show the information on number of households available in the dataset and number of households actually included in it. Column number 4 of the table shows the percentage of household actually dropped due to missing price information. As depicted in Table 3.8, number of households that were dropped due to missing price information is below 1% for each calendar year.

Table 3.8: Number of Households Available and Used in the Nutrition Study for Each Calendar Year: 1998 through 2003

Year	Total number of households available	Total number of households used in the nutrition study	Percentage of households dropped due to missing price information
1998	7624	6087	0.47%
1999	7124	6376	0.33%
2000	7523	6555	0.68%
2001	8216	7103	0.55%
2002	8685	7384	0.74%
2003	8833	7566	0.99%

Demographic and price (unit value) variables considered in this study are same as such variables used in above probability work (section 3.4.3). However, we also wanted nutrition information related to the consumption of non-alcoholic beverages. They were not included in the Nielsen HomeScan scanner data. Therefore, this information had to be developed from additional information obtained from USDA (please see the Appendix D of Pittman (2004) for nutrient conversions for non-alcoholic beverages). Finally, calories, caffeine and nutrients derived (calcium, vitamin C) from consumption of non-alcoholic beverages at home per person per day was calculated. Units of measurement are as follows: calories in kilo calories per person per day, calcium, vitamin C and caffeine in milligrams per person per day. As such, we now have observations of calories, caffeine and necessary vitamin data associated with non-alcoholic beverages for each household concerned for each year.

Our next step is to pool/stack the demographic, total expenditure, volume and nutrition data into one large sample by placing data from calendar years 1998 through 2003 one-on-top of the other. As such, we created a large sample of 41,071 households and all of above information to go along with. Such pooling of data from 1998 through 2003 would allow us to investigate possible structural influences of USDA Dietary Guidelines on intake of calories, calcium, vitamin C and caffeine. To accommodate such inquiry we created yearly dummy variable as follows. The base year was taken as calendar years 1998, 1999 and 2000 (all three put together) and separate yearly dummies were created for calendar years 2001, 2002 and 2003.

Data Preparation for Demand Systems Study

Initially, monthly household purchases of nonalcoholic beverages (expenditure and quantity information) are generated for each household in the Nielsen HomeScan Panel data over the period January 1998 through December 2003. Next, the expenditure and quantity data are summed over all households for each month for each of the aforementioned nonalcoholic beverage categories. As such, we generate monthly purchase data to arrive at a total of 72 observations (72 months) for each nonalcoholic beverage category. Quantity data are standardized in terms of gallons for all nonalcoholic beverages considered in this study and expenditure data are expressed in terms of dollars. Taking into account household size and the U.S. population numbers for every month from January 1998 through December 2003, our volume data and expenditure data are expressed in terms of gallons purchased and dollars spent per person per month. Then taking the ratio of expenditure to volume, we generate unit values (or price) for each nonalcoholic beverage category for each month. These prices were adjusted for inflation using the consumer price index data (CPI) for each month to generate a real price series for each beverage category. Using real prices and monthly per capita consumption values, finally we generate expenditure share information for the ten nonalcoholic categories previously discussed. The real per capita total expenditure was generated using real price and per capita consumption of all ten nonalcoholic beverages put together.

We are not aware of past efforts to generate this type of time-series data for the purpose of conducting demand analyses. To lend support to this approach, we find strong correlations of our data on an annual basis with annual USDA Economic Research Service disappearance data (also called food supply data or food availability data) for similar beverage categories. Even though we lose household demographic information with this aggregation, we do not encounter data censoring problems inherent in trying to use micro-level data in estimating demand systems.

In Table 3.9 we show the Nielsen annual volume data and USDA-ERS disappearance data, both gallons per person per year. The latter contains both at-home and away-from-home consumption/supply information. As a result, we see large volume values with respect to USDA-ERS data compared to our Nielsen HomeScan scanner data which accounts only for at-home consumption.

Table 3.9: Volume Comparison of Nielsen HomeScan Scanner Data Versus USDA-ERS[14] Disappearance Data on Annual Basis: 1998 through 2003

Time	Regular Soft Drink	Regular Soft Drink (ERS)	Diet Soft Drink	Diet Soft Drink (ERS)	Milk	Milk (ERS)	Fruit Juice	Fruit Juice (ERS)
1998	12.54	39.90	7.49	13.90	12.93	23.00	5.85	9.10
1999	11.97	39.70	7.14	13.80	12.13	22.90	5.80	9.00
2000	11.19	39.40	6.75	13.80	11.42	22.50	5.71	8.90
2001	10.96	39.00	6.62	13.90	10.87	22.00	5.53	9.00
2002	9.58	38.40	6.09	14.40	9.37	21.90	4.85	7.90
2003	9.32	37.50	6.37	15.00	9.29	21.60	4.68	8.50

Time	Bottled Water	Bottled Water (ERS)	Coffee	Coffee (ERS)	Tea	Tea (ERS)
1998	3.20	14.40	11.97	18.30	4.18	8.30
1999	3.66	15.80	11.97	19.30	4.14	8.20
2000	3.86	16.70	12.02	20.00	4.32	7.80
2001	4.54	18.20	11.97	18.50	4.29	8.20
2002	4.64	20.10	9.41	18.10	3.81	7.80
2003	5.15	21.60	9.68	18.50	3.76	7.50

[14] ERS: United States Department of Agriculture Economic Research Service

Correlation analysis of Nielsen HomeScan data with USDA-ERS disappearance data are shown in Table 3.10. Correlation coefficient values were as follows: regular soft drinks 0.96; beverage milk 0.95; fruit juice 0.82; bottled water 0.98; coffee 0.54; tea 0.67. According to correlation coefficient values, we find strong correlations of our Nielsen data on annual basis with annual USDS-ERS disappearance data for similar beverage categories.

Table 3.10: Correlation Coefficients of Nielsen HomeScan Scanner Data and USDA-ERS Disappearance Data for the Period 1998-2003

Beverage Category	Correlation Coefficients
Regular soft drinks	0.96
Diet soft drinks	-0.64
Milk	0.95
Fruit juice	0.84
Bottled water	0.98
Coffee	0.54
Tea	0.67

CHAPTER IV

ECONOMIC AND DEMOGRAPHIC TENDENCIES IN CONSUMPTION OF NON-ALCOHOLIC BEVERAGES: CHOICE AND LEVEL OF CONSUMPTION

In this chapter, we discuss the model development, data analysis and discussion of the *demographic study*. In the demographic analysis, our interest is to find out, first the demographic factors affecting probability (or choice) of consumption of non-alcoholic beverages. A probit model will be used to achieve above objective. In the presence of a censoring data sample, next we will use Heckman two-step procedure to model factors affecting the volume of non-alcoholic beverage consumption conditioned on the decision to purchase. Economic (price of non-alcoholic beverages) and host of demographic factors will be considered here.

Demographic Study: Choice to Consume

In this section, first, we offer a narrative on model development to carry out the choice of consumption of a given non-alcoholic beverage. We provide an explanation on procedures, and variables used. Second, we discuss the empirical results associated with choice of consumption investigated through a probit analysis.

Model Development: Probit Analysis

Choice to purchase or not to purchase a given non-alcoholic beverage could be affected by various demographic factors. Above type of choice is a dichotomous discrete one (buy or not-to buy or “one” if buy and “zero” if do not buy) and a probit model is used generally to model such choice decisions. The dependent variable is a zero one type dummy variable which is created to reflect the non-purchase or purchase respectively of a non-alcoholic beverage. It is regressed on a weighted average price variable calculated using all three broad categories (dry, frozen and dairy) of non-alcoholic beverages. Other explanatory variables used are demographic factors. When appropriately modeled, probit analysis will provide statistically significant findings of which demographics and economic factors increase or decrease the probability of consumption of non-alcoholic beverages.

Demographic and economic factors hypothesized to be affecting the probability of purchase of a given non-alcoholic beverage are listed on Table 4.1 We also provide different categories used in each factor along with base category for dummy variables. All of the demographic categories are expressed using a dummy (or indicator) variable. Since we expect to use an intercept term in the probit model, all base categories are not included in equations to avoid perfect multicollinearity problem. Therefore, all of our findings have to be explained relative to the base category. The choice of base category is arbitrary, nevertheless, we will keep it same across all non-alcoholic beverages in this study. For example, we have picked Whites as our base category in explaining race in probit models. As a result, one would see statements like, “Blacks consume more bottled water compared to Whites”. We used year 2003 Nielsen HomeScan scanner panel with 7642 household level observations.

Table 4.1 Description of the Right-Hand Side Variables Used in the Econometric Analysis

Variable	Explanation
PRICE	Weighted Average Price of Non-alcoholic Beverages
AGEHHLT25	*Age of Household Head less than 25 years (Base category)*
AGEHH2529	Age of Household Head between 25-29 years
AGEHH3034	Age of household Head between 30-34 years
AGEHH3544	Age of household Head between 35-44 years
AGEHH4554	Age of household Head between 45-54 years
AGEHH5564	Age of household Head between 55-64 years
AGEHHGT64	Age of household Head greater than 64 years
EMPHHNFP	*Household Head not employed for full pay (Base category)*
EMPHHPT	Household Head Part-time Employed
EMPHHFT	household Head Full-time Employed
EDUHHLTHS	*Education of Household Head: Less than high school (Base category)*
EDUHHHS	Education of Household Head: High school only
EDUHHU	Education of Household Head: Undergraduate only
EDUHHPC	Education of Household Head: Some post-college
REG_EAST	*Region: East (Base category)*
REG_CENTRAL	Region: Central (Midwest)
REG_SOUTH	Region South
REG_WEST	Region West
RACE_WHITE	*Race White (Base category)*
RACE_BLACK	Race Black
RACE_ORIENTAL	Race Oriental
RACE_OTHER	Race Other (non-Black, non-White, non-Oriental)
HISP_NO	*Non-Hispanic Ethnicity (Base category)*
HISP_YES	Hispanic Ethnicity

Table 4.1 Continued

Variable	Explanation
NPCLT_18	*No Child less than 18 years (Base category)*
AGEPCLT6_ONLY	Age and Presence of Children less than 6-years
AGEPC6_12ONLY	Age and Presence of Children between 6-12 years
AGEPC13_17ONLY	Age and Presence of Children between 13-17 years
AGEPCLT6_6_12ONLY	Age and Presence of Children less than 6 and 6-12 years
AGEPCLT6_13_17ONLY	Age and Presence of Children less than 6 and 13-17 years
AGEPC6_12AND13_17ONLY	Age and Presence of Children between 6-12 and 13-17 years
AGEPCLT6_6_12AND13_17	Age and Presence of Children less than 6, 6-12 and 13-17 years
FHMH	*Household Head both Male and Female (Base category)*
MHONLY	Household Head Male only
FHONLY	Household Head Female only
POVLT_185	*Below 185% Poverty Household (Non-Poverty Households) (Base category)*
POV185	Over 185% Poverty Households (Poverty Households)
D1998, D1999, D2000	*Indicator variable for 1998, 1999, and 2000 (Base category)*
D2001	Indicator variable for year 2001
D2002	Indicator variable for year 2002
D2003	Indicator variable for year 2003

In this study we used binary probit model to generate probability of consumption of non-alcoholic beverages given a host of demographic factors and a weighted average price of non-alcoholic beverages. Following is a technical note on probit model and its estimation (borrowed from multiple sources: Griffiths, Hill and Judge (1993), EViews User Guide, (2004), AGEC 661, Applied Econometrics, Spring 2005, Texas A&M University). A dichotomous dependent variable can be regressed on a host of explanatory variables (continuous or discrete) to obtain an index value for each observation, i.e. Z_i where $Z_i = X'\beta$. In this equation, explanatory variables are depicted by X and associated regression coefficients are represented by β. This index value Z_i lies on the real line between negative infinity and positive infinity, i.e. $-\infty < Z_i < \infty$. However, we regressed a variable that had only two outcomes, thus, 0 for non-purchase and 1 for purchase. Above index value puts us out of the range giving predictions that are positive and negative and does not stick on to 0-1 range. If we run our index values through a standard normal cumulative distribution function, $F_P(Z_i)$, we get at probabilities that are bounded by 0-1 interval, hence giving rise to probit model. Therefore, probit model can be depicted as follows:

(4.1) $$P_i = F_P(X_i'\beta) = F_P(Z_i) = \int_{-\infty}^{Z_i} \frac{1}{\sqrt{2\pi}} e^{Z_i^2/2} \, ds$$

hence we can write, for our dichotomous event:

(4.2) $$\Pr(Z = 1 \mid X, \beta) = F_P(Z_i)$$

(4.3) $$\Pr(Z = 0 \mid X, \beta) = 1 - F_P(Z_i)$$

Unknown parameters β in the above probit model are estimated via maximum likelihood estimation technique (maximizing a log-likelihood function and obtaining β s at the maximum of log-likelihood function)[15].

Let us take a sample of *n* individual observations (in our study *n* number of households) on individual choices y_i. First step toward the maximum likelihood estimation of unknown parameters β of the probit model is to specify probability density functions of the observable variables y_i. They can be specified as follows:

(4.4) $$g(y_i) = P_i^{y_i}(1 - P_i)^{1-y_i}$$

Maximum likelihood estimation is based on the following relationship. Joint probability density function of the sample of *n* independent observations is the product of the *n* probability density functions $g(y_i)$. Mathematically:

(4.5) $$g(y_1, y_2, y_3, ..., y_n) = \prod_{i=1}^{n} g(y_i)$$

Substituting (4.4) in (4.5) gives us the following:

(4.6) $$g(y_1, y_2, y_3, ..., y_n) = \prod_{i=1}^{n} P_i^{y_i}(1 - P_i)^{1-y_i}$$

However, we know the following:

(4.7) $$P_i = F_P(Z_i) = F_P(x_i'\beta)$$

Substituting (4.7) in (4.6) gives us the following likelihood function:

[15] We use maximum likelihood estimation technique because of discrete nature of dependent variable, and the nonlinear in the parameters functional relation between choice probability and the explanatory variables.

(4.8) $$g(y_1, y_2, y_3, ..., y_n) = \prod_{i=1}^{n} F_P(x_i'\beta)^{y_i} [1 - F_P(x_i'\beta)]^{1-y_i}$$

(4.9) $$l(\beta) = \prod_{i=1}^{n} F_P(x_i'\beta)^{y_i} [1 - F_P(x_i'\beta)]^{1-y_i}$$

In probit model estimation either the researcher can maximize (4.9) and solve for β s or can maximize the log of the likelihood function stated in equation 4.10:

(4.10) $$l(\beta) = \sum_{i=1}^{n} y_i \ln(F_P(x_i'\beta)) + \sum_{i=1}^{n} (1 - y_i) \ln(1 - F_P(x_i'\beta))$$

Above maximum likelihood estimator for probit model has large sample properties where, with large *n*, the maximum likelihood estimator $\hat{\beta}$ has a sampling distribution that is approximately normal with mean β and covariance matrix:

(4.11) $$\text{cov}(\hat{\beta}) = (X'DX)^{-1}$$

where *X* is the $(n \times k)$ design matrix of observations on *k* explanatory variables for *n* individuals. Design matrix has diagonal elements as depicted in equation 4.12:

(4.12) $$d_i = \frac{[f(x_i'\beta)]^2}{F(x_i'\beta)[1 - F(x_i'\beta)]}$$

where $f(x_i'\beta)$ and $F(x_i'\beta)$ are the probability density function and cumulative distribution function for standard normal random variable, respectively.

It is important to know at this point that Yatchew and Griliches (1984) studied specification tests for probit (and logit) models, more specifically the effect of heteroskedasticity on the estimates[16]. However, reviewing past work on probit models shows that they are not generally adjusted for heteroskedasticity. Therefore, in this dissertation we go by the latter convention.

Unlike the usual linear statistical model, the parameter value of β in probit model cannot be directly interpretable as the effect of change of explanatory variable on the mean of the dependent variable. Let us differentiate equation for probit model (equation 4.1) with respect to X_{ik}. With the help of the chain rule in differentiation, we can write the following:

(4.13) $$\frac{\partial P_i}{\partial X_{ik}} = \frac{\partial F(Z_i)}{\partial Z_i} * \frac{\partial Z_i}{\partial X_{ik}} = f(Z_i) * \beta$$

where $f(Z_i)$ is the probability density function of the standard normal distribution. Therefore, to calculate the marginal effect of a continuous explanatory variable in probit model, first we need to calculate the probability density value for a given value of explanatory variable and multiply that by the parameter estimate of the respective explanatory variable.

Marginal effect calculation for a discrete explanatory variable (0-1 type dummy variable) is different from above approach. The appropriate marginal effect for a binary independent variable, say *d*, would be as follows:

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[16] Using general formulation analyzed by Harvey (1976), $Var[\varepsilon] = [\exp(z'\gamma)]^2$ for probit model $y = x'\beta + \varepsilon$, the variance now can be written as $Var[\varepsilon \mid x, z] = [\exp(z'\gamma)]^2$. Then the log of the likelihood function changes as follows:

$$l(\beta) = \sum_{i=1}^{n} y_i \ln(F_P(\frac{x_i'\beta}{\exp(z'\gamma)})) + \sum_{i=1}^{n} (1 - y_i) \ln(1 - F_P(\frac{x_i'\beta}{\exp(z'\gamma)}))$$

(4.14) $\frac{\partial P_i}{\partial d_{ik}} = f(x_i'\beta, d=1) - f(x_i'\beta, d=0)$

where $f(x_i'\beta)$ is the probability density function of the standard normal distribution[17].

The probit model for each non-alcoholic beverage can be written as follows:

$$\begin{aligned}
&\Pr(Y=1 \mid x_i'\beta) = \beta_1 + \beta_2 PRICE_i + \beta_3 AGEHH2529_i + \beta_4 AGEHH3034_i + \\
&\beta_5 AGEHH3544_i + \beta_6 AGEHH4554_i + \beta_7 AGEHH5564_i + \beta_8 AGEHHGT64_i + \\
&\beta_9 EMPHHPT_i + \beta_{10} EMPHHFT_i + \beta_{11} EDUHHHS_i + \beta_{12} EDUHHU_i + \\
&\beta_{13} EDUHHPC_i + \beta_{14} REG_CENTRAL_i + \beta_{15} REG_SOUTH_i + \\
&\beta_{16} REG_WEST_i + \beta_{17} RACE_BLACK_i + \beta_{18} RACE_ORIENTAL_i + \\
&\beta_{19} RACE_OTHER_i + \beta_{20} HISP_YES_i + \beta_{21} AGEPCLT6_ONLY_i + \\
&\beta_{22} AGEPC6_12ONLY_i + \beta_{23} AGEPC13_17ONLY_i + \\
&\beta_{24} AGEPCLT6_6_12ONLY_i + \beta_{25} AGEPCLT6_13_17ONLY_i + \\
&\beta_{26} AGEPC6_12AND13_17ONLY_i + \beta_{27} AGEPCLT6_6_12AND13_17_i + \\
&\beta_{28} MHONLY_i + \beta_{29} FHONLY_i + \beta_{30} POV185_i
\end{aligned} \tag{4.15}$$

where $i = 1, \ldots\ldots, n$ is the number of observations (households in our work) in the model. Y corresponds to the decision to buy a selected non-alcoholic beverage. In the Table 4.1, we have defined the variables used in the equation 4.15.

We will calculate marginal effects associated with each explanatory variable. The level of significance we will be using in this study is 0.05. We further conduct an F-test for demographic variable categories to find statistically significant demographics. Analysis and discussion pertaining to probit modeling exercise of non-alcoholic beverages will be taken up in the next section.

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[17] However, Green, W.H., Econometric Analysis, 5th edition, page 668, paragraph 4 states that in calculating marginal effect for a binary explanatory variable; "simply taking the derivative with respect to the binary variable as if it were continuous provides an approximation that is often surprisingly accurate". He further shows above argument numerically in Example 21.3 on page 675-676.

Empirical Results: Probit Analysis

In this section, we offer a discussion on empirical results from ten probit models dealing with the choice of consumption of non-alcoholic beverages. As result of the presence of zero expenditure observations for all categories of beverage data, we could not model the price of a given beverage on the probability of consumption. Therefore, we used a weighted average price calculated across all non-alcoholic beverages, which resulted in all non-zero expenditure observations. Through the probit analysis, we could determine the economic and demographic factors which are responsible for household choosing to consume or not choosing to consume a non-alcoholic beverage. This analysis will reveal the statistically significant demographic characteristics associated with the choice of consumption of non-alcoholic beverages.

First we conducted an *F*-test on all demographic categories for all ten non-alcoholic beverages to determine the statistically significant factors. We used a 0.5 significance level in our decision on what demographic factor affect the choice of consumption of a beverage. Table 4.2 shows the statistically significant demographic category that affects the decision to consume a beverage ("Y" in the table represents the statistically significant demographic factor). Appendix 1 shows the appropriate test statistics (*chi*-squared statistic) and associated hypothesis tests and *p*-values for above tests on demographic categories pertaining to the probit analysis.

Table 4.2 Summary of Probit Model Findings: Significant Demographic Categories[18]

	Age of Household Head	Household Head Employment	Household head Education	Region	Race	Hispanic Status	Age & presence of Children	Gender	Poverty Status
Isotonics	X	X	X	X	X	X	X	X	
Regular Soft Drinks	X	X	X		X		X	X	
Diet Soft Drinks	X				X			X	X
High Fat Milk			X	X	X		X	X	
Low Fat Milk		X	X	X	X			X	X
Fruit Drinks	X		X		X		X	X	
Fruit Juices				X	X		X	X	X
Bottled Water	X			X	X	X		X	X
Coffee	X			X	X	X		X	X
Tea	X	X		X				X	

Table 4.3: Summary of Heckman Second-Step Findings: Significant Demographic Categories

	Age Household Head	Household Head Employment	Household head education	Region	Race	Hispanic status	Age & presence of Children	Gender	Poverty status
Isotonics	X	X		X	X	X	X	X	
Regular Soft Drinks	X		X	X	X		X	X	X
Diet Soft Drinks	X			X	X			X	
High Fat Milk			X	X			X	X	X
Low Fat Milk			X	X			X	X	
Fruit Drinks				X			X	X	
Fruit Juices	X				X		X	X	X
Bottled Water	X	X		X	X			X	X
Coffee	X			X		X		X	
Tea	X	X		X	X	X	X	X	

[18] X represents statistical significance at 0.10 level

Race, region and gender of household head are the three most important factors affecting the decision to purchase most non-alcoholic beverages. In particular, gender of the household head is an important factor for decision to purchase of all ten non-alcoholic beverages considered. Race is an important factor for all but decision to consume tea. Age of the household head was not significant for the decision to consume milk (both high-fat and low-fat) and fruit juices. Region of the country where the household is located was an important factor in the choice to consume isotonics, milks, fruit juices, bottled water, coffee and tea.

Employment, education and poverty status and presence of children in the household were not as much important as region, race, age and gender of household head in the decision to buy a non-alcoholic beverage. The decision to consume isotonics, regular soft drinks, milk and fruit drinks was influenced by the education status of the household head. Presence of children in the household has an impact on the decision to buy isotonics, regular soft drinks, high fat milk, fruit juices and drinks. Poverty status of the household determined the choice of consumption of diet soft drinks, low-fat milk, fruit juice, bottled water and coffee. Hispanic status of the household head was significant only with respect to the choice to consumption of isotonics, coffee and tea.

For each beverage category, a probit model was run and *p*-values associated with each beverage category were obtained. Furthermore, marginal effects of each demographic category were calculated. They show the probability of increase or decrease of consumption of a non-alcoholic beverage pertaining to each demographic category relative to a base category.

Next we discuss the probit results for ten non-alcoholic beverage categories considered. We will explain the direction and marginal effects of influence for each significant demographic category.

Probit Results for Isotonics

Probit regression results and marginal effects for the decision to purchase isotonics are shown in the Appendix 3. The older the household head is, the lower the probability of purchase of isotonics. Household heads that are post-college educated have a low probability to consume isotonics compared to household heads that are educated below high school level. Full time employed household heads have a slightly lower probability of purchase of isotonics in comparison to those heads that are not employed.

The probability of consumption of isotonics is higher for households that are located in western and southern parts of the United States compared to those in the East, respectively. Blacks have a low probability to purchase of isotonics compared to Whites. Hispanics are more likely to purchase isotonics. Presence of children is a clear indication in the decision to purchase isotonics in contrast to those households without children. In particular, households with children who are less than six-years of age and teens have more probability to purchase isotonics compared to those households without children. Overall, there is a high probability to purchase isotonics, if there is a child in the household.

Probit Results for Regular Soft Drinks

We show the regression results from probit model in the decision to purchase regular soft drinks in the Appendix 3. Household heads that are employed full time and post-college educated are less likely to purchase regular soft drinks for at-home consumption compared to those who are not employed and educated below high school level, respectively. Blacks have a higher probability to purchase regular soft drinks compared to Whites. Teenagers are as twice as much likely to purchase regular soft drinks compared to non-teens. A household with a female or a male head only, is less likely to purchase regular soft drinks compared to those with a male and a female.

Probit Results for Diet Soft Drinks

Probit results and appropriate marginal effects from the decision to purchase diet soft drinks are depicted in the Appendix 3. Households which are post-college educated are more likely to purchase diet soft drinks compared to those who are educated below high school level. Midwestern households have a high probability to purchase diet soft drinks compared to households in East. Blacks and Asians have a low probability to purchase diet soft drinks in comparison to Whites. Households headed by a male have a low probability to purchase diet soft drinks compared to those households that have both male and female participants. Probability of the decision to purchase diet soft drinks by poverty households is lower than that of non-poverty households.

Probit Results for High Fat Milk

Probit estimates and marginal effects associated with each variable with respect to high-fat milk purchase decision are shown in the Appendix 3. The more educated a household head is, lower the probability of purchase of high fat milk. Households with children have a high probability to purchase high-fat milk compared to those without children. As far as the age of children is concerned, households with children below 12-years of age have a high probability to purchase high fat milk. Households with female only or male only heads have a low probability of purchase of high-fat milk compared to those with both female and male heads.

Probit Results for Low Fat Milk

Probit model and marginal effects for the decision to buy low-fat milk are shown in the Appendix 3. Full time employed households have a low probability to purchase low fat milk compared to those that are not fully employed. The more educated the household head, the higher the probability of purchase of non-fat milk. Southern and Western households have a low probability to purchase low-fat milk compared to those in the East. Black are less likely to consume low-fat milk compared to Whites. Households represented by a male head have a low chance to purchase low-fat milk compared to those represented by both male and a female. Poverty households are less likely to purchase low-fat milk compared to non-poverty households.

Probit Results for Fruit Drinks

Probit regression results from the decision to buy fruit drinks and associated marginal effects are shown in the Appendix 3. Household heads that are over 64 years of age are less likely to purchase fruit drinks compared to those who are below 25 years of age. Blacks have a high probability to consume fruit drinks compared to Whites. Age and presence of children is a major factor determining the likelihood of purchase of fruit drinks. Presence of children (age one through 18) increases the probability of purchase of fruit drinks compared to those households without children. Households with children aged less than six-years and in between six and twelve are more likely to purchase fruit drinks. Presence of teenagers in the household increase the probability of purchase of fruit drinks. Male headed households have more chance to purchase fruit drinks compared to households with both males and female heads.

Probit Results for Fruit Juices

Regression results from probit model on decision to purchase fruit juices are depicted in the Appendix 3. It also shows the appropriate marginal effects associated with each explanatory variable. Sothern and Western households are less likely to purchase fruit drinks compared to those in the East. Blacks are more prone to purchase fruit juices in contrast to Whites. Presence of children is a major contributory factor for the probability of fruit juice purchases. Households with children below six-years of age are more likely to purchase fruit juices. Having teenagers in the household too significantly increase the likelihood of purchase of fruit juices. Households with male head only and female head only have a low chance of purchase of fruit juices compared to those with both male and females in the household. Probability of poverty households' purchase of fruit juices is lower than that of non-poverty households.

Probit Results for Bottled Water

Probit results from the decision to buy bottled water and associated marginal effects are shown in the Appendix 3. Households with full-time and part-time employed household heads are more likely to purchase bottled water compared to those who are not employed. Probability of purchase of bottled water is more among Blacks compared to Whites. Hispanic households are more likely to purchase bottled water compared to non-Hispanic households. Households where the male plays a role in food choices are less likely to purchase bottled water in comparison to those managed by both male and a female. The likelihood of a poverty household's decision to purchase bottled water is less compared to a non-poverty household.

Probit Results for Coffee

Probit regression results from the analysis of the decision to purchase coffee are shown in the Appendix 3. Appropriate marginal effects associated with each explanatory variable are also included in the Appendix 3. The older the household head is, the more the probability to purchase coffee. The likelihood of purchase of coffee by a household located in Midwest and West is low, in comparison to those in the East. Blacks are less likely to purchase coffee compared to Whites. Being Hispanic has a higher chance of purchasing coffee in comparison to non-Hispanic. Households with a single (female only and male only) food manager have a less probability to purchase coffee than those managed by both groups. Poverty households are less likely to consume coffee compared to non-poverty households.

Probit Results for Tea

Probit regression results from the decision to purchase tea and associated marginal effects for each explanatory variable are shown in the Appendix 3. Fully employed household heads are less likely to consume tea at home compared to those who are not fully employed. Probability of consumption of tea is lower in Midwestern,

Western and Southern households compared to those in the East. Households where the male is the household food manager have less probability to purchase tea in comparison to those with both male and a female food manager.

Demographic Study: Volume of Consumption

In the following section, first we offer a discussion employing *figures and cross tabulations* of various explanatory variables against the dependent variable. Next, we use the Heckman two-step procedure where in the first stage a decision to consume a good is made and in the second stage, the volume of consumption is modeled. We also will explain the variables used in modeling the volume of consumption. Final section will be devoted to explain the empirical results.

Model Development: Heckman Two-Step Analysis

A common characteristic in micro level data (data gathered at consumer level such as at individual or household level) is a situation where some consumers do not purchase some items during the sampling period and presence of them in the sample creates a zero consumption level for that data period. The data used in this dissertation (Nielsen HomeScan scanner data for consumer purchases) also are gathered at household level and due to that it suffers from zero consumption data.

In the Figure 4.1, we show the percentage at-home market penetration values for ten non-alcoholic beverages considered in this study. Market penetration value tells the percentage of consumers who actually bought a given beverage during that calendar year (year 2003 in this analysis) and 100% minus the market penetration value for each beverage communicates the value responsible for zero observations. For example, only

21.05% of households did purchase isotonics during calendar year 2003 (or 78.95% of households did not purchase isotonics in year 2003, which are zero observations). Most heavily purchased beverages were fruit juices (93.42%) and regular soft drinks (90.57%). High-fat milk was purchased more compared to low-fat counterpart. About 70% of households did purchase bottled water, while about 72% purchased coffee and tea.

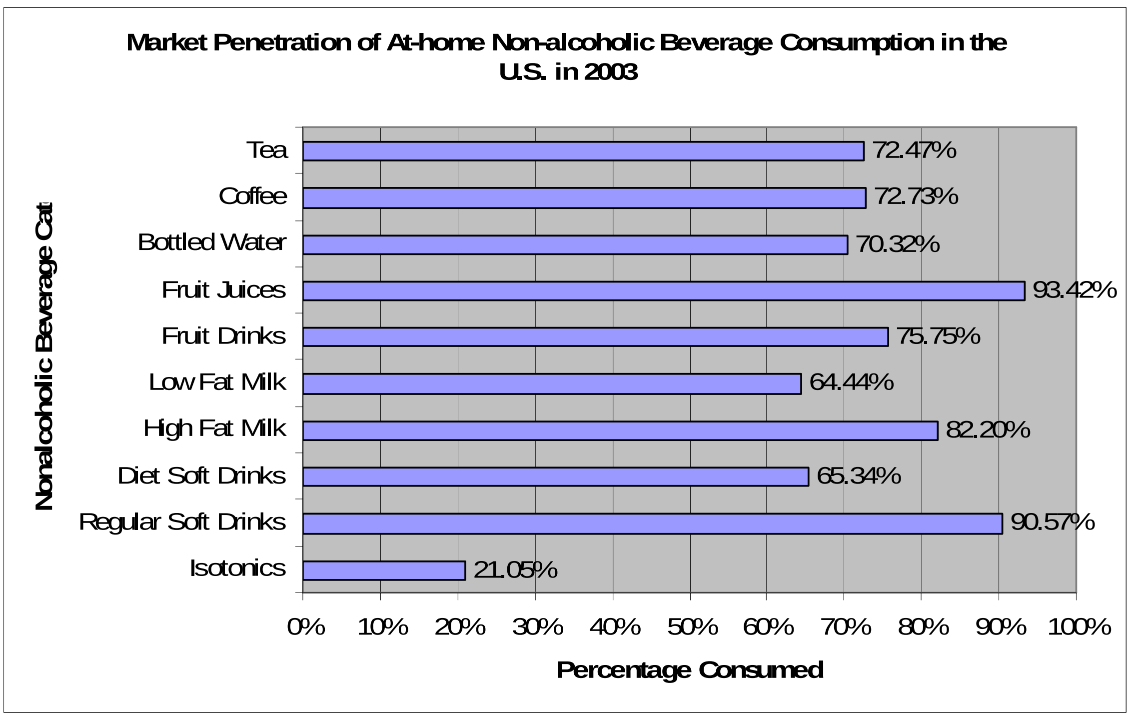

Figure 4.1: Market penetration of at-home non-alcoholic beverage consumption in the United States (2003)

There can be many reasons for non-consumption of a beverage. According to Cheng and Capps (1988), the reasons for non-consumption of a good might be non-preference, inventory effects, price effects, or the duration of the survey period. They further suggest that the longer the survey period, the higher the chance of reveling non-preference toward a particular commodity. Considering the frequency of our data (our data corresponds to an annual period) we can assume that zeros in our data may be due to non-preference.

As such we face a censored sample of data (values of dependent variable, which us the total expenditure on beverage purchases, are not observable to corresponding known values of explanatory variables). Application of ordinary least squares (OLS) to estimate a regression with a limited dependent variable (such as in a censored sample like ours) usually give rise to biased estimates, even asymptotically (Kennedy, 2003). Removing all observations pertaining to zero purchases and estimating regression functions only for non-zero purchases too creates a bias in the estimates. This phenomenon also is known as *sample selection bias*. Heckman (1979) stated that not adjusting for sample selection may result in biased estimates of the demand parameters. Furthermore, Heckman (1979), discussed the sample selection bias as a specification error, and developed a simple consistent estimation method that eliminates the specification error for the case of censored samples. It is known as Heckman-type correction procedure. Other competitive models in the literature to deal with such zero dependent variable observations (or sample selection problem) are Tobit model and double-hurdle model. All these models are designed to deal with zero consumption in a two-stage decision process.

There are two estimation methods facilitating Heckman-type correction. They are Heckman's (1976, 1979) two-step procedure and the full information maximum likelihood estimator (Amemiya, 1985). Relative inefficiencies of two-step procedure compared to full information maximum likelihood technique is highlighted in Shonkwiler and Yen (1999). Nevertheless, Puhani (2000) had a different perspective to above argument put forward by Shonkwiler and Yen (1999) and said that Heckman-two-step procedure supersedes full information maximum likelihood estimator under strong collinearity conditions of explanatory variables. Furthermore, Puhani (2000) said that strong collinearity is expected in models with a large number of same variables involved in both stages (decision stage as well as actual purchase stage). Our data and analysis fall into the scenario explained by Puhani (2000), hence we use of Heckman-two-step procedure in modeling demand for non-alcoholic beverages[19].

The first stage of the Heckman-two-step sample selection procedure, involves in decision to purchase a given non-alcoholic beverage. It is modeled through a probit model. The theoretical information pertaining to probit model is explained in the previous section. A binary dependent variable is observed (purchase or not purchase), where purchase is represented by one (1) and not purchase is given by a zero (0). The latent selection equation can be written as follows:

(4.16) $Z_{hi} = w'_{hi}\gamma_i + \varepsilon_{hi}$

where Z_k represents a latent selection variable (buy or not to buy type dichotomous variable):

[19] The two-step Heckman sample selection procedure is essentially the single equation version of Shonkwiler and Yen (1999) procedure enabling zero consumption in demand systems.

$$(4.17) \quad Z_{hi} = \begin{cases} 1 \ if \ \ Z_{hi} > 0 \\ 0 \ if \ \ Z_{hi} < or = 0 \end{cases}$$

w_{hi} is a vector of explanatory variables in the latent decision making variable, γ_h is a vector of parameters to be estimated in the decision making equation, ε_h is the error term, and $h = 1,2,.....,N$ is the number of observations (in our work the number of households in the sample in year 2003; 7642 households) in the sample and $i = 1,2,......,M$ is the number of commodities considered (ten non-alcoholic beverages in our study). Modeling above equation 4.16 through probit model gives us following relationships:

$$(4.18) \quad \Pr[Z_{hi} = 1] = \phi(w_{hi}, \gamma_i) \text{ and}$$

$$(4.19) \quad \Pr[Z_{hi} = 0] = 1 - \phi(w_{hi}, \gamma_i)$$

where ϕ is the normal cumulative probability distribution function (cdf). The first stage estimation provides estimates of γ_i and the inverse of the Mills Ratio (IMR hereinafter). We also generate the associated probability density function (pfd). Inverse of Mills Ratio is calculated taking the ratio of pdf to cdf. Mathematically, it is as follows:

$$(4.20) \quad \text{for } Z_k = 1, \ IMR_{hi} = \frac{\varphi(w_{hi}\hat{\gamma}_i)}{\phi(w_{hi}\hat{\gamma}_i)}$$

where φ represents the probability density function. Inverse mills ratio is a monotone decreasing function of the probability that an observation is selected into the sample, $\phi(w_k \hat{\gamma}_k)$ (Heckman, 1979). In particular:

$$(4.21) \quad \lim_{\phi(Z_{hi}) \to 1} IMR_{hi} = 0$$

(4.22) $\lim_{\phi(Z_{hi})\to 0} IMR_{hi} = \infty$

(4.23) $\dfrac{\partial IMR_{hi}}{\partial \phi(Z_{hi})} < 0$

The calculated IMR, will be used as an additional explanatory variable in the second stage volume equation, which takes care of the sample selection bias in the data. Second stage equation is given as follows:

(4.24) $E[Y_{hi} \mid Z_{hi} = 1] = X'_{hi}\beta_i + \alpha_i \dfrac{\varphi(w_{hi}\hat{\gamma}_i)}{\phi(w_{hi}\hat{\gamma}_i)}$

(4.25) $E[Y_{hi} \mid Z_{hi} = 1] = X'_{hi}\beta_i + \alpha_i IM\hat{R}_{hi}$

where X_k is a vector of explanatory variables considered in the second stage.

Importantly, only data points associated with non-zero observations on Y_k are considered here. The IMR calculated using information retrieved from first stage probit model is used as an explanatory variable in the second stage (see equations 4.24 and 4.25). Presence of a sample selection bias in data will be communicated through statistical significance of the coefficient associated with IMR, i.e. α_k . If α_k is statistically not different from zero, we conclude that there is no sample selection bias in the data and result in the following regression model:

(4.26) $E[Y_{hi} \mid Z_{hi} = 1] = X'_{hi}\beta_i$

It is important to know that the explanatory variables in first stage and second stage equations may or may not be the same. In our work, the price variables in both equations differ (in the first stage we used a weighted average price constructed using information from all non-alcoholic beverages considered and in the second stage we used the actual price or unit value of each non-alcoholic beverage considered) however, rest of the demographic variables is exactly the same in the first stage and in the second stage.

Choice of explanatory variables in the first stage and second stage has an implication on the derivation and interpretation of marginal effects associated with variables in the second stage. This is because in the second stage, we have the IMR term augmenting the regular regression function with other explanatory variables. Therefore, in calculating marginal effects, the influence of IMR and its associated regression coefficient on the other coefficients have to be taken into consideration.

Suppose X_{kj} denote the *j*th regressor that is common to both first stage regressors, w_k and, second stage regressors, X_j. Differentiating equation 4.25 with respect to *j*th regressor, the marginal effect is given by the following relationship (following explanation is borrowed from lecture notes from AGEC 661, Applied Econometrics Spring 2005 class at Texas A&M University and Saha, Capps and Byrne (1997)):

$$(4.27) \quad \frac{\partial E[Y_{hi} \mid Z_{hi} = 1]}{\partial X_{kj}} = \beta_{ij} + \alpha_i \frac{\partial (IM\hat{R}_{hi})}{\partial X_{hj}}$$

It is evident from 4.27 that marginal effect of the *j*th regressor on Y_{ki} consists of two parts: a change in X_j which affects the probability of consuming the commodity (this effect is represented by $\frac{\partial (IM\hat{R}_{hi})}{\partial X_{hj}}$ in 4.27); a change in X_j which affects the level of consumption (or expenditure of consumption) which is conditional upon the household choosing to consume the *i*th commodity (this is represented by β_{ij} in equation 4.27). The former of the above two expression is important, because the sign and magnitude of the marginal effect depends not only on the β_{ij} , but also that of the $\frac{\partial(IM\hat{R}_{hi})}{\partial X_{hj}}$. According to Saha, Capps and Byrne (1997), after some simplification we arrive at the following relationship for the Heckman second stage marginal effects:

$$(4.28)\quad M\hat{E}_{kj} = \frac{\partial E[y_k \mid Z=1]}{\partial X_{kj}} = \beta_j - \alpha\gamma_{ij}\{W\gamma IMR_k + (IMR_k)^2\}$$

In general the marginal effect $M\hat{E}_{kj} \neq \hat{\beta}_j$; however the only case where $M\hat{E}_{kj} = \hat{\beta}_j$ is where $\hat{\alpha} = 0$ which is a situation where the errors in the first-stage and second-stage estimation equations have zero covariance. It must be noted that the $M\hat{E}_{kj}$ estimation depends on a local set of co-ordinates. Therefore, we estimate the $M\hat{E}_{kj}$ at the sample means. Equation 4.29 shows this result. For simplicity, let us use letter λ in lieu of IMR :

$$(4.29)\quad M\hat{E}_{kj}\,|_{samplemean} = \hat{\beta}_j - \hat{\alpha}_i\hat{\gamma}_j\{(\overline{W}\hat{\gamma})\overline{\hat{\lambda}} + \overline{\hat{\lambda}}^2\}$$

where $\overline{W}$ denotes the vector of regressor sample means in the probit equation (the first stage equation of the Heckman two-step model and:

$$(4.30)\quad \overline{\hat{\lambda}} = \frac{\varphi(\overline{W}\hat{\gamma})}{\phi(\overline{W}\hat{\gamma})}$$

is the inverse Mills ratio evaluated at those means.

The Heckman two-step demand model for each non-alcoholic beverage can be written as follows:

$$\begin{aligned}
\log(q_i) = {} & \beta_1 + \beta_2 \log(P_i) + \beta_3 AGEHH2529_i + \beta_4 AGEHH3034_i + \\
& \beta_5 AGEHH3544_i + \beta_6 AGEHH4554_i + \beta_7 AGEHH5564_i + \beta_8 AGEHHGT64_i + \\
& \beta_9 EMPHHPT_i + \beta_{10} EMPHHFT_i + \beta_{11} EDUHHHS_i + \beta_{12} EDUHHU_i + \\
& \beta_{13} EDUHHPC_i + \beta_{14} REG_CENTRAL_i + \beta_{15} REG_SOUTH_i + \\
& \beta_{16} REG_WEST_i + \beta_{17} RACE_BLACK_i + \beta_{18} RACE_ORIENTAL_i + \\
& \beta_{19} RACE_OTHER_i + \beta_{20} HISP_YES_i + \beta_{21} AGEPCLT6_ONLY_i + \\
& \beta_{22} AGEPC6_12ONLY_i + \beta_{23} AGEPC13_17ONLY_i + \\
& \beta_{24} AGEPCLT6_6_12ONLY_i + \beta_{25} AGEPCLT6_13_17ONLY_i + \\
& \beta_{26} AGEPC6_12AND13_17ONLY_i + \beta_{27} AGEPCLT6_6_12AND13_17_i + \\
& \beta_{28} MHONLY_i + \beta_{29} FHONLY_i + \beta_{30} POV185_i + \alpha_i IMR + \varepsilon_i
\end{aligned} \tag{4.31}$$

where $i = 1,......,n$ is the number of observations (households in our work) in the model. q_i corresponds to the quantity of purchase of a given non-alcoholic beverage and P_i variable represent the price the respective non-alcoholic beverage. We have defined the variables in the equation 4.31 in Table 4.1. Notice that we use the log-log functional specification in modeling the quantity of purchase. In the equation 4.31, *IMR* stands for the Inverse Mills ratio and α_i corresponds to the coefficient associated with *IMR*. Presence of sample selection bias is determined looking at the significance of α_i. If we have sample selection bias, we have to do an adjustment to the coefficient estimates in the second stage estimation in trying to get at correct marginal effects. Procedure to adjust for marginal effects was elaborated in the preceding section.

As such, we will calculate marginal effects associated with each explanatory variable. The level of significance we will be using in this study is 0.05. We further conduct an *F*-test for demographic variable categories to find statistically significant demographics. Analysis and discussion pertaining to Heckman second stage will be taken up next.

It should be noted that the second stage volume regression was corrected for heteroskedasticity using the method suggested by Harvey (1976).

Empirical Results: Cross Tabulations

Initially, cross tabulations were used to uncover demographic tendencies to consume various levels of non-alcoholic beverages. In exercising this procedure, mean consumption levels (in gallons per capita) of each non-alcoholic beverage was calculated corresponding to each demographic criteria. This average value includes the values from the households that actually consumed a non-alcoholic beverage. For example, the demographic variable, "household Race" includes four categories: White, Black, Asian, and Other. Average level of consumption per person per year pertaining to each Race category was calculated. A comparison among the households in the four Race categories reveals if there are differences in the level of consumption from one Race category to another.

The demographic variables used in the cross tabulation exercise include the following: age of household head; employment status of household head; education status of household head; Region; Race; Hispanic status; age and presence of children in the household; gender of the household food manager; and poverty status of household. Beverage consumption differences within each demographic category are emphasized.

Age of the Household Head

Figure 4.2 shows the per capita volume (in gallons) of various non-alcoholic beverages consumed at home in the U.S. in calendar year 2003 delineated by age category. There are seven age categories of interest to us. They are: under 25; age 25-29, age 30-34; age 35-44; age 45-54; age 55-64; age 65 and older. The most heavily consumed non-alcoholic beverage category among households where household head is 25 years or younger, was regular soft drinks. It was about 18 gallons per capita per year. They also consumed a considerable amount of other non-alcoholic beverages taking a range of about 3-5 gallon per capita per year. Isotonics is the least amount consumed at home by household heads of age group less than 25, even though it was the highest contrast to other age groupings.

Household heads in the age category of 55-64, do take a lead on diet soft drink consumption, taking up to about 8 gallons per person per year. Highest coffee consumption is recorded among the oldest household heads (age group 65 and up) and it is about 12 gallons per person per year. Highest high-fat milk consumption on average was observed in the household heads with age category 30-34 years, whereas the lowest was among the household heads above 55 years of age. Lowest low-fat milk consumption is associated with households with age category 30-34 years. Household heads over 64 years of age had the lowest per capita consumption of fruit drinks, while the household heads in the age category 35-44 consumed the highest.

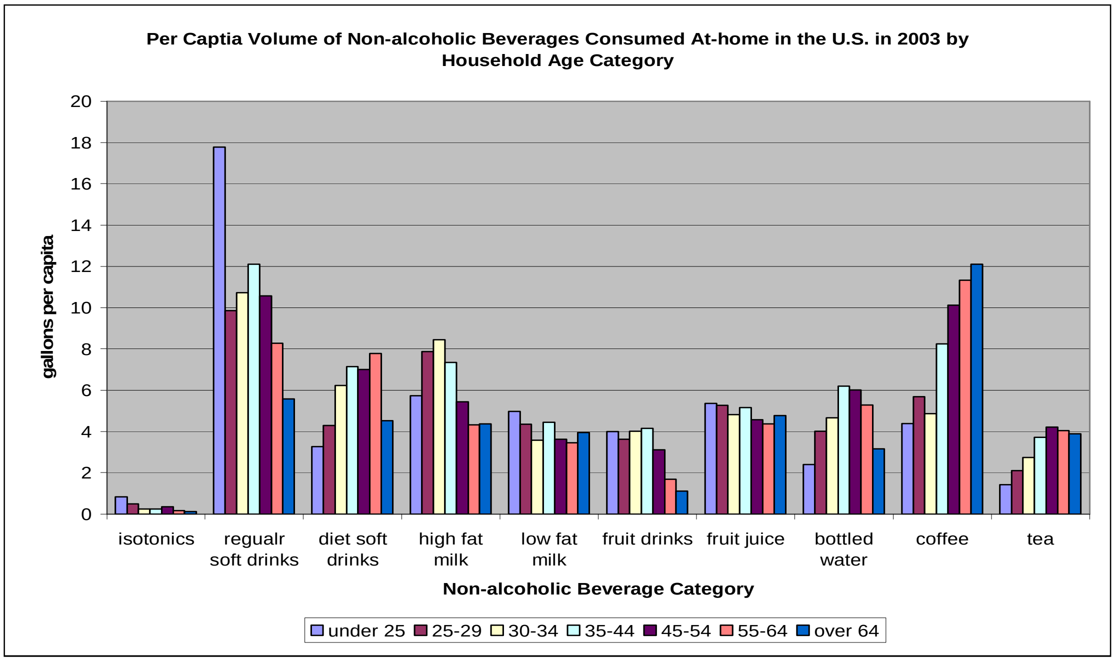

Figure 4.2: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by household age category

Fruit juice consumption was highest among the household heads that are under age 25 and it was about 6 gallons per capita per year. Household heads that are below 29 years and above 25 years showed the second highest consumption level of fruit juices. The lowest level of fruit juice consumption was with household heads that are between age group 55-64 years.

The highest level of bottled water consumption was observed with household heads that are in between 35-44 years. It was slightly over 6 gallons per person per year at home. Household heads that are below 25 years of age showed lowest level of at-home consumption of bottled water.

The highest level of tea consumption was observed among the household heads that are 45-54 years of age, which is about 5 gallons per person per year at home. On the other hand the lowest level of tea intake was seen within younger household heads (below 25 years).

Employment Status of the Household Head

In the Figure 4.3, we show the per capita volume of non-alcoholic beverages consumed at home in the U.S. in year 2003 by household employment status. The highest levels of consumption of regular soft drinks, high-fat milk, low-fat milk, fruit drinks, fruit juices and tea were observed among household heads that are employed part-time. In particular, part-time employed household heads consumed on average up to about 11 gallons of regular soft drinks, about 5 gallons of fruit juices, 3.5 gallons of fruit drinks, and 6 gallons of high-fat milk per person per year at home. Full-time employed household heads consume the highest volume of diet soft drinks (about 6.5 gallons per capita per year) and bottled water (about 6 gallons per capita per year) compared to other households. Coffee consumption was highest among the household heads that are not employed for full pay.

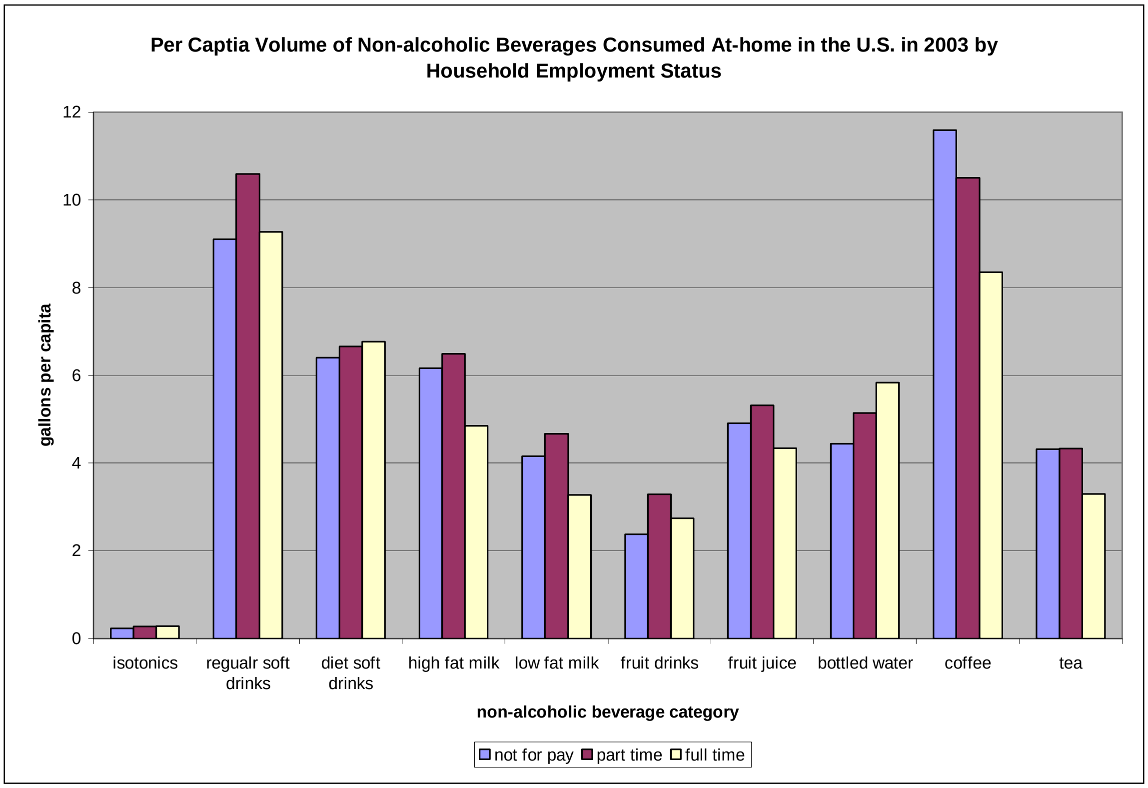

Figure 4.3: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by household employment status

Education Status of Household Head

We show the per capita volume of non-alcoholic beverages consumed at home in the U.S. in year 2003 by household education status in Figure 4.4. Less than high-school educated household heads did consume the highest levels of regular soft drinks, high-fat milk, fruit drinks, coffee and tea. More specifically, less than high-school educated household heads intake about 13 gallons of carbonated soft drinks, 8 gallons of high-fat milk, 3 gallons of fruit drinks, 12.5 gallons of coffee, and about 5 gallons of tea, per capita per year.

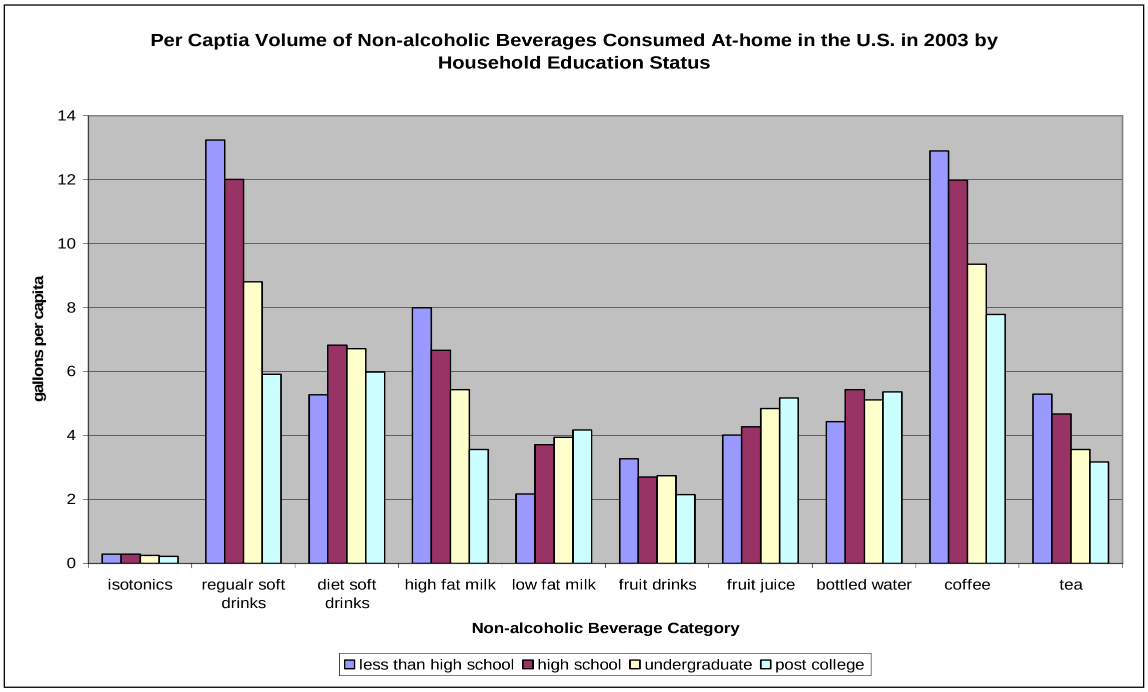

Figure 4.4: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by household education status

Post-college educated household heads consumed the lowest per capita volume of regular soft drinks at home (about 6 gallons per person per year). Lowest per capita amounts of diet soft drinks were consumed by household heads that are educated below high-school level (about 5 gallons per person per year), while highest per capita volume of diet soft drinks was taken by high-school level educated household heads (about 7 gallons per capita per year). Household heads that are educated at post-college level consumed lowest levels of high-fat milk, fruit drinks and tea. They were, respectively 3.5, 2 and 3 gallons per person per year. On the other hand, lowest per capita intake of low-fat milk and fruit juices were observed through household heads that have less than high school level education. More specifically, they were about 2 and 4 gallons per person per year.

Bottled water consumption was high amongamong household heads with all levels of education categories; however, it was slightly higher for household heads that are educated at high-school level compared to other levels. Lowest tea consumption, which was about 3 gallons per person per year, was observed with post-college level educated household heads.

Region

In the Figure 4.5 we show per capita volume of non-alcoholic beverage consumption at home by region. Four regions of the United States are considered in this analysis. They are East, South, West and Midwest. Southern and Midwestern households consumed more regular soft drinks compared to Eastern and Western households. Sothern households had the highest regular soft drink consumption of them all and it was as high as 10.5 gallons per person per year at home. The lowest with respect to the consumption of regular soft drinks was recorded in Western households which was about 7.5 gallons per person per year at home.

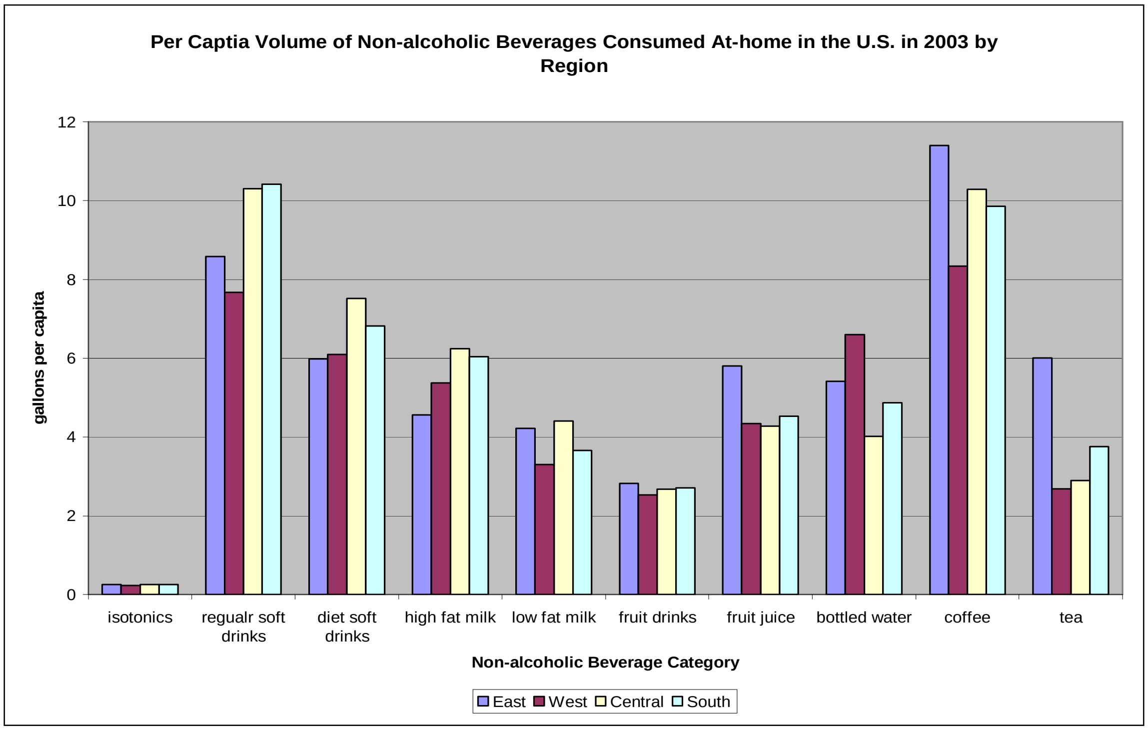

Figure 4.5: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by region

Midwestern households consumed the highest amounts of diet soft drinks, high-fat milk, and low-fat milk compared to households in other regions. Households in the East consumed about 6 gallons of diet soft drinks per person per year, which was the lowest considering contribution from different regions. Midwestern households consumed about 7.5 gallons of diet soft drinks per person per year, which is the highest among all regions. Lowest high fat milk consumption was observed in Eastern households (about 4.5 gallons per capita per year), Midwestern households consumed about 6.5 gallons per capita per year.

Western households consumed about 3 gallons of low-fat milk per person per year, which is the lowest. Households in the East consumed about 3 gallons of fruit drinks per person per year at home, which is the highest among all regions. Eastern households consume the highest amount of fruit juice amounting up to 6 gallons per capita per year. Highest bottled water consumption was observed in Western households which was about 7 gallons per capita per year. Midwestern households drank the lowest amount of bottled water in 2003 at home which was about 4 gallons per capita per year.

Households in the East consumed about 11.5 gallons of coffee per capita per year in 2003, which was the highest. Lowest coffee consumption was recorded in Western households which was about 8 gallons per capita per year. Similar trend follows for the consumption of tea at home in 2003. Again, the households in the East showed the highest consumption of tea per capita per year (6 gallons) while those in the West consumed only about 2.5 gallons per capita per year. Households in all regions consumed less than one gallon of isotonics per capita at home in year 2003.

Race

Per capita volume of non-alcoholic beverages consumed at home by Race category is shown in Figure 4.6. Asians consumed the lowest amount of regular soft drinks (about 7 gallons per capita per year) compared to Other category (non-Asians, non-Whites and non-Blacks) which ingested the highest amount regular soft drinks (13 gallons per capita per year). Whites purchased the highest volume of diet soft drinks to consume at home, which is close to 8 gallons per person per year. Black households consumed the lowest volume of diet soft drinks amounting up to 2.5 gallons per person per year.

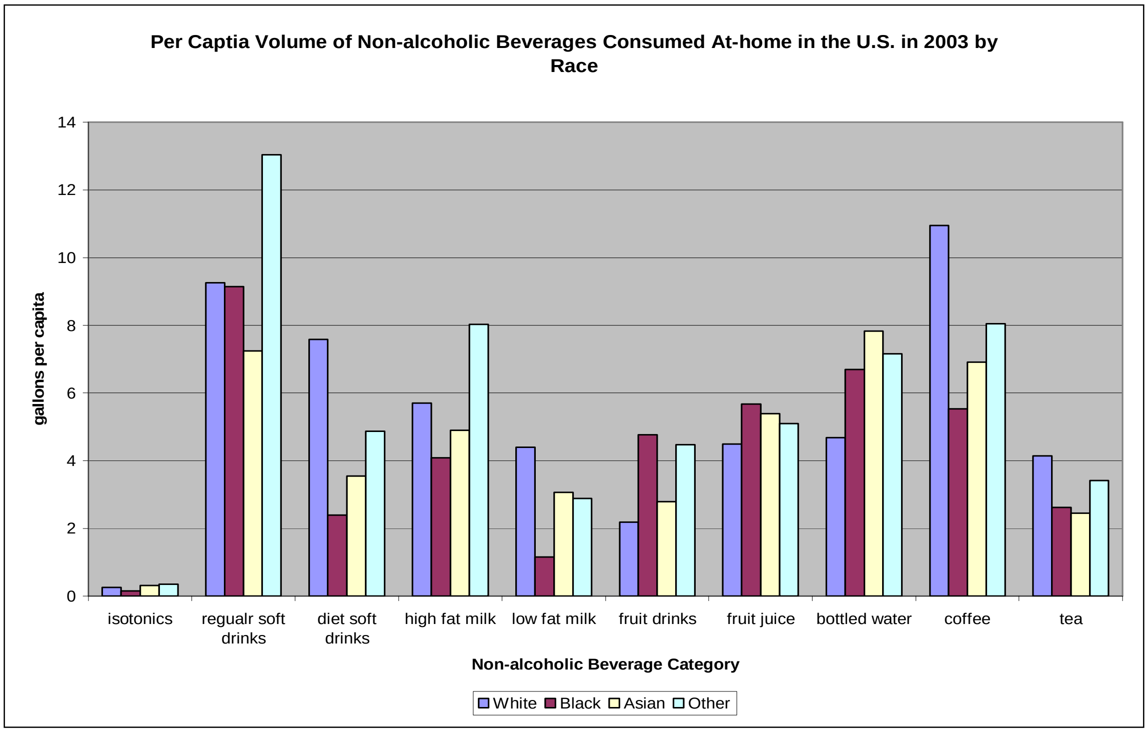

Figure 4.6: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by race

Other race category consumed 8 gallons of high-fat milk per person per year, which is the highest among all races. Blacks consumed the lowest volume of high-fat milk, which was about 2.5 gallons per capita per year. Whites stand the second highest consumers of high-fat milk. However, Whites were the highest in terms of low-fat milk consumption averaging up to about 6 gallons per capita per year at home. The lowest level of low-fat milk consumption was recorded among Black households.

Black households consumed highest volumes of both fruit drinks and fruit juices; respectively they are five and six gallons per capita per year. On the other hand, White households consumed the lowest volume of both fruit drinks and fruit juices which were two and 4.5 gallons per capita per year respectively.

Lowest volume of bottled water consumption was recorded from White households (about 4.5 gallons per capita per year), while Asian showed the highest level of bottled water consumption (about 8 gallons per person per year). White households consumed highest levels of coffee and tea per capita at home. In particular, coffee intake was 11 gallons per capita per year and tea intake was about 4 gallons per person per year, respectively. The lowest coffee intake was recorded among Black households where they only consumed about 5 gallons per capita per year. Other race category consumed the highest volume of isotonics while Black households consumed the lowest volume.

Hispanic Status

Figure 4.7 show the per capita consumption of non-alcoholic beverages in year 2003 delineated based on Hispanic status. Hispanic households purchased more of the following non-alcoholic beverages in comparison to non-Hispanic households. They are isotonics, regular soft drinks, high-fat milk, fruit drinks, fruit juices, and bottled water. In particular, Hispanic households consumed about one gallon of isotonics, 12 gallons of regular soft drinks, 8 gallons of high-fat milk, 4.5 gallons of fruit drinks, 5.5 gallons of fruit juices, and 6.5 gallons of bottled water per capita par year.

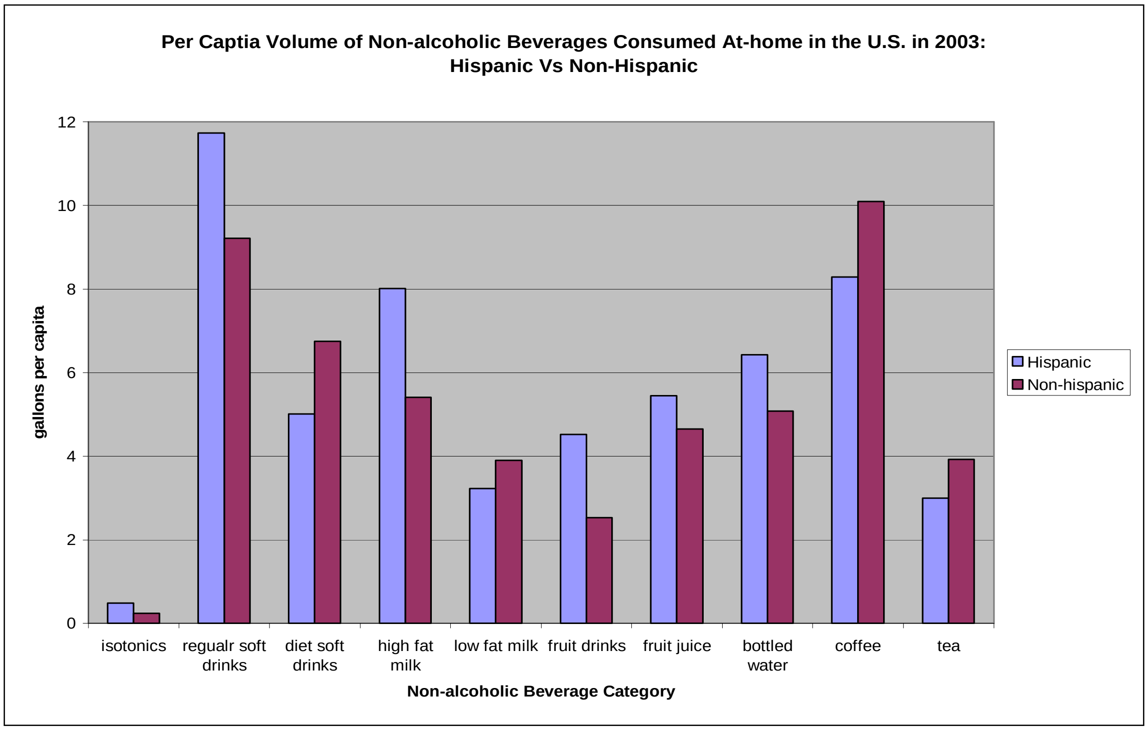

Figure 4.7: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003: hispanic Versus non-hispanic

On the other hand, non-Hispanic households consumed the highest volumes of diet soft drinks (7 gallons per person per year), low-fat milk (4 gallons per capita per year), coffee (10 gallons per person per year) and tea (about 4 gallons per capita per year) compared to Hispanic households.

Age and Presence of Children

Per capita volume of non-alcoholic beverages consumed at home in the U.S in 2003 by age and presence of children is shown in Figure 4.8. There are eight categories to deal with age and presence of a child in a household. Presence of a child in the category *"less than 6 years, 6-12 years and 13-17 years"* contributed to the highest consumption of regular soft drinks, high-fat milk, fruit drinks and fruit juice in a household. In particular, 20 gallons of regular soft drinks, 19 gallons of high-fat milk, 8 gallons of fruit drinks and 9 gallons of fruit juices per capita per year were consumed in households with aforementioned age and presence of children category. Not having a child in the household contributed to the lowest intake of isotonics, regular soft drinks, high-fat milk, low-fat milk, fruit drinks, and fruit juices. In numbers they were 8 gallons of regular soft drinks, 4 gallons of high-fat milk, 3 gallons of low-fat milk, about 1.5 gallons of fruit drinks, and 4 gallons of fruit juices per capita per year.

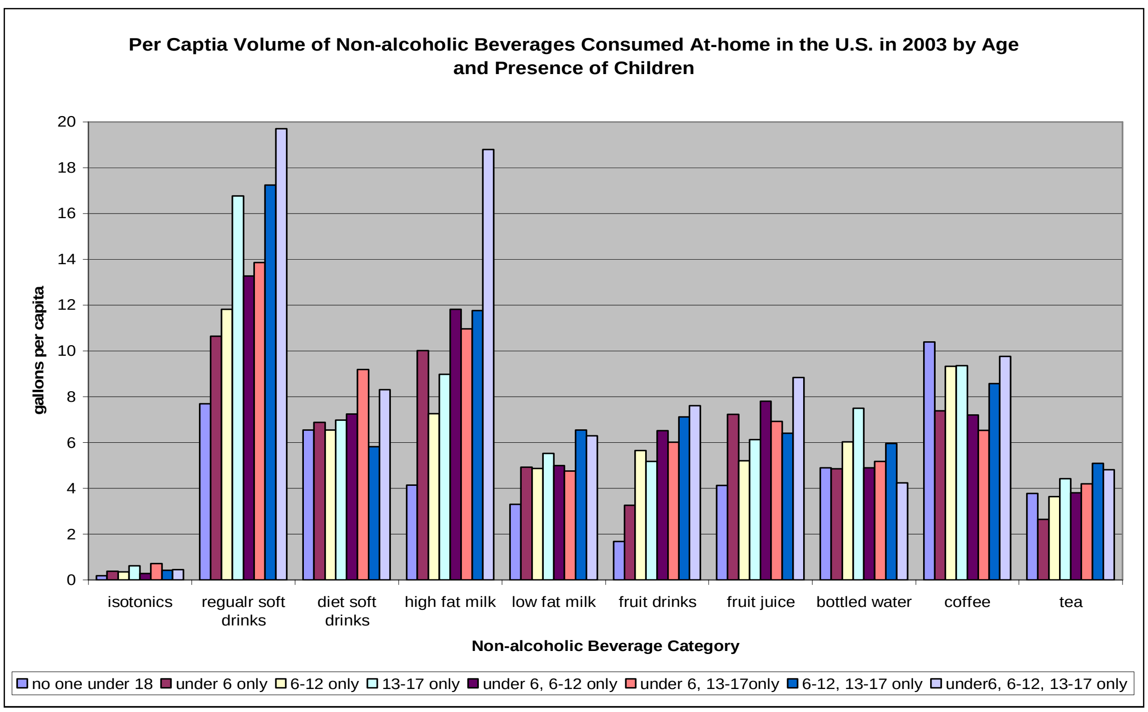

Figure 4.8: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by age and presence of children

Highest diet soft drinks consumption was recorded among children less than 6 years of age and teenagers (13-17 years of age). Highest low-fat milk consumption was observed in households where children were children were above 6 years of age and below 17 years. Teenagers (children in the age category 13-17 years) consumed about 7 gallons of bottled water per capita per year, which is the highest among the all age categories.

Households without children showed the highest amount per capita of coffee consumption, which is about 11 gallons. Lowest amount of coffee consumption was observed in the age category *"under 6, 13-17 only"*. Tea consumption was the lowest among the households with children below 6 years of age (about 3 gallons of tea per capita per year at home), however, it was higher among the children who are above 6 years and below17 years.

Gender of Household Food Manager

Gender of the household food manager and its impact on per capita intake of non-alcoholic beverages consumed at home is shown in Figure 4.9. Presence of both male and female household food managers in a household dominated the highest consumption of all beverages considered. For example, 11 gallons of regular soft drinks, nearly 12 gallons of coffee, 7 gallons of diet soft drinks, and 6 gallons of bottled water per capita per year were consumed for households with both male and female food managers. Consumption of lowest amounts varies and gave mix results between male only or female only food manager dominated households.

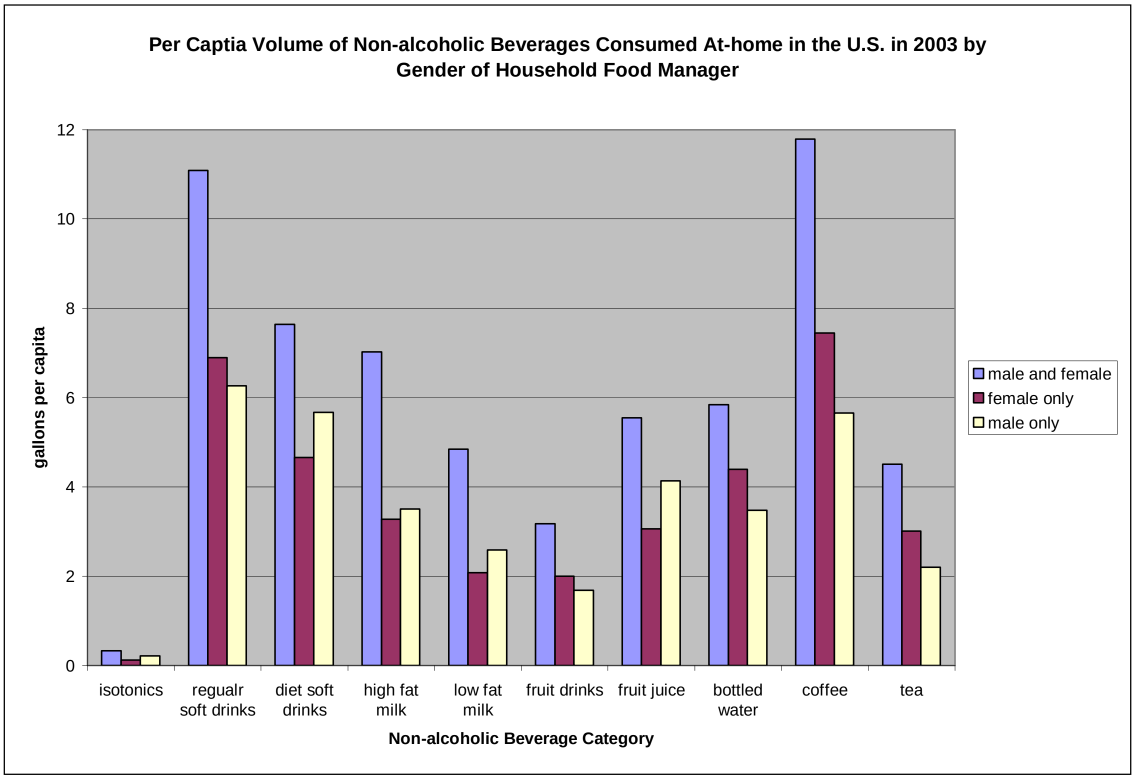

Figure 4.9: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by gender of household food manager

Lowest volume of isotonics, diet soft drinks, high fat milk, low fat milk, and fruit juices was consumed among female food manager dominated households. In numbers aforementioned consumption levels are as follows: about 0.5 gallons of isotonics; 5 gallons of diet soft drinks; 3 gallons of high fat milk; 2 gallons of low-fat milk; and 3 gallons of fruit juices per capita per year. Lowest levels of regular soft drinks, fruit drinks, bottled water, coffee, and tea were associated with households where the food manager was a male. In particular, they were 6 gallons of regular soft drinks, 1.5 gallons of fruit drinks, about 3 gallons of bottled water, about 5 gallons of coffee and 2 gallons of coffee per capita per year.

Poverty Status of Household

Poverty status was designated using 185% poverty line defined by USDA. Any household which is below the 185% poverty line were considered poor and if not otherwise. Figure 4.10 illustrates the per capita volume of non-alcoholic beverage consumption at home and its relationship with poverty status of the household. Poverty households consumed highest levels of regular soft drinks (close to 12 gallons per capita per year), high-fat milk (7 gallons per capita per year), fruit drinks (3 gallons per capita per year), and tea (about 4 gallons per capita per year).

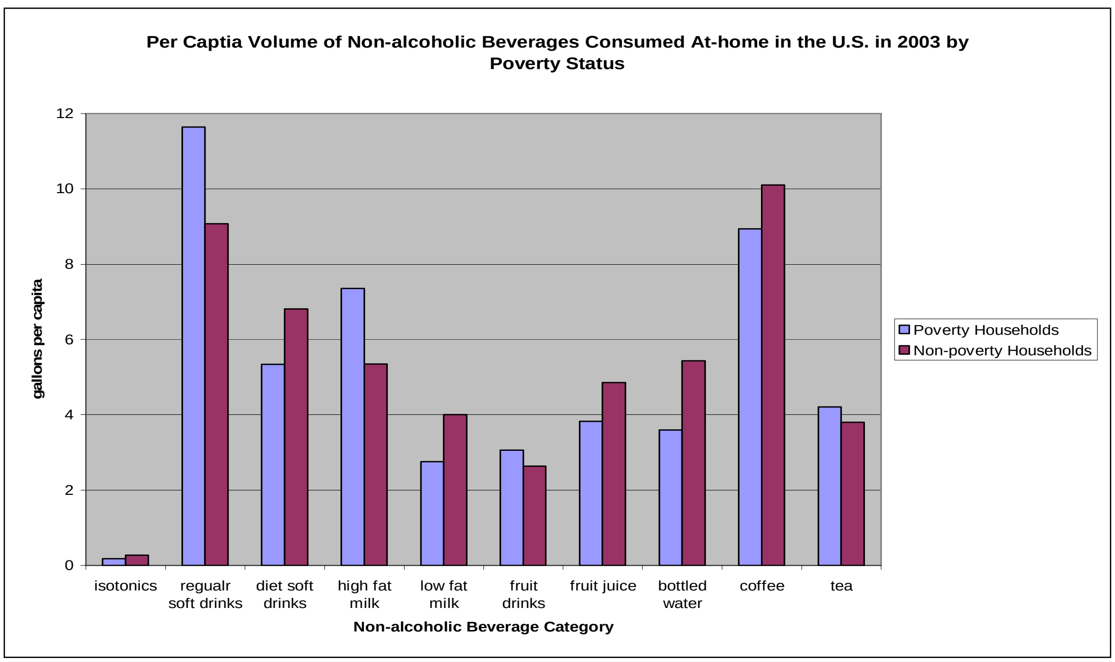

Figure 4.10: Per capita volume of non-alcoholic beverages consumed at home in the United States in 2003 by poverty status

On the other hand, non-poverty households enjoyed the consumption of highest levels of isotonics, diet soft drinks, low-fat milk, fruit juice, bottled water and coffee. In particular, they consumed about 1 gallon of isotonics, 7 gallons of diet soft drinks, low-fat milk, fruit juice, bottled water, and coffee.

Empirical Results: Heckman Two-Step Analysis

This section is devoted to a discussion on empirical results from ten Heckman type models dealing with the level of consumption of non-alcoholic beverages at home in calendar year 2003. Current section exclusively deals with the second stage conditional volume of purchase and factors affecting such purchase volume of non-alcoholic beverages. We bring in the inverse Mill's ratio as an additional explanatory variable in addition to the price of non-alcoholic beverages and other demographic factors. We only use the observations associated with a non-zero purchase of a given beverage, thereby taking all zero expenditure (or zero quantity) observations out from the data. The possible sample selection bias due to such an act is circumvented by introducing the inverse of Mill's ratio to the right hand side of the regression model.

Cross tabulations discussed in the previous section gave an indication of which demographic variables were important in level of consumption analysis. However, such cross tabulation analysis lacks statistical backing. Therefore, Heckman type analysis is used to determine statistically important factors responsible for the level of consumption of a household. Demographic variables and respective categories in each group were discussed in a previous section. This analysis reveals the statistically significant economic and demographic characteristics associated with the volume of consumption of non-alcoholic beverages.

First, we conducted an *F*-test on all demographic categories for all ten non-alcoholic beverages to determine the statistically significant factors. Again, we used a 0.5 level of significance in our decision on what economic and demographic factors affect the level of consumption of a non-alcoholic beverage. Table 4.3 depicts statistically significant demographic categories that affect the level of consumption of a non-alcoholic beverage (X in the table represents the statistically significant demographic factor for each non-alcoholic beverage). Appendix 2 shows the appropriate test statistics (*chi*-squared statistic) and associated hypothesis tests and *p*-values for above tests on demographic categories pertaining to Heckman second stage volume analysis.

Age of the household head, region, race, presence of a child in the household, and gender of the household food manager are the most important demographic determinants of the volume of purchase of most non-alcoholic beverages. In particular, gender of the household food manager was a factor affecting demand for all ten beverage categories, Region was a factor affecting all but fruit juice consumption, and presence of a child was an important factor for all but diet soft drinks, bottled water and coffee.

Age of the household head was not a significant factor for the volume of purchase of high-fat milk, low-fat milk, and fruit drinks. Volume of consumption of high-fat milk, low-fat milk, fruit drinks and coffee were not significantly affected by the race category of a household head. Hispanic status of the household head significantly affected the quantity of purchase of isotonics, coffee and tea. Education status of a household head significantly determined the volume of purchase of regular soft drinks, high-fat milk and low-fat milk. Quantity of purchase of isotonics, bottled water and tea was significantly affected by employment status of household. Poverty was a significant factor affecting the volume of purchase of regular soft drinks, high-fat milk, fruit juices and bottled water.

For each beverage category, Heckman two-step quantity model was run incorporating inverse Mill's ratio as an additional explanatory variable to get around with the sample selection bias problem present due to missing observations. Moreover, appropriate marginal effects and elasticity values for economic and demographic categories were obtained, adjusting for sample selection bias if proved statistically significant. They show the percentage increase or decrease in the quantity of purchase of non-alcoholic beverage pertaining to each demographic category relative to a base category.

Results from Heckman two-step quantity models for ten non-alcoholic beverage categories are discussed in the next section. Log of quantity of each non-alcoholic beverage was regressed on log of price of each non-alcoholic beverage (in separate equations), host of demographic factors and inverse Mill's ratio calculated using probabilities retrieved in the probit model estimation. We will explain the direction, marginal effects and elasticities where appropriate, of influence for each significant economic and demographic factor.

Note that in our analysis, we have used different price variables in the first stage probit model and in the second stage demand model. As result of that, marginal effects and hence elasticities associated with price variable is not affected by the presence of inverse Mill's ratio in the second stage equation. Therefore, in our log-log specification model in the second stage, the coefficient associated with price of non-alcoholic beverage gives out the own-price elasticity of demand for a given non-alcoholic beverage (of cause these are conditional elasticities, conditional on households decision to purchase a given beverage).

However, we have exactly same demographic variables and categories both in the first stage probit model as well as the second stage Heckman model. Consequently, there is an influence of first stage parameter estimates of each demographic variables in the first stage on second stage parameters (this influence come through the introduction of the inverse Mill's ratio in the second stage to take care of sample selection bias). In other words, coefficient estimates associated with each demographic category have to be adjusted for sample selection bias before percentage changes can be calculated. After adjusting for sample selection bias, using adjusted coefficients, we calculated the adjusted marginal effect of each explanatory variable. Owing to the log-log form of the regression model, we use the formula $(e^{\beta} - 1) * 100\%$ (e is the exponential operator and β is the adjusted coefficient in this model) to calculate percentage change effects for each demographic variable.

Heckman Analysis for Isotonics

Regression results of log of quantity of isotonics on log of price of isotonics, host of demographic dummy variables and inverse Mills ratio is shown in Appendix 3. Parameter associated with inverse Mills ratio is statistically significant at 5% level, and it is indicative of presence of sample selection bias in isotonics data where a regression of isotonics quantity on just isotonics price and demographic variables could have been biased. Having inverse Mills ratio in the second stage equation and that being significant takes care of the censoring problem. Price of isotonics, age household head, employment status of household head, region, race, age and presence of children in the household, gender of household food manager are among other statistically significant factors. Owing to the log-log form of the estimated equation, we find that the own-price elasticity of demand for isotonics is -0.53.

Since we find a statistically significant inverse Mills ratio, we have to do an adjustment for the marginal effects we retrieve from the second stage regression. Calculated appropriate marginal effects are depicted in the Appendix 3. The column “Adjusted Coefficient” shows the correct marginal effects associated with each explanatory variable.

Household heads that are between 45-54 years of age, 55-64 years and over 64 years of age purchase 13.5%, 12.7% and 25.3% low isotonics respectively compared to household heads that are below 25 years of age. Full time employed household heads purchase 8% more isotonics compared those who are not employed for full pay.

Lowest amount of isotonics are purchased in the Sothern United States (13% low compared to East). Also, isotonics purchase is low by about 10% and 6.5% in Midwestern and Western parts of United States respectively in comparison to East. Asians consume about 8% more isotonics compared to White households. Hispanics consume about 2.5% more isotonics relative to those who are non-Hispanic. Households with adolescent children (between 13 and 17 years of age) consume the highest volume (37% more) of isotonics compared to those who do not have children. Households with pre-adolescent (ages 6-12 years) and adolescent children put together consume the second highest level of isotonics (about 24% more compared to those without children).

Households managed by a female household food manger consume about 19% low isotonics compared to those with both female and male food managers. On the other hand, when the household food manager is a male, purchase of isotonics goes up by about 21%.

Heckman Analysis for Regular Soft Drinks

Regression results from the Heckman second stage volume model is depicted in the Appendix 3. Notice that inverse mills ratio is taken up as an additional explanatory variable to handle the sample selection bias in the estimation. However, it must be emphasized that inverse Mills ratio is not statistically significant in the regular soft drinks volume model, indicating the absence of sample selection bias. Therefore, one does not have to have inverse mills ratio in the model estimation. However, we have preserved the inverse Mills ratio in the model to illustrate change in marginal value calculation.

Marginal value calculation with respect to the volume model is shown in the Appendix 3. Even though we have an “Adjusted Coefficients” column, we did not use it to calculate the percentage chance values on the final column on to the right. Rather we have used the “Estimated Coefficient” column to calculate appropriate percentage change effects.

Own-price elasticity of demand for regular soft drinks is -0.84, indicating an inelastic demand. Coefficient associated with inverse Mills ratio was not statistically significant at 5% level. This result tells us there is no sample selection bias in estimating demand for regular soft drinks and we could have estimated the second stage demand model without employing the inverse of mills ratio as additional explanatory variable. To support this contention, notice that estimated coefficients and adjusted coefficients on do not differ drastically.

Households where the household head is below 25 years of age consume the highest amount of regular soft drinks compared to any other age category. Furthermore, household heads that are above 64 years of age consume 61% less regular soft drinks compared to a household head that is below 25 years of age. Undergraduate and post college educated household heads purchase about 37% and 49% less regular soft drinks compared to those household heads that are less that high school educated, respectively. Households located in Midwest and South consume about 25% more regular soft drinks relative to those in the East. Western households’ intake of regular soft drinks is up by about 11% compared to those in the East.

Asian household heads purchase about 24% less regular soft drinks compared to Whites, while Other category (non-White, non-Black, and non-Asian) consumes about 28% more. Having a child in the household (any person below 17 years of age) increase the regular soft drinks consumption by about 95% compared to those without children. Households with adolescents (13 to 17-year-olds) are the highest contributor for the purchase of regular soft drinks, which is about 77% higher than those households without children. Having a child who is less than 6 years of age in the household contributes to about 22% more purchase of regular soft drinks.

Households with a male household food manager and a female household food manager purchase respectively, 18% and 26% less regular soft drinks compared to those with food managers represented by both a male and a female. Poverty households consume 15% more regular soft drinks compared to non-poverty households.

Heckman Analysis for Diet Soft Drinks

Heckman second stage regression results for purchase of diet soft drinks are shown in the Appendix 3. Notice that we have inverse Mills ratio among the explanatory variables to account for possible sample selection bias. However, it is not significant at 5% level, indicating no sample selection bias. Other significantly affecting explanatory variables are price of diet soft drinks, region, race, and age and presence of children in the household. Owing to the log-log form of the regression model, the estimated own-price elasticity of demand for diet soft drinks is -0.76, indicating an inelastic demand.

Marginal effect calculation for the second stage volume model is shown in the Appendix 3. Even though the inverse Mills ratio is not statistically significant, we have calculated the adjusted coefficients just to show the deviation of estimated coefficients from the adjusted coefficients. Notice that they do not differ much and all cases the signs are preserved too. Since, the inverse Mills ratio is statistically not significant, we do not use the adjusted coefficients as new coefficients in explaining marginal effects.

Households that are located in the Midwest, South and West purchase respectively, 30%, 25% and 27% more diet soft drinks compared to those located in the East. Blacks consume the least amount of diet soft drinks and it is lower by about 48% compared to diet soft drink consumption by Whites. Asians too consume about 42% less diet soft drinks compared to that of Whites.

Households with pre-adolescent (6 to 12 years of age) and adolescent (13 to 17 years of age) children purchase 23% less diet soft drinks relative to those without children. Households managed by a female household head purchase about 25% less diet soft drinks compared to those managed by both a female and a male.

Heckman Analysis for High-Fat Milk

Regression results from the Heckman second stage quantity model are shown in the Appendix 3. It should be noted that the coefficient associated with inverse Mills ratio is significant at 5% level, indicating sample selection bias in the model. Marginal effects calculation is depicted in the Appendix 3. Calculated own-price elasticity of demand for high-fat milk is -2.19 indicting an elastic demand. Other significant factors affecting the demand for high-fat milk are education status of the household, region, age and presence of children in the household, household food manager’s gender, and poverty status of the household.

In particular, household heads that are educated at undergraduate and post college level, respectively consume 24% and 41% less high-fat milk compared to those educated below high school level. Households located in the Southern U.S. consume about 58% more high-fat milk while those in West purchase about 39% more high-fat milk, both compared to those live in East. Age and presence of children is the biggest contributor for high-fat milk consumption. Households with children consume one and half times as much high-fat milk as compared to those without children. Households with children below 6-years of age consume about 62% more high-fat milk compared to those without children. Households with pre-adolescents (age 6 to 12) consume about 36% more high fat milk, while those with adolescents (age 13 to 17) intake about 58% more high-fat milk, both compared to those households without children.

Households with female household food manager and those with a male household food manager consume respectively 28% and 21% less high-fat milk compared to those with both male and a female household food manager. Poverty households consume about 18% more high-fat milk in contrast to non-poverty households.

Heckman Analysis for Low-Fat Milk

Regression results from second stage Heckman analysis is shown in the Appendix 3. Notice the presence the inverse Mills ratio, which is included to take care of the censoring problem in the data. The coefficient associated with inverse Mills ratio is statistically significant at 5% level. This result is indicative of the presence of sample selection bias in the data. Therefore we need to do an adjustment to the coefficient values recovered from the second stage volume equation before we try to interpret them. Calculation performed to obtain the correct marginal effects in the presence of sample selection bias is shown in the Appendix 3. Other significant variables in the second stage regression are price of low-fat milk, education status of the household head, region, age and presence of children, and gender of household food manager.

Owing to the log-log specification of the model, the calculated own-price elasticity for low-fat milk is -2.18, indicating an elastic demand.

More educated household heads purchase more of low-fat milk compared to less educated household heads. In particular, undergraduate and post college educated household heads to purchase, respectively 30% and 51% more low-fat milk compared to those household heads that are educated below high school level. Midwestern, Sothern and Western households consume about 27%, 8% and 16% respectively less low-fat milk compared to households located in the Eastern part of U.S.

Other racial category (non-White, non-Black and non-Asian) purchase about 13% less low-fat milk compared to White households. Households with adolescent children consume 35% more low-fat milk compared to those without children. Households where the food manager is a male do purchase 23% less low-fat milk compared to those households with both male and female food manager. Poverty status and age of the household head are not statistically significant with respect to low-fat milk purchases.

Heckman Analysis for Fruit Drinks

Regression results from Heckman second stage analysis for fruit drink consumption are depicted in the Appendix 3. It should be noted that the inverse Mills ratio is statistically significant at 5% level, indicating the presence of sample selection bias in the data. Other explanatory variables that are significant at 5% level are price of fruit drinks, region, race, age and presence of children, and gender of household food manager. Calculated own-price elasticity of demand for fruit drinks is -0.93. This shows that fruit drinks are price inelastic.

Since the inverse Mills ratio is significant, we have to make adjustments to the coefficient estimates of the second stage regression before we interpret them. The corrected coefficient estimates are reported in the Appendix 3.

Households located in the Midwest and South do buy about 6% and 11% less fruit drinks, respectively compared to those located in the East. Western households purchase 11% more fruit drinks. Blacks consume about 88% more fruit drinks compared to Whites.

The major contributing factor for a household to consume more fruit drinks is the presence of children in the household. Households with children consume three times as much fruit drinks as those without children. Presence of preschool children in the household alone doubles the consumption of fruit juices compared to those households without children. Least amount of fruit drinks are consumed by households with adolescents and that is still higher compared to those without children.

Households where the food manager is a male consumes about 7% less fruit drinks compared to those with both male and a female food manager. Poverty status of the household is not a significant factor determining the intake of fruit drinks.

Heckman Analysis for Fruit Juices

Results from the regression analysis of fruit juice quantity consumed on price of fruit juices, a host of demographic variables and inverse Mills ratio is shown in Appendix 3. Notice that the coefficient associated with inverse Mills ratio is significant at 5% level, indicting the presence of a censoring problem in the sample data with respect to the fruit juice expenditures. Other statistically significant explanatory variables are age of the household head, employment status of the household head, region, race, and age and presence of children in the household.

Owing to the log-log form of the functional form, own-price elasticity of demand for fruit juices is -0.73, indicating an inelastic demand. Households with household heads that are below 25 years of age consume the highest level of fruit juices. On average it is about 60% higher than the households with heads in age category 25-64. Households with household heads in the age category 30-34 buy the lowest amount of fruit juices (about 69% lesser than those with household heads below 25 years).

Part-time employed household heads consume about 5% less fruit juices compared to those who are not employed for full pay. Households that are located in the Midwest and South consume, respectively, 21% and 19% less fruit juices in comparison to those located in the East. Black households consume about 3% more fruit juices compared to Whites, while Other racial category buys about 16% more fruit juices.

Households with children consume about 76% more fruit juices compared to those who do not have children. Households with pre-adolescent (6 to 12 years) and adolescent (13-17 years) children consume about 32% more fruit juices compared to those who do not have children.

Heckman Analysis for Bottled Water

Regression results from the Heckman second stage analysis on bottled water demand is depicted in the Appendix 3. The inverse Mills ratio is not statistically significant at 5% level. This result tells us that there is no sample selection bias in bottled water data and due to that we do not have to make any corrections to the Heckman second stage regression coefficients. However, we have calculated the adjusted coefficients just to show the little deviation of adjusted coefficients from the estimated coefficients. Subsequently, we have used the estimated coefficients to calculate the percentage changes.

Statistically significant factors that are affecting bottled water demand are price of bottled water, employment status of the household head, region, race, age and presence of children in the household, gender of household food manager, and poverty status of the household.

In particular, full-time employed household heads consume about 17% more bottled water compared to a household head that is not employed for full pay. Midwestern and Southern households purchase about 20% less bottled water in comparison to those in the East. Black households purchase about 30% more bottled water compared to Whites. Households with adolescent children (ages 13-17) buy about

20% more bottled water compared to those without children. Households where the household food manager is a female consume about 16% less bottled water compared to those managed by both a male and a female. Poverty households consume about 21% less bottled water compared to non-poverty households.

Heckman Analysis for Coffee

Results from Heckman two-step regression on estimating demand for coffee are shown in the Appendix 3. Notice that the coefficient associated with the inverse Mills ratio is statistically significant at 5% level, indicating sample selection bias in the coffee expenditure data. Other explanatory variables that are statistically significant at 5% level are price of coffee, age of the household head, education status of the household head, region, Hispanic status of the household head, age and presence of children in the household, and gender of the household food manager.

Given the log-log nature of the regression function, the own-price elasticity of demand for coffee is -0.73, indicating an inelastic demand. Heckman second stage estimated coefficients and adjusted coefficients calculated due the presence of sample selection bias in the data are shown in the Appendix 3. Households where household head is in the age category 30-34 consume about 71% more coffee compared to household heads that are below 25 years of age. Post-college educated households consume about 3% less coffee compared to those household heads that are educated below high school level. Midwestern and Southern households consume respectively 10% and 7% less coffee compared to households located in the East, while Western households purchase about 2.5% more.

Hispanic households consume about 7% less coffee compared to non-Hispanic households. Households with pre-kindergarten and adolescents consume about 12% less coffee compared to those without children. Households where the household food manager is a male consume about 27% less coffee compared to those with both a male and a female household food manager.

Heckman Analysis for Tea

Heckman second stage regression results from the estimation of demand for tea is shown in the Appendix 3. Notice that the inverse Mills ratio is not statistically significant at 5% level, indicating no sample selection bias in tea expenditure data. However, we show the calculation of the adjusted coefficient for the Heckman second stage parameter estimates just to show the small difference in the estimated coefficients compared to adjusted coefficients in the absence of a statistically significant inverse Mills ratio.

Other statistically significant factors affecting the tea consumption are price of tea, age of the household head, region, race, Hispanic status of the household head, age and presence of children in the household, and gender of the household food manager. In particular, household heads in the age category 45-54 consume the highest volume of tea (about twice as much as) compared to those who are below 25 years of age. Households located in Midwest, South and West consume respectively, about 63%, 47% and 56% less tea compared to those in the East. Black and Asian households drink about 16% and 30% less tea compared to their White counterpart while the Other racial category drinks

23% more. Hispanic households purchase about 30% less tea compared to non-Hispanic households.

Households with preschool children (below 6 years) consume 21% low tea compared to those without children. On the other hand, households with adolescents (13-17-year-olds) consume about 24% more tea compared to those without children. Households where the household food manager is a male and consume about 57% less tea compared to those managed both by a male and a female, while households with female food manager consume about 30 % less tea.

CHAPTER V

PROBABILITY FORECAST EVALUATION THROUGH CALIBRATION, RESOLUTION, THE BRIER SCORE AND THE YATES PARTITION OF THE BRIER SCORE

In this chapter we discuss the data preparation, model development, data analysis and discussion on the *probability study*. There are four major sections to the chapter. Probabilities that are generated trough dichotomous choice models (probit and logit models) in the decision to purchase or not-to-purchase a non-alcoholic beverage is evaluated through expectation-prediction success tables, calibration, resolution, the Brier score and the Yates partition of the Brier score. Advantages and disadvantages of each method will be discussed and eventually a superior method for evaluation of forecast probabilities will be identified.

Data Preparation

For forecast probability evaluation study, we used data from 2003 Nielsen HomeScan scanner panel on household purchases of selected non-alcoholic beverages (quantity and total expenditure information) (beverages considered are, isotonics, regular soft drinks, diet soft drinks, high-fat milk, low-fat milk, fruit drinks, fruit juices, bottled water, coffee and tea) and relevant demographic information. Such information was observed for 7642 households in calendar year 2003.

To evaluate forecast probabilities, we generated two samples of observations and estimated the model using one sample and reserved the data from the second sample to perform out-of-sample analysis. We divided the sample of 7642 observations in half to generate two random samples of data, each with 3821 household level observations using SAS Enterprise Minor data mining software. We called these samples, Sample A and Sample B.

Initially, Sample A was used to fit probit and logit models for decision to buy a non-alcoholic beverage. Subsequently, within-sample forecast probabilities were generated. Next, we ran the estimated coefficients from Sample A model, through data from Sample B to generate index values (latent variable values). Such index values were ultimately used to generate probabilities according to underlying cumulative distribution functions (cdf) of probit (standard normal cumulative distribution function) and logit (logistic cumulative distribution function) models. As such we generated out-of-sample forecast probabilities.

Next, we used the methods discussed in this chapter to evaluate within-sample and out-of-sample forecast probabilities. The methods used are, expectation-prediction success tables, calibration and calibration graphs, resolution and resolution graphs, the Brier score and the Yates partition of the Brier score.

Expectation-Prediction Success Tables

This section is devoted to the model/theoretical development of expectation-prediction success tables and their empirical applications to forecast probabilities generated through probit and logit models. These probit and logit models are used in the analysis of factors affecting the decision to purchase non-alcoholic beverages by a sample of U.S households in calendar year 2003.

Theoretical Development

Expectation-prediction success tables are printed out in most of econometric computer packages (for example, SHAZAM, EViews) as a goodness of fit measure in estimating dichotomous choice models (such as probit and logit models). It is a two-way table that shows the relationship between the expected outcome and predicted outcome. Expected outcome is known beforehand; such as decision to buy or not-to-buy a beverage expressed using an index (or latent) variable where index variable equals 1 if a purchase occurs and equal zero if a purchase does not occur. Predicted outcome is generated through the model given the information available at hand (exogenous variables) and it is a probability value when dealing with dichotomous choice models. The underlying probability distribution from which the probability value is generated depends on the assumption one makes about the probability distribution of the error term of a regression where the latent variable is regressed on host of explanatory variables. For probit models, above error term is assumed to have a *standard normal distribution* and for logit model, it is assumed to have a *logistic distribution*.

Two-by-two contingency table on expected outcome and predicted probabilities provide the number of $y=1$ values correctly and incorrectly predicted, and the number of $y=0$ values correctly and incorrectly predicted. For classification purposes, conventionally, the cut-off probability value used was 0.5 (or 50%) level of probability. Therefore, estimation is predicted as $y=1$, if the estimated probability of $y=1$ exceeds 0.5. In other words, if predicted probability is greater than 0.5, that observation is said to be associated with an event that occurred (say purchase of a non-alcoholic beverage).

The other side of the scenario, is where if an event actually did not occur (non-purchase of a non-alcoholic beverage), the predicted probability for that event is below 0.5. As a result, the cut-off level 0.5 classifies the predicted probabilities for events that occurred versus events that did not occur. The overall percentage of correct predictions ($y=1$ or $y=0$) can be used as a measure of goodness of fit.

Let us take a look at the following classification table that shows correct and incorrect predictions of an event. One can use 0.5 level of cut-off (deviations from 0.5 cut-off value will be discussed later in this chapter). There are two events in the example, *0* for not observing the behavior and *1* for observing the behavior. Let *a*, *b*, *c,* and *d* be number of occurrences for an event.

		Actual	
		0	**1**
Predicted	**0**	**a**	**b**
	1	**c**	**d**

The number of correct predictions is given by $(a+d)$. Percentage of correct predictions is given by $\frac{(a+d)}{(a+b+c+d)}*100\%$. The fraction of $y=1$ observations that are correctly predicted is termed "*sensitivity*" and is depicted as $\frac{d}{(b+d)}$. The fraction of $y=0$ observations that are correctly predicted is termed "*specificity*" and is denoted by $\frac{a}{(a+c)}$.

A better measure of goodness of fit of forecast probabilities is the sum of the fraction of ones correctly predicted plus the fraction of zeros correctly predicted, a number which should exceed unity if the prediction method is of value (Kennedy, 2003). In other words, it is the sum of *sensitivity* and *specificity* that must exceed the value one.

Choice of cut-off probability level to correctly classify forecast probabilities depends on the researcher. However, cut-off probability level 0.5 is used as the convention. This is too naïve such that a predicted probability value that is close to 0.5 (say 0.51) or 1 (say 0.99) is associated with an event actually occurs and a predicted probability values that is close to 0 (say 0.01) or 0.5 (say 0.49) is associated with an event that did not occur. According to preceding argument, choice of probability 0.5 as cut-off probability value is appropriate for an event that has realized relative frequency value close to 0.5 (event occurs only 50% of the time). Therefore, choice of cut-off probability value that is close to the realized relative frequency value to correctly classify predicted probabilities would be a better way to classify probabilities. Above realized relative frequency value is also can be identified as “market penetration” for a good. For example, say the market penetration value for bottled water is 70% (or probability 0.7). Hence, the cut-off probability value that can be used to correctly classify the predicted probabilities is 0.70 in this situation and is must not be naïve 0.5 value[20].

[20] Alternatives to selecting one cut-off probability value to correctly classify probabilities are the receiver operating characteristic curve (ROC chart) and cumulative accuracy profile charts (CAP charts). A ROC chart uses a series of cut-off probability values, say from 0.01 through 0.99 and plots the number of correct classifications of probabilities. The decision rule is to maximize the area below the ROC curve, which will be in par with the best scenario. The area is 0.5 for a random model without discriminatory power and is 1 for a perfect model. It is between 0.5 and 1 for most of reasonable models in practice. A CAP chart has a similar interpretation to ROC curve; where for a good model, the area between the perfect model and random model must be maximized. This ROC and CAP charts are not dealt in this dissertation and reserved for future research. Theoretical framework for above charts can be found in Mann and Whitney (1947) and Bamber (1975).

Data Analysis and Discussion

Within-sample and out-of-sample forecast probabilities were generated for probit and logit models. Next, forecast probabilities were evaluated using a conventional 0.5 cut-off probability level and cut-off probability level generated using the frequency of purchase of a given non-alcoholic beverage (or market penetration level). Such analysis was done for all ten non-alcoholic beverages considered in this dissertation.

Isotonics

Tables 5.1 through 5.4 show the results from expectation-prediction success table for isotonics. They are generated for forecast probabilities recovered from within-sample and out-of-sample forecasts obtained from probit and logit models. We have generated number of correct predictions, percentage of correct predictions, sensitivity, specificity, and sensitivity plus specificity for two cut-off probability levels. On the left hand side we have the cut-off probability obtained in par with market penetration value and its associated measures and on the right hand side we have the cut-off probability obtained from naïve probability 0.5 and probability classification obtained according to that. We pay attention to sensitivity and specificity values and their summation. Such summation must be equal to one or higher for good classification of probabilities. Also, we pay attention to individual values of sensitivity and specificity for each beverage for each cut-off probability value.

Table 5.1: Expectation-Prediction Success Table for Isotonics; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.22		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	2063	346	**<= cut off**	2923	779
> cut off	911	500	**> cut off**	51	67
number of correct predictions	2563		number of correct predictions	2990	
percentage of correct predictions	67.09%		percentage of correct predictions	78.27%	
Sensitivity	0.59		Sensitivity	0.08	
Specificity	0.69		Specificity	0.98	
Sensitivity+Specificity	1.28		Sensitivity+Specificity	1.06	

Table 5.2: Expectation-Prediction Success Table for Isotonics; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.20		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	1889	276	**<= cut off**	2984	720
> cut off	1667	487	**> cut off**	72	43
number of correct predictions	2376		number of correct predictions	3027	
percentage of correct predictions	55.01%		percentage of correct predictions	79.26%	
Sensitivity	0.64		Sensitivity	0.06	
Specificity	0.53		Specificity	0.98	
Sensitivity+Specificity	1.17		Sensitivity+Specificity	1.03	

Table 5.3: Expectation-Prediction Success Table for Isotonics; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.22		success cutoff probability	0.50	
	Actual			Actual	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	2075	352	**<= cut off**	2914	772
> cut off	899	494	**> cut off**	60	74
number of correct predictions	2569		number of correct predictions	2988	
percentage of correct predictions	67.25%		percentage of correct predictions	78.22%	
Sensitivity	0.58		Sensitivity	0.09	
Specificity	0.70		Specificity	0.98	
Sensitivity+Specificity	1.28		Sensitivity+Specificity	1.07	

Table 5.4: Expectation-Prediction Success Table for Isotonics; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.20		success cutoff probability	0.50	
	Actual			Actual	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	1902	280	**<= cut off**	2982	717
> cut off	1154	483	**> cut off**	74	46
number of correct predictions	2385		number of correct predictions	3028	
percentage of correct predictions	62.45%		percentage of correct predictions	79.29%	
Sensitivity	0.63		Sensitivity	0.06	
Specificity	0.62		Specificity	0.98	
Sensitivity+Specificity	1.26		Sensitivity+Specificity	1.04	

For Isotonics, market penetration cut-off probability level is 0.22 for within-sample forecasts and it is 0.20 for out-of-sample forecasts. It must be noted that for both within-sample and out-of-sample forecast probabilities, we observe similar sensitivity and specificity values (for both probit and logit models). They are approximately 0.60 for sensitivity for within-sample estimates for both probit and logit models. In terms of specificity, they are about 0.70 for both probit and logit models. This gave rise to a total of about 1.30. If we use the naïve 0.50 probability to classify probit and logit within-sample probabilities, we get about 0.08 and 0.98 for sensitivity and specificity respectively, totaling 1.06. This result is observed because sensitivity is under-estimated and specificity is over estimated. Similar result is reported with respect to out-of-sample forecast probabilities as well. This latter result is inferior to the former where market penetration value is used to classify forecast probabilities. Therefore, we can conclude that use of market penetration values to classify forecast probabilities is preferred compared to naïve 0.50 cut-off.

Regular Soft Drinks

Tables 5.5 through 5.8 depict the expectation-prediction success tables for forecast probability evaluation for regular soft drinks, generated within and out-of sample probit and logit models. The market penetration or the number of times a purchase actually did occur is 0.90 for regular soft drinks. In other words, all most all households did buy a regular soft drink in 2003. Very similar results were observed for probit and logit models, both in within-sample and out-of-sample forecast probability evaluation. Forecast evaluations gave higher sensitivity plus specificity value (1.32) when classified using the market penetration value as a cut-off probability level, compared to the use of naïve 0.50 as the cut-off probability level.

When cut-off probability 0.50 is used to classify forecast probabilities, model consistently gave a lower specificity value. This is because most of probabilities associated with a non-purchase are greater than 0.50 and less than 0.90. Therefore, selecting 0.50 as a cut-off level to classify probabilities of events that occurred and did not occur was not a good choice.

Table 5.5: Expectation-Prediction Success Table for Regular Soft Drinks; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.90		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	255	1235	**<= cut off**	0	1
> cut off	121	2209	**> cut off**	376	3443
number of correct predictions	2464		number of correct predictions	3443	
percentage of correct predictions	64.50%		percentage of correct predictions	90.13%	
Sensitivity	0.64		Sensitivity	1.00	
Specificity	0.68		Specificity	0.00	
Sensitivity+Specificity	1.32		Sensitivity+Specificity	1.00	

Table 5.6: Expectation-Prediction Success Table for Regular Soft Drinks; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.91		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	223	1180	**<= cut off**	0	0
> cut off	119	2297	**> cut off**	342	3477
number of correct predictions	2520		number of correct predictions	3477	
percentage of correct predictions	65.99%		percentage of correct predictions	91.04%	
Sensitivity	0.66		Sensitivity	1.00	
Specificity	0.65		Specificity	0.00	
Sensitivity+Specificity	1.31		Sensitivity+Specificity	1.00	

Table 5.7: Expectation-Prediction Success Table for Regular Soft Drinks; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.90		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	241	1158	**<= cut off**	3	0
> cut off	135	2286	**> cut off**	373	3444
Number of correct predictions	2527		number of correct predictions	3447	
percentage of correct predictions	66.15%		percentage of correct predictions	90.24%	
Sensitivity	0.66		Sensitivity	1.00	
Specificity	0.64		Specificity	0.01	
Sensitivity+Specificity	1.30		Sensitivity+Specificity	1.01	

Table 5.8: Expectation-Prediction Success Table for Regular Soft Drinks; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.91		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	219	1109	**<= cut off**	1	0
> cut off	123	2368	**> cut off**	341	3477
number of correct predictions	2587		number of correct predictions	3478	
percentage of correct predictions	67.74%		percentage of correct predictions	91.07%	
Sensitivity	0.68		Sensitivity	1.00	
Specificity	0.64		Specificity	0.00	
Sensitivity+Specificity	1.32		Sensitivity+Specificity	1.00	

Diet Soft Drinks

We show the expectation-prediction success tables associated with forecast probability evaluations for diet soft drinks taking both within and out-of-sample probit and logit analysis in Tables 5.9 through 5.12. Within-sample sensitivity plus specificity measure is consistently higher (1.22) compared to that of out-of-sample measure (1.18). When market penetration value is used to classify forecast probabilities (which is 0.65), it also gives higher sensitivity plus specificity value, compared to the use of naïve 0.50 to classify forecast probabilities. This is indicative of superiority of the use of market penetration values to classify probabilities compared to use of naïve cut-off of 0.50. Again, use of cut-off 0.50 underestimates the specificity and overestimates the sensitivity value. Results from both probit and logit models are very similar.

Table 5.9: Expectation-Prediction Success Table for Diet Soft Drinks; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.65		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	680	723	**<= cut off**	332	251
> cut off	646	1771	**> cut off**	994	2243
number of correct predictions	2451		number of correct predictions	2575	
percentage of correct predictions	64.16%		percentage of correct predictions	67.41%	
Sensitivity	0.71		Sensitivity	0.90	
Specificity	0.51		Specificity	0.25	
Sensitivity+Specificity	1.22		Sensitivity+Specificity	1.15	

Table 5.10: Expectation-Prediction Success Table for Diet Soft Drinks; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.65		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	614	702	**<= cut off**	288	259
> cut off	706	1797	**> cut off**	1032	2240
number of correct predictions	2411		number of correct predictions	2528	
percentage of correct predictions	63.13%		percentage of correct predictions	66.20%	
Sensitivity	0.72		Sensitivity	0.90	
Specificity	0.47		Specificity	0.22	
Sensitivity+Specificity	1.18		Sensitivity+Specificity	1.11	

Table 5.11: Expectation-Prediction Success Table for Diet Soft Drinks; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.65		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	680	709	**<= cut off**	336	249
> cut off	646	1785	**> cut off**	990	2245
Number of correct predictions	2465		number of correct predictions	2581	
percentage of correct predictions	64.53%		percentage of correct predictions	67.57%	
Sensitivity	0.72		Sensitivity	0.90	
Specificity	0.51		Specificity	0.25	
Sensitivity+Specificity	1.23		Sensitivity+Specificity	1.15	

Table 5.12: Expectation-Prediction Success Table for Diet Soft Drinks; Logit Model Generated Probabilities Within-Sample

success cutoff probability		0.65	success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	605	675	**<= cut off**	257	241
> cut off	715	1824	**> cut off**	1063	2258
number of correct predictions	2429		number of correct predictions	2515	
percentage of correct predictions	63.60%		percentage of correct predictions	65.85%	
Sensitivity	0.73		Sensitivity	0.90	
Specificity	0.46		Specificity	0.19	
Sensitivity+Specificity	1.19		Sensitivity+Specificity	1.10	

High-Fat Milk

Tables 5.13 through 5.16 show forecast probability classification results in an expectation-prediction success table for forecast probabilities generated through probit and logit models for within-sample and out-of-sample scenarios. Within-sample forecast probabilities are stronger with respect to producing large sensitivity plus specificity numbers (1.24) compared to out-of-sample generated numbers (1.21). When the market penetration value is used as a cut-off probability level to correctly classify forecast probabilities we observe a high sensitivity plus specificity value. This is high in comparison to such a value observed when naïve probability (probability 0.5) is used to classify probabilities. We observed a consistently over specified sensitivity and under specified specificity when cut-off value 0.5 was used in comparison to market penetration cut-off value. Above result was true for both probit and logit generated forecasts for both within-sample and out-of-sample. Forecast probability classification results are very similar for probit and logit models.

Table 5.13: Expectation-Prediction Success Table for High-Fat Milk; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.82			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	466	1334		**<= cut off**	6	3
> cut off	233	1787		**> cut off**	693	3118
number of correct predictions	2253			number of correct predictions	3124	
percentage of correct predictions	58.98%			percentage of correct predictions	81.78%	
Sensitivity	0.57			Sensitivity	1.00	
Specificity	0.67			Specificity	0.01	
Sensitivity+Specificity	1.24			Sensitivity+Specificity	1.01	

Table 5.14: Expectation-Prediction Success Table for High-Fat Milk; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.83			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	470	1590		**<= cut off**	1	0
> cut off	188	1571		**> cut off**	657	3161
number of correct predictions	2041			number of correct predictions	3162	
percentage of correct predictions	53.44%			percentage of correct predictions	82.80%	
Sensitivity	0.50			Sensitivity	1.00	
Specificity	0.71			Specificity	0.00	
Sensitivity+Specificity	1.21			Sensitivity+Specificity	1.00	

Table 5.15: Expectation-Prediction Success Table for High-Fat Milk; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.82			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	464	1312		**<= cut off**	8	5
> cut off	235	1809		**> cut off**	691	3116
number of correct predictions	2273			number of correct predictions	3124	
percentage of correct predictions	59.50%			percentage of correct predictions	81.78%	
Sensitivity	0.58			Sensitivity	1.00	
Specificity	0.66			Specificity	0.01	
Sensitivity+Specificity	1.24			Sensitivity+Specificity	1.01	

Table 5.16: Expectation-Prediction Success Table for High-Fat Milk; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.83			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	468	1561		**<= cut off**	2	2
> cut off	190	1600		**> cut off**	656	3159
number of correct predictions	2068			number of correct predictions	3161	
percentage of correct predictions	54.15%			percentage of correct predictions	82.77%	
Sensitivity	0.51			Sensitivity	1.00	
Specificity	0.71			Specificity	0.00	
Sensitivity+Specificity	1.22			Sensitivity+Specificity	1.00	

Low-Fat Milk

Tables 5.17 through 5.20 show the results from classification of forecast probabilities generated through probit and logit models in the decision to purchase low-fat milk. Within-sample and out-of-sample forecast probabilities were generated for each case and two levels of cut-off values were used to correctly classify probabilities.

Market penetration value for low-fat milk is 0.61 for with-sample data and it was 0.64 for out-of-sample data. Use of market penetration value to classify probabilities compared to naïve 0.5 probability value gave us high sensitivity plus specificity value (1.21). Again, just as in the case of high-fat milk, we observed a consistently overvalued sensitivity and undervalued specificity numbers when we used naïve 0.5 cut-off probability value to classify probabilities compared to the use of market penetration value as the cut-off probability level. Probability classification results were similar across probit and logit models.

Table 5.17: Expectation-Prediction Success Table for Low-Fat Milk; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.61		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	828	802	**<= cut off**	400	268
> cut off	660	1530	**> cut off**	1088	2064
number of correct predictions	2358		number of correct predictions	2464	
percentage of correct predictions	61.73%		percentage of correct predictions	64.50%	
Sensitivity	0.66		Sensitivity	0.89	
Specificity	0.56		Specificity	0.27	
Sensitivity+Specificity	1.21		Sensitivity+Specificity	1.15	

Table 5.18: Expectation-Prediction Success Table for Low-Fat Milk; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.64		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	926	1094	**<= cut off**	372	304
> cut off	453	1346	**> cut off**	1007	2136
number of correct predictions	2272		number of correct predictions	2508	
percentage of correct predictions	59.49%		percentage of correct predictions	65.67%	
Sensitivity	0.55		Sensitivity	0.88	
Specificity	0.67		Specificity	0.27	
Sensitivity+Specificity	1.22		Sensitivity+Specificity	1.15	

Table 5.19: Expectation-Prediction Success Table for Low-Fat Milk; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.61	
	Actual	
Predicted	**0**	**1**
<= cut off	825	798
> cut off	663	1534
number of correct predictions	2359	
percentage of correct predictions	61.75%	
Sensitivity	0.66	
Specificity	0.55	
Sensitivity+Specificity	1.21	

success cutoff probability	0.50	
	Actual	
Predicted	**0**	**1**
<= cut off	401	268
> cut off	1087	2064
number of correct predictions	2465	
percentage of correct predictions	64.53%	
Sensitivity	0.89	
Specificity	0.27	
Sensitivity+Specificity	1.15	

Table 5.20: Expectation-Prediction Success Table for Low-Fat Milk; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.64	
	Actual	
Predicted	**0**	**1**
<= cut off	923	1086
> cut off	456	1354
number of correct predictions	2277	
percentage of correct predictions	59.62%	
Sensitivity	0.55	
Specificity	0.67	
Sensitivity+Specificity	1.22	

success cutoff probability	0.50	
	Actual	
Predicted	**0**	**1**
<= cut off	371	307
> cut off	1008	2133
number of correct predictions	2504	
percentage of correct predictions	65.57%	
Sensitivity	0.87	
Specificity	0.27	
Sensitivity+Specificity	1.14	

Fruit Drinks

Tables 5.21 through 5.24 show the expectation-prediction success tables for forecast probabilities generated using probit and logit models for the decision to purchase fruit drinks. Also, we have used market penetration probability level (0.75 and 0.77 for within-sample and out-of-sample probabilities respectively) and naïve 0.50 probability level as cut-off probability levels.

Sensitivity plus specificity value was 1.29 for within-sample probabilities with market penetration taken as the cut-off probability for both probit and logit models and it was 1.26 for out-of-sample generated probabilities.

We observe high sensitivity and specificity value for probabilities classified using market penetration cut-off probability level (such as 1.29 for probit within-sample analysis) compared to that of naïve 0.50 cut-off probability (such as 1.07 for probit within-sample analysis). This result indicates that use of market penetration cut-off probability level to classify forecast probabilities is superior to the use of naïve 0.50 probability cut-off. We also find that sensitivity value is consistently over valued and specificity is consistently undervalued when naïve 0.50 probability is used to classify probabilities compared to the use of market penetration cut-off probability.

Table 5.21: Expectation-Prediction Success Table for Fruit Drinks; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.75		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	646	1119	**<= cut off**	93	68
> cut off	308	1747	**> cut off**	861	2798
number of correct predictions	2393		number of correct predictions	2891	
percentage of correct predictions	62.64%		percentage of correct predictions	75.68%	
Sensitivity	0.61		Sensitivity	0.98	
Specificity	0.68		Specificity	0.10	
Sensitivity+Specificity	1.29		Sensitivity+Specificity	1.07	

Table 5.22: Expectation-Prediction Success Table for Fruit Drinks; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.77		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	605	1227	**<= cut off**	28	36
> cut off	291	1696	**> cut off**	868	2887
number of correct predictions	2301		number of correct predictions	2915	
percentage of correct predictions	60.25%		percentage of correct predictions	76.33%	
Sensitivity	0.58		Sensitivity	0.99	
Specificity	0.68		Specificity	0.03	
Sensitivity+Specificity	1.26		Sensitivity+Specificity	1.02	

Table 5.23: Expectation-Prediction Success Table for Fruit Drinks; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.75		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	644	1105	**<= cut off**	98	72
> cut off	310	1761	**> cut off**	856	2794
number of correct predictions	2405		number of correct predictions	2892	
percentage of correct predictions	62.96%		percentage of correct predictions	75.71%	
Sensitivity	0.61		Sensitivity	0.97	
Specificity	0.68		Specificity	0.10	
Sensitivity+Specificity	1.29		Sensitivity+Specificity	1.08	

Table 5.24: Expectation-Prediction Success Table for Fruit Drinks; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.77		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	604	1215	**<= cut off**	29	36
> cut off	292	1708	**> cut off**	867	2887
number of correct predictions	2312		number of correct predictions	2916	
percentage of correct predictions	60.54%		percentage of correct predictions	76.36%	
Sensitivity	0.58		Sensitivity	0.99	
Specificity	0.67		Specificity	0.03	
Sensitivity+Specificity	1.26		Sensitivity+Specificity	1.02	

Fruit Juices

Tables 5.25 through 5.28 show the classification of forecast probabilities through expectation-prediction success table for probabilities generated using probit and logit models in modeling the decision to consume fruit juices. The market penetration cut-off probability level used was 0.93 for within-sample analysis and 0.94 for out-of-sample analysis.

We find high sensitivity plus specificity value for within-sample forecast probability classification compared to that of out-of-sample forecast probability classification. This result shows evidence for more accurate probability forecasts within-sample compared to that of out-of-sample.

Also, we find high sensitivity plus specificity value for (1.33) classified forecast probabilities when classification was based on market penetration level of cut-off compared to that based on naïve 0.50 cut-off probability (at 0.50 cut-off probability, the sum of sensitivity and specificity was 1.00). Again, we find consistently over valued sensitivity value and undervalued specificity value for forecast probabilities associated with naïve 0.5 cut-off probability compared to market penetration cut-off probability. In particular, we find specificity to be zero for naïve 0.5 cut-off level, even though it was about 0.69 when market penetration was taken as the cut-off value. That is to say, none of the probabilities associated with events that did not occur does not fall in the category of probability below 0.50, all lies in the range of probability from 0.50 through 0.93. The latter only can be captured if one classifies the probabilities based on market penetration cut-off.

Table 5.25: Expectation-Prediction Success Table for Fruit Juices; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.93			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	180	1243		**<= cut off**	0	0
> cut off	85	2312		**> cut off**	265	3555
number of correct predictions	2492			number of correct predictions	3555	
percentage of correct predictions	65.24%			percentage of correct predictions	93.06%	
Sensitivity	65.04%			Sensitivity	1.00	
Specificity	67.92%			Specificity	0.00	
Sensitivity+Specificity	1.33			Sensitivity+Specificity	1.00	

Table 5.26: Expectation-Prediction Success Table for Fruit Juices; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.94			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	162	1500		**<= cut off**	0	0
> cut off	73	2084		**> cut off**	235	3584
number of correct predictions	2246			number of correct predictions	3584	
percentage of correct predictions	58.81%			percentage of correct predictions	93.85%	
Sensitivity	0.58			Sensitivity	1.00	
Specificity	0.69			Specificity	0.00	
Sensitivity+Specificity	1.27			Sensitivity+Specificity	1.00	

Table 5.27: Expectation-Prediction Success Table for Fruit Juices; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.93		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	182	1168	**<= cut off**	1	0
> cut off	83	2387	**> cut off**	264	3555
number of correct predictions	2569		number of correct predictions	3556	
percentage of correct predictions	67.25%		percentage of correct predictions	93.09%	
Sensitivity	0.67		Sensitivity	1.00	
Specificity	0.69		Specificity	0.00	
Sensitivity+Specificity	1.36		Sensitivity+Specificity	1.00	

Table 5.28: Expectation-Prediction Success Table for Fruit Juices; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.94		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	156	1420	**<= cut off**	0	1
> cut off	79	2164	**> cut off**	235	3583
number of correct predictions	2320		number of correct predictions	3583	
percentage of correct predictions	60.75%		percentage of correct predictions	93.82%	
Sensitivity	0.60		Sensitivity	1.00	
Specificity	0.66		Specificity	0.00	
Sensitivity+Specificity	1.27		Sensitivity+Specificity	1.00	

Bottled Water

Forecast probability classification based on a cut-off probability value for forecast probabilities generated for the decision to buy bottled water modeled through probit and logit models are explained in expectation-prediction success tables shown in Tables 5.29 through 5.32. Again, we have used two cut-off probability levels; 0.70 market penetration level and 0.50 naïve probability.

Sum of sensitivity and specificity value is high for forecast probabilities classified using market penetration level (1.22) compared to that of naïve cut-off (1.08), indicating the superiority of use of market penetration cut-off probability compared to 0.50 level of cut-off probability. Also, in terms of getting a large value for sum of specificity and sensitivity, within-sample forecasts out performs the out-of-sample forecasts. We observe consistently high sensitivity and low specificity values when forecasts probabilities are classified using a naïve 0.50 cut-off probability compared to that of using market penetration cut-off probability level. That is to say, only a very small fraction of probabilities fall below 0.50 for events that did not occur and therefore, use of market penetration value (0.70) allows realized probabilities that are below 0.70 to be associated with events that did not occur (event where a purchase did not take place). We did not find a large discrepancy between the results obtained from probit model compared to logit model.

Table 5.29: Expectation-Prediction Success Table for Bottled Water; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.70	
	Actual	
Predicted	**0**	**1**
<= cut off	636	920
> cut off	491	1773
number of correct predictions	2409	
percentage of correct predictions	63.06%	
Sensitivity	0.66	
Specificity	0.56	
Sensitivity+Specificity	1.22	

success cutoff probability	0.50	
	Actual	
Predicted	**0**	**1**
<= cut off	126	87
> cut off	1001	2606
number of correct predictions	2732	
percentage of correct predictions	71.52%	
Sensitivity	0.97	
Specificity	0.11	
Sensitivity+Specificity	1.08	

Table 5.30: Expectation-Prediction Success Table for Bottled Water; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.70	
	Actual	
Predicted	**0**	**1**
<= cut off	621	932
> cut off	517	1749
number of correct predictions	2370	
percentage of correct predictions	62.06%	
Sensitivity	0.65	
Specificity	0.55	
Sensitivity+Specificity	1.20	

success cutoff probability	0.50	
	Actual	
Predicted	**0**	**1**
<= cut off	78	45
> cut off	1060	2636
number of correct predictions	2714	
percentage of correct predictions	71.07%	
Sensitivity	0.98	
Specificity	0.07	
Sensitivity+Specificity	1.05	

Table 5.31: Expectation-Prediction Success Table for Bottled Water; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.70			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	632	906		**<= cut off**	130	92
> cut off	495	1787		**> cut off**	997	2601
number of correct predictions	2419			number of correct predictions	2731	
percentage of correct predictions	63.32%			percentage of correct predictions	71.49%	
Sensitivity	0.66			Sensitivity	0.97	
Specificity	0.56			Specificity	0.12	
Sensitivity+Specificity	1.22			Sensitivity+Specificity	1.08	

Table 5.32: Expectation-Prediction Success Table for Bottled Water; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.70			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	616	922		**<= cut off**	83	51
> cut off	522	1759		**> cut off**	1055	2630
number of correct predictions	2375			number of correct predictions	2713	
percentage of correct predictions	62.19%			percentage of correct predictions	71.04%	
Sensitivity	0.66			Sensitivity	0.98	
Specificity	0.54			Specificity	0.07	
Sensitivity+Specificity	1.20			Sensitivity+Specificity	1.05	

Coffee

Tables 5.33 through 5.36 show the results from forecast probability classification of forecast probabilities generated for the decision to purchase coffee using probit and logit models employing two cut-off probability levels. Cut-off probability levels used were: 0.74 market penetration probability level and 0.50 naïve probability level. Both within-sample and out-of-sample probabilities were generated and classified using above cut-off probability values.

Higher sum of sensitivity and specificity is reported (1.37) when forecast probabilities are classified using market penetration cut-off level and it is lower for naïve classification of probabilities (1.19), indicating the better classification of forecast probabilities associated with market penetration level. Also, we observe consistently higher sensitivity value and a lower specificity value associated with forecast probability classification associated with naïve 0.50 cut-off probability level compared to the use of market penetration cut-off probability value. Both probit and logit analysis produce a similar analysis and results.

Table 5.33: Expectation-Prediction Success Table for Coffee; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.74			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	697	910		**<= cut off**	247	159
> cut off	311	1902		**> cut off**	761	2653
number of correct predictions	2599			number of correct predictions	2900	
percentage of correct predictions	68.04%			percentage of correct predictions	75.92%	
Sensitivity	0.68			Sensitivity	0.94	
Specificity	0.69			Specificity	0.25	
Sensitivity+Specificity	1.37			Sensitivity+Specificity	1.19	

Table 5.34: Expectation-Prediction Success Table for Coffee; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.72			success cutoff probability	0.50	
	Actual				**Actual**	
Predicted	**0**	**1**		**Predicted**	**0**	**1**
<= cut off	657	812		**<= cut off**	284	179
> cut off	416	1934		**> cut off**	789	2567
number of correct predictions	2591			number of correct predictions	2851	
percentage of correct predictions	67.84%			percentage of correct predictions	74.65%	
Sensitivity	0.70			Sensitivity	0.93	
Specificity	0.61			Specificity	0.26	
Sensitivity+Specificity	1.32			Sensitivity+Specificity	1.20	

Table 5.35: Expectation-Prediction Success Table for Coffee; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.74		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	689	875	**<= cut off**	255	163
> cut off	319	1937	**> cut off**	753	2649
number of correct predictions	2626		number of correct predictions	2904	
percentage of correct predictions	68.74%		percentage of correct predictions	76.02%	
Sensitivity	0.69		Sensitivity	0.94	
Specificity	0.68		Specificity	0.25	
Sensitivity+Specificity	1.37		Sensitivity+Specificity	1.20	

Table 5.36: Expectation-Prediction Success Table for Coffee; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.72		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	648	791	**<= cut off**	293	185
> cut off	425	1955	**> cut off**	780	2561
number of correct predictions	2603		number of correct predictions	2854	
percentage of correct predictions	68.16%		percentage of correct predictions	74.73%	
Sensitivity	0.71		Sensitivity	0.93	
Specificity	0.60		Specificity	0.27	
Sensitivity+Specificity	1.32		Sensitivity+Specificity	1.21	

Tea

Classification of forecast probabilities generated through probit and logit models (see Tables 5.37 through 5.40) for the decision to purchase tea was done employing two cut-off probability levels, such as 0.72 market penetration level and 0.50 naïve probability level. Both within-sample and out-of-sample probabilities are generated and classified using above cut-off levels.

We found high sum of sensitivity and specificity level (1.21) for forecast probabilities classified using market penetration cut-off probability level compared to that of naïve 0.50 probability level (1.04), indicting the superiority of the use of market penetration level to classify forecast probabilities compared to naïve 0.50 level. Similar to other non-alcoholic beverages we studied, we see a consistently high sensitivity value and a consistently low specificity value for forecast probabilities classified using a 0.50 naïve cut-off probability value compared to that of market penetration cut-off value. Furthermore, very small fraction of probabilities falls below the 0.50 probability level that are associated with the event that did not occur, and that is the reason for very low specificity value recorded with naïve probability classification.

We did not observe a large difference between probit and logit model generated probabilities.

Table 5.37: Expectation-Prediction Success Table for Tea; Probit Model Generated Probabilities Within-Sample

success cutoff probability	0.72		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	644	1071	**<= cut off**	71	68
> cut off	423	1682	**> cut off**	996	2685
number of correct predictions	2326		number of correct predictions	2756	
percentage of correct predictions	60.89%		percentage of correct predictions	72.15%	
Sensitivity	0.61		Sensitivity	0.98	
Specificity	0.60		Specificity	0.07	
Sensitivity+Specificity	1.21		Sensitivity+Specificity	1.04	

Table 5.38: Expectation-Prediction Success Table for Tea; Probit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.73		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	626	1191	**<= cut off**	62	62
> cut off	408	1594	**> cut off**	972	2723
number of correct predictions	2220		number of correct predictions	2785	
percentage of correct predictions	58.13%		percentage of correct predictions	72.92%	
Sensitivity	0.57		Sensitivity	0.98	
Specificity	0.61		Specificity	0.06	
Sensitivity+Specificity	1.18		Sensitivity+Specificity	1.04	

Table 5.39: Expectation-Prediction Success Table for Tea; Logit Model Generated Probabilities Within-Sample

success cutoff probability	0.72		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	637	1056	**<= cut off**	72	70
> cut off	430	1697	**> cut off**	995	2683
number of correct predictions	2334		number of correct predictions	2755	
percentage of correct predictions	61.10%		percentage of correct predictions	72.12%	
Sensitivity	0.62		Sensitivity	0.97	
Specificity	0.60		Specificity	0.07	
Sensitivity+Specificity	1.21		Sensitivity+Specificity	1.04	

Table 5.40: Expectation-Prediction Success Table for Tea; Logit Model Generated Probabilities Out-of-Sample

success cutoff probability	0.73		success cutoff probability	0.50	
	Actual			**Actual**	
Predicted	**0**	**1**	**Predicted**	**0**	**1**
<= cut off	622	1180	**<= cut off**	63	62
> cut off	412	1605	**> cut off**	971	2723
number of correct predictions	2227		number of correct predictions	2786	
percentage of correct predictions	58.31%		percentage of correct predictions	72.95%	
Sensitivity	0.58		Sensitivity	0.98	
Specificity	0.60		Specificity	0.06	
Sensitivity+Specificity	1.18		Sensitivity+Specificity	1.04	

Probability Calibration and Calibration Graphs

In the following sections we discuss the theoretical development and empirical analysis with respect to calibration of probabilities generated through probit and logit models in the decision to purchase non-alcoholic beverages by U.S households in calendar year 2003. A graphical and a mathematical analysis is performed

Theoretical Development

Calibration is a metric of goodness of performance. It is the correspondence between the issued probability for an event *ex-ante* and its long run realized relative frequency (or truth of the propositions) *ex-post*. Calibration has also been called realism (Brown and Shuford, 1973), external validity (Brown and Shuford, 1973), realism of confidence (Adams and Adams, 1961), appropriateness of confidence (Oskamp, 1962), secondary validity (Murphy and Winkler, 1971) and reliability (Murphy, 1973). Calibration criterion is similar to the relative frequency definition of probability. However, calibration does not require a background of repeated trials under identical conditions (Dawid, 1982 and Kling & Bessler, 1989). More formally, for a model to be well calibrated, for all those events where an x percent probability was assessed, the frequency of occurrence must indeed be x percent for all x (Bunn, 1984). For example, if a qualitative choice model issues a probability of 0.25 for an event, it should be observed *(ex post)* 25 percent of the time, if this model is to be well-calibrated (or perfectly calibrated). In graphical lingo, a well calibrated qualitative choice model should plot along a 45-degree line with issued probability on x-axis and realized long run relative frequency on the y-axis. Above plot is called a calibration graph or a calibration function. The closer the calibration function is to the 45-degree line, the better the probabilities issued from the qualitative choice model. On the other hand, a model can be consistently overconfident if it issues high probabilities for events that actually do not occur in such a relative frequency after the fact, resulting in a calibration curve below the 45-degree line and a model can also be consistently issuing lower probabilities for events that actually have higher relative frequencies of occurrence after the fact showing underconfidence, resulting in a calibration curve that is above the 45-degree line. Calibration plots have been used to analyze subjective probabilities for many years (Lichtenstein et al., 1982) and also in the recent times to evaluate objective model generated probabilities (King and Bessler, 1989; Bessler and Ruffley, 2004; Casillas-Olvera and Bessler, 2006).

Sanders (1963) was the first to introduce a numerical measure of calibration through the decomposition of the Brier score (Brier, 1950), i.e. Sanders decomposition of the Brier score (Sanders decomposition of the Brier score was explained in Chapter II). It was followed by Murphy and Epstein (1967), Murphy (1972a), Murphy (1972b), Murphy (1973), Murphy and Winkler (1977) and Yates (1982). These latter papers elaborated on the calibration component of the probability forecasts evaluated through Brier Score and its various decompositions. For the most part, such analyses have stopped with graphical representation. Therefore, it was up to the reader to decide by looking at the graph to see how far the plot deviates from the 45-degree line to reject perfect calibration. In other words, we find that little formal tests have been done in most calibration studies, in particular in articles published in 1960's, 1970's and in early 1980's.

According to Dawid (1984, page 281) and Bunn (1984 page 150), a continuous random variable (X_n) with a continuous distribution function (F_n), the random fractiles generated (U_n) are distributed independent uniform $U[0,1]$, i.e. $U_n = F_n(X_n)$. Above result is obtained through the *probability integral transform* method explained in Rosenblatt (1952). In other words, when the outcome of the variable (X_n) becomes known, we can define (U_n) as $U_n = F_n(X_n)$, which is the fractile of the distribution function that was actually realized. Since (U_n) is distributed independent uniform, it takes the values between 0 and 1. For a perfectly calibrated estimator, the probability for a particular value U^* would be $P(U \leq U^*) = U^*$ (this implies that U should have a uniform probability density function in the ideal situation of perfect calibration (Bunn, 1984)). Therefore, the cumulative density function for U, which is $F_u(U)$ will in this case describe a straight line, on a graphical representation where U is on the horizontal axis and $F_u(U)$ on the vertical axis. Furthermore, the straight line is $F_u(U) = U$. This graphical representation gives us a perfect calibration function for a continuous random variable. For a more realistic situation of imperfect calibration, above calibration function is generated as follows. Let us suppose that a set of n values of U are available from the realized sequence and they are arranged in the ascending order $U_1, U_2 .... U_n$. To estimate $F_u(U)$ from above data, we can use the following relationship:

(5.1) $F_U(U) = {}^{j}\!/_{n}$ for $j = 1,2,\ldots\ldots,n$

In our analysis of purchase decisions of non-alcoholic beverages, we have a discontinuous random variable to begin with, i.e. purchase or do not purchase (this is a *0,1 type* dichotomous random variable). When the random variable under consideration is discontinuous, the generation of the calibration function takes a slightly different path. Let us suppose the dichotomous random variable is Y and the associated cumulative distribution function is $F_Y(Y)$. When the outcome of the variable becomes known, we can define V as $V = F_Y(Y)$. The realized fractile in this case is V. According to David and Johnson (1950), such a realized fractile from a discontinuous random variable is not uniformly distributed; rather they give rise to different moments. In our work on purchase decisions of non-alcoholic beverages, the realized fractile is the probability of purchase of a given non-alcoholic beverage by a household. When the realized fractile is not uniformly distributed, a calibration function with the realized fractile on the horizontal axis and the cumulative probability density function of the realized fractile on the vertical axis cannot be generated. The alternative calibration function we can generate for such a satiation is as follows.

First, the realized fractiles (in this case probability) are arranged in ascending order and discretized them so that they form desired number of discrete class intervals with a desired class width (selection procedure of the width and number of class intervals is explained below). Then for such class intervals, we need to find out the relative frequency of occurrence of the event after the event occurred. Now we are ready plot the calibration function for a discrete random variable, where, the probability of occurrence is on the horizontal axis and the realized relative frequency on the vertical axis. The 45-degree line explains the scenario of perfectly calibrated probabilities, while any deviation from that gives us imperfectly calibrated (*over-calibrated or under-calibrated*) probabilities.

A statistical test for calibration (Dawid, 1984) can be made by testing the observed fractiles from a discrete random variable (V_n 's this case) from the sequence of probability forecasts (they are probabilities of purchase of a given non-alcoholic beverage). If we have *J* non-overlapping probability subintervals[21] that exhaust the unit interval, then we can calculate a goodness-of-fit statistic X^2 as follows:

(5.2) $$X^2 = \sum_{j=1}^{J} \frac{(a_j - n\pi_j)^2}{n\pi_j}$$

[21] Historically, the number of sub intervals that has to be included in calculating a chi-square test has always been a debate amongst researchers. One of main reasons for this being the influence on the power of the test by the number of sub intervals that one chooses in calculating the *chi-squared* test. Seiller and Dawid (1993) use 11 sub intervals and their justification for that is rather simple, thus, *"all forecasts were given to one decimal place, thus dividing the unit interval into 11 ranges"*, However, Mann and Wald (1942) and Williams (1950) suggest a formula to come up with an optimum number of sub intervals as follows; if number of sub intervals in denoted by J: $J = 4 * \sqrt[5]{\frac{2(N-1)^2}{c^2}}$ where *N* is the total number of observations, and *c* is the probability of the critical region under the null hypothesis assuming a standard normal distribution, i.e. $c = \int_c^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} ds$. Furthermore, a similar formula to Mann and Wald (1942) is arrived at by Schorr (1974) using an alternative distance norm (please see Schorr (1974) page 358 for Mann and Wald (1942) distance norm and page 359 for Schorr (1974) distance norm). Nevertheless, Hamdan (1963) states that Mann and Wald (1942) procedure gives too many class intervals and that reduces the power of the *chi*-square test. Therefore, Hadman (1963) argues that optimum number of class intervals that one can take is about 10 to 20 to maintain a high power of the test. In our analysis of testing for calibration of probabilities generated through qualitative choice models using the *chi*-square test, we use 11 equally distributed class intervals (uniformly distributed class intervals) within the unit interval. Our results are robust for class intervals as less as 11 and as high as 22. Therefore, we stick with 11 uniformly distributed class intervals for our analysis.

In equation 5.2, a_j is the actual number of observed fractiles in the interval *j* (in our study the actual number of observed fractiles is the number of households that did purchase a given non-alcoholic beverage), π_j is the length of probability interval *j* (or the midpoint of probability class as stated in Seillier and Dawid, 1993) where $(0 \leq \pi \leq 1)$ (Kling and Bessler, 1989 and Seillier and Dawid, 1993), *n* is the frequency or the total number of households that are found under each probability class (or *n* such probability forecasts) and $n * \pi$ gives us the expected number of fractiles under each probability class interval. In establishing the test statistic in equation 5.2, the expected number of fractiles, i.e. $n\pi_j$ is compared against the actual number of observed fractiles, i.e. a_j. The number calculated in equation 5.2 is compared against the *chi*-squared distribution with $J-1$ degrees of freedom. Seillier and Dawid, 1993 recently have shown under very weak conditions (not requiring independence) on the distributions underlying the forecasts and under the null hypothesis of calibration, aforementioned test statistic is distributed *chi*-squared asymptotically (Kling and Bessler, 1989).

Goodness-of-fit test statistic calculation takes a slightly different path in Seillier and Dawid, 1993 compared to for example Kling and Bessler, 1989. We used the Seillier and Dawid, 1993 approach to evaluate probabilities generated using probit and logit models for calibration. For each probability class interval, Seillier and Dawid, 1993 calculated a test statistic which has properties of asymptotic standard normal distribution irrespective of the properties of the joint distribution associated with observed and expected fractiles. It is called a *Z* statistic and is calculated as follows[22]:

(5.3) $$Z_j = \frac{(a_j - n\pi_j)}{\sqrt{n\pi_j}} \text{ where } j = 1,2,\ldots\ldots,n$$

Lets define the observed relative frequency of the probabilities as ρ_j where $\rho_j = \frac{a_j}{n_j}$. For probabilities generated through qualitative choice models to be regarded as to be "empirically valid" as stated in Seillier and Dawid, 1993 or well calibrated, the discrepancy between ρ_j and π_j must be tend to zero at least as sample size increases. In other words, if the observed relative frequency and expected probabilities were extended to infinity, we might demand that the forecasts to be valid, they have to be perfectly calibrated in the limit: $\rho_j - \pi_j \to 0$ as $n \to \infty$ (Seillier and Dawid, 1993). Therefore, Z_j statistic calculated in equation 5.3 is a normalized measure of discrepancy which is trying to find out deviation from perfect calibration (note that we say probabilities are perfectly calibrated if there is no discrepancy between observed relative frequency and

[22] In calculating the *Z* statistic, Seillier and Dawid, 1993 brings in a small correction for grouping called Sheppard's correction (see Hald, 2001, Sheppard's second moment correction for grouping) through a weight variable introduced to the denominator of equation 3.27 above. The weight variable *w* is calculated using the *n*, the number of forecast probabilities and π_j, the width of the probability class interval. Hence the weight: $w = n_j \pi_j (1 - \pi_j)$. According to Seillier and Dawid, 1993, the equation for *Z* statistic is as follows: $Z_j = \frac{(a_j - n\pi_j)}{w_j^{1/2}}$. However, according to Ferguson (1941) and Davies and Burner (1943), use of Sheppard's correction may introduce a downward bias for the moments of grouped data especially if the underlying distribution of the random variable does not taper off at extreme points. In other words for Sheppard's correction to work, the underlying distribution for the random variable concerned must taper-off to zero at extreme points. In our analysis of probabilities generated through qualitative choice models for purchase decisions of selected non-alcoholic beverages, we observe distributions that are not tapering off to zero at extreme points. Therefore, we do not use the Sheppard's correction to adjust for grouping of data in calculating the above *Z* statistic.

expected probabilities). This property constitutes to our null hypothesis. Our null hypothesis states that probabilities are well (perfectly) calibrated. Any statistically significant deviation from perfect calibration gives rise to imperfect calibration or over or under-calibrated scenarios.

According to Seillier and Dawid, 1993, distribution of the Z_j statistic is standard normal regardless of the joint distribution between expected probabilities and observed events and under such an independence structure; we could simply examine such a test statistic. If the test statistic is too far out in the tail of the standard normal distribution, we can regard this case as evidence against perfect calibration. Under the same independence structure, we could form a “portemanteau” test statistic $X^2 = \sum_{j-1}^{J} Z_j^2$, which is referred to have an asymptotic *chi*-squared distribution. Above calculated number is compared with table *chi*-squared distribution values with $J-1$ degrees of freedom. If we fail to reject the null hypothesis, our model generated probability forecasts are said to be well calibrated (we fail to reject the null hypothesis of perfect calibration).

Data Analysis and Discussion

We have analyzed probabilities generated through probit and logit models (both within-sample and out-of-sample scenarios) for calibration using graphical and a mathematical/statistical approach. Results are discussed beverage-by-beverage basis below. Graphical analysis on calibration is focused on over or under-calibration (or over and under-confident probabilities issued by the model) looking at the deviation of the calibration plot away from a 45-degree perfect calibration line. Statistical analysis is performed focusing on the statistical significance of the calculated X^2 statistic which is distributed *chi*-squared with degrees of freedom $J-1$. Notice that we have used 11 probability classes in calculating above statistic, hence the degrees of freedom for the *chi-squared* test is 10. The critical $\alpha = 0.05$ level *chi-squared* value to test the null hypothesis is 18.31. Our null hypothesis is *"issued probabilities are well calibrated"*. If we fail to reject the null hypothesis, we state that our model issued probabilities are well calibrated and vice versa.

Isotonics

Figures 5.1 through 5.4 show calibration graphs for probabilities generated through probit and logit models (both within-sample and out-of-sample). According to Figures 5.1 and 5.3, we observe a very similar pattern for probit and logit model generated within-sample probabilities. Model issued probabilities are consistently over calibrated (over-confident) for low probability values (up about probability 0.6) and beyond that, probabilities are under calibrated (under-confident). However, for probabilities below 0.6, calibration curve is quite tight and moves close to 45-degree line.

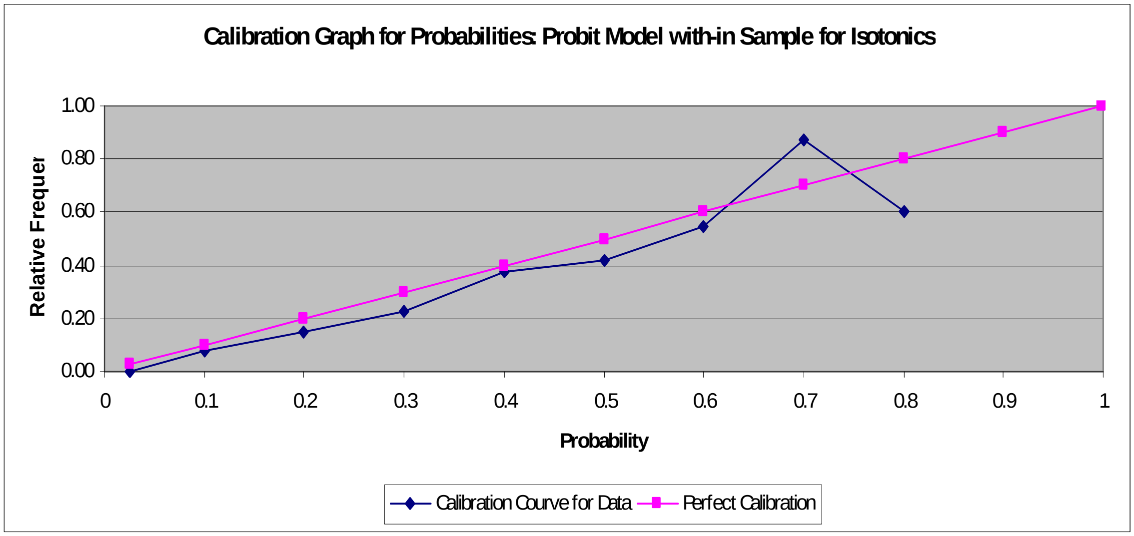

Figure 5.1: Calibration graph for probabilities: probit model within-sample for isotonics

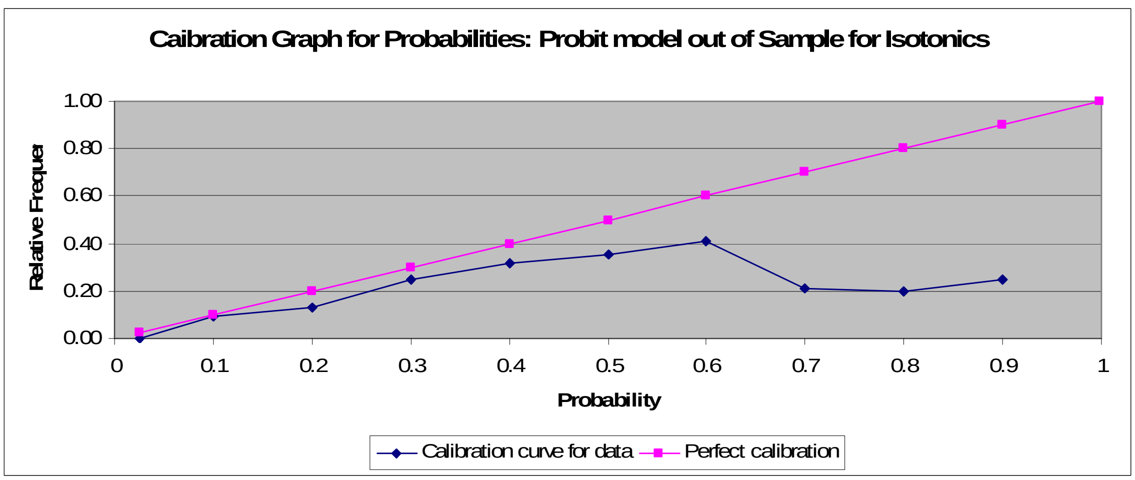

Figure 5.2: Calibration graph for probabilities: probit model out-of-sample for isotonics

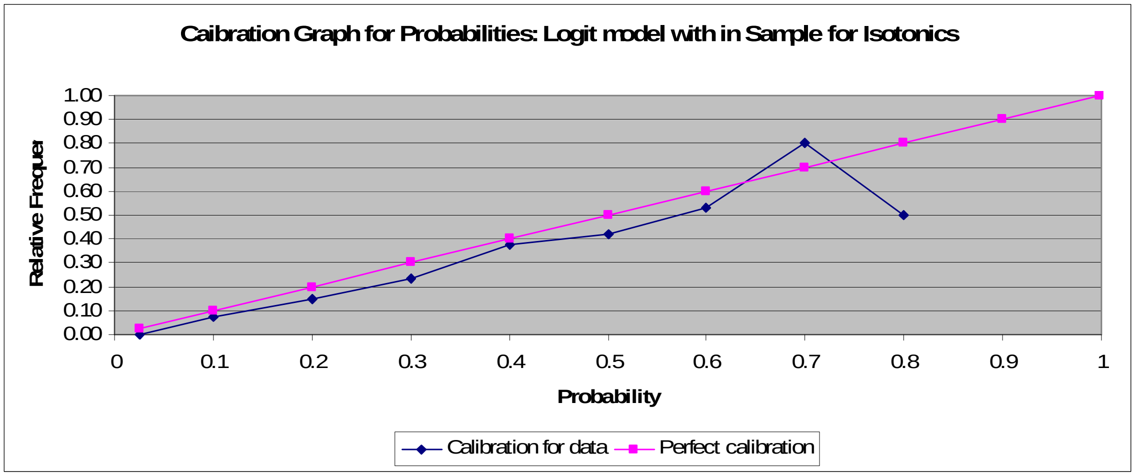

Figure 5.3: Calibration graph for probabilities: logit model within-sample for isotonics

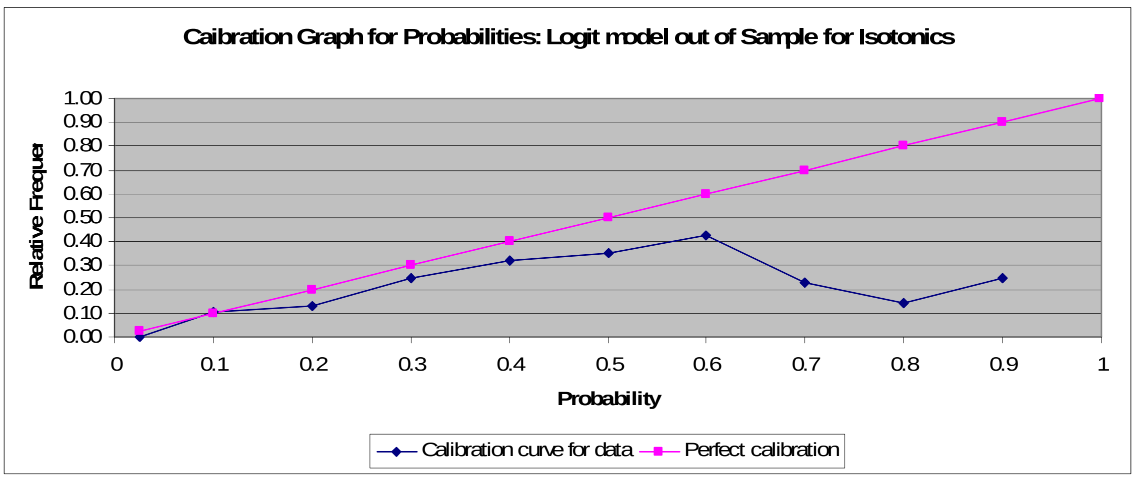

Figure 5.4: Calibration graph for probabilities: logit model out-of-sample for isotonics

For probit and logit model generated out-of-sample probabilities, we observe a consistently over calibrated probabilities (see Figures 5.2 and 5.4) and the over confidence gets really high for probabilities that are greater than 0.60. Beyond probability 0.60, the calibration curve moves away from the 45-degree line, even though it was tight around the 45-degree line for probabilities below 0.60.

Tables 5.41 through 5.44 show the calculated chi-square statistic for issued probabilities and realized relative frequency. According to them, the calculated *chi-squared* statistic is greater the critical value, hence we reject the null hypothesis. In other words, for isotonics, probit and logit model generated probabilities are not well calibrated (both within-sample and out-of-sample).

Regular Soft Drinks

Figures 5.5 through 5.8 show calibration graphs generated for within-sample and out-of-sample forecast probabilities modeled through probit and logit models for the decision to purchase regular soft drinks. Within-sample forecast probabilities are consistently over-confident while out-of-sample forecast probabilities show mixed results. They were over-confident for probabilities up to 0.80 and within the range 0.80 through 0.90, they were under-confident. For within-sample probabilities, the calibration curve moves close to 45-degree line for higher probabilities.

Table 5.41: Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Isotonics

Range	Mid Point	Frequency	Purchase	Relative Frequencies	Expected	Test statistic	
j	Pi	N	d=1	Rho=d/n	e=n*Pi	z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	343	26	0.08	34.3	-1.42	2.01
3	0.2	1801	270	0.15	360.2	-4.75	22.59
4	0.3	790	182	0.23	237	-3.57	12.76
5	0.4	453	170	0.38	181.2	-0.83	0.69
6	0.5	314	131	0.42	157	-2.08	4.31
7	0.6	105	57	0.54	63	-0.76	0.57
8	0.7	8	7	0.88	5.6	0.59	0.35
9	0.8	5	3	0.60	4	-0.50	0.25
10	0.9						
11	0.999						
						Chi-squared	**43.55**

Table 5.42: Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Isotonics

Range	Mid Point	Frequency	Purchase	Relative Frequencies	Expected	Test statistic	
j	Pi	n	d=1	Rho=d/n	e=n*Pi	z=(d-e)/e*0.5	z-squared
1	0.025	2	0	0.00	0.05		0
2	0.1	322	31	0.10	32.2	-5.67	32.20
3	0.2	1841	245	0.13	368.2	-17.57	308.81
4	0.3	776	191	0.25	232.8	0.80	0.64
5	0.4	452	142	0.31	180.8	0.76	0.58
6	0.5	311	111	0.36	155.5	-1.08	1.17
7	0.6	92	38	0.41	55.2	7.51	56.41
8	0.7	14	3	0.21	9.8	-2.17	4.72
9	0.8	5	1	0.20	4	-1.50	2.25
10	0.9	4	1	0.25	3.6	-1.37	1.88
11	0.999						
						Chi-squared	**408.65**

Table 5.43: Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Isotonics

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	294	21	0.07	29.4	-1.55	2.40
3	0.2	1875	278	0.15	375	-5.01	25.09
4	0.3	774	180	0.23	232.2	-3.43	11.73
5	0.4	443	168	0.38	177.2	-0.69	0.48
6	0.5	299	125	0.42	149.5	-2.00	4.02
7	0.6	118	63	0.53	70.8	-0.93	0.86
`	0.7	10	8	0.80	7	0.38	0.14
9	0.8	6	3	0.50	4.8	-0.82	0.68
10	0.9						
11	0.999						
						Chi-squared	**45.42**

Table 5.44: Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Isotonics

Range J	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	294	31	0.11	29.4	0.30	0.09
3	0.2	1887	249	0.13	377.4	-6.61	43.68
4	0.3	779	192	0.25	233.7	-2.73	7.44
5	0.4	427	136	0.32	170.8	-2.66	7.09
6	0.5	311	109	0.35	155.5	-3.73	13.91
7	0.6	96	41	0.43	57.6	-2.19	4.78
8	0.7	13	3	0.23	9.1	-2.02	4.09
9	0.8	7	1	0.14	5.6	-1.94	3.78
10	0.9	4	1	0.25	3.6	-1.37	1.88
11	0.999	0	0		0		0.00
						Chi-squared	**86.76**

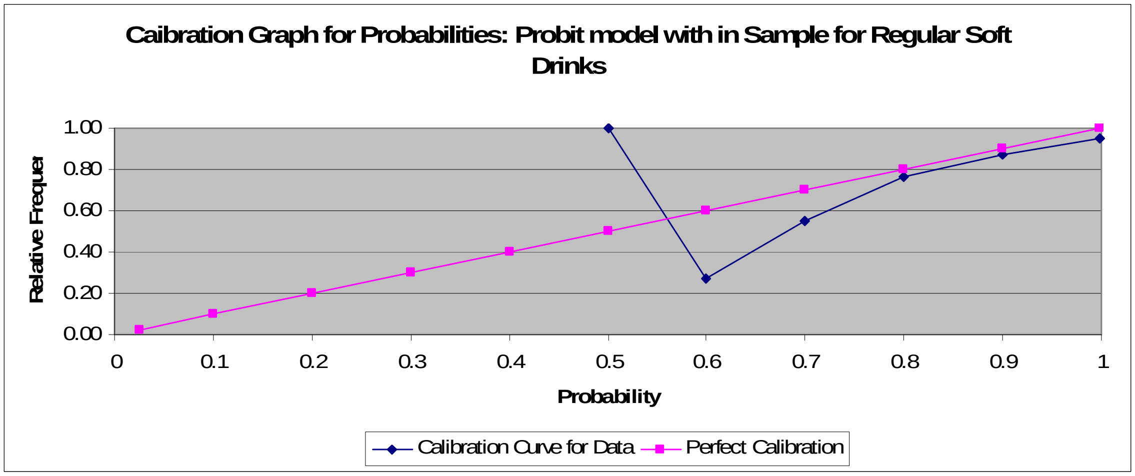

Figure 5.5: Calibration graph for probabilities: probit model within-sample for regular soft drinks

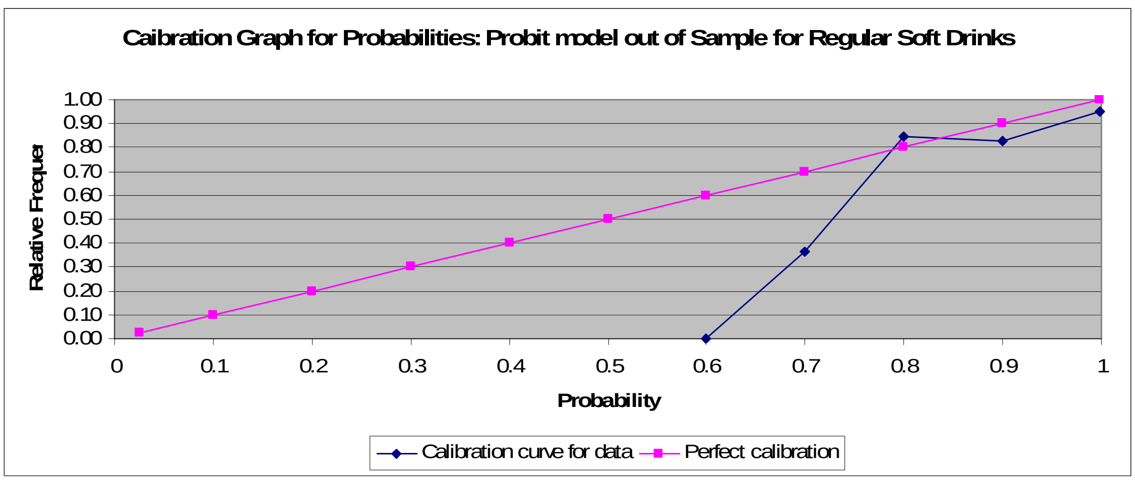

Figure 5.6 Calibration graph for probabilities: probit model out-of-sample for regular soft drinks

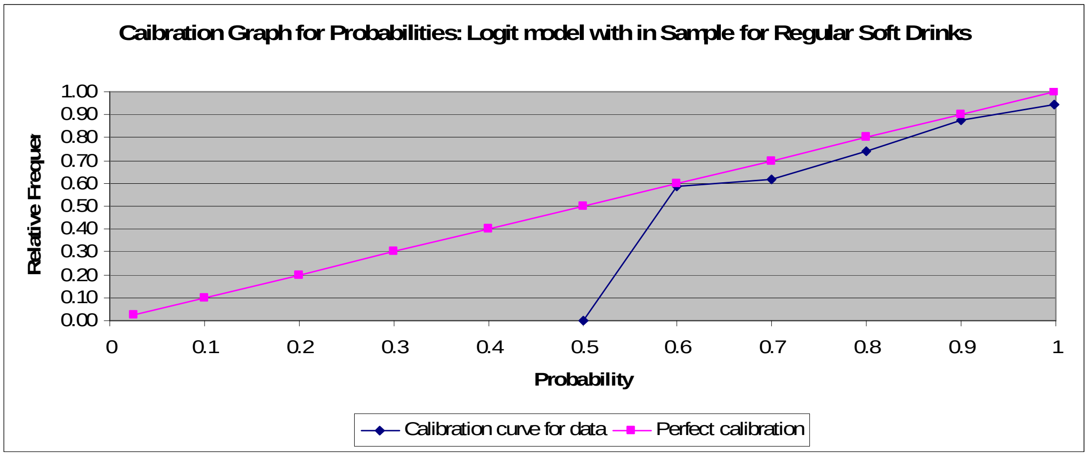

Figure 5.7 Calibration graph for probabilities: logit model within-sample for regular soft drinks

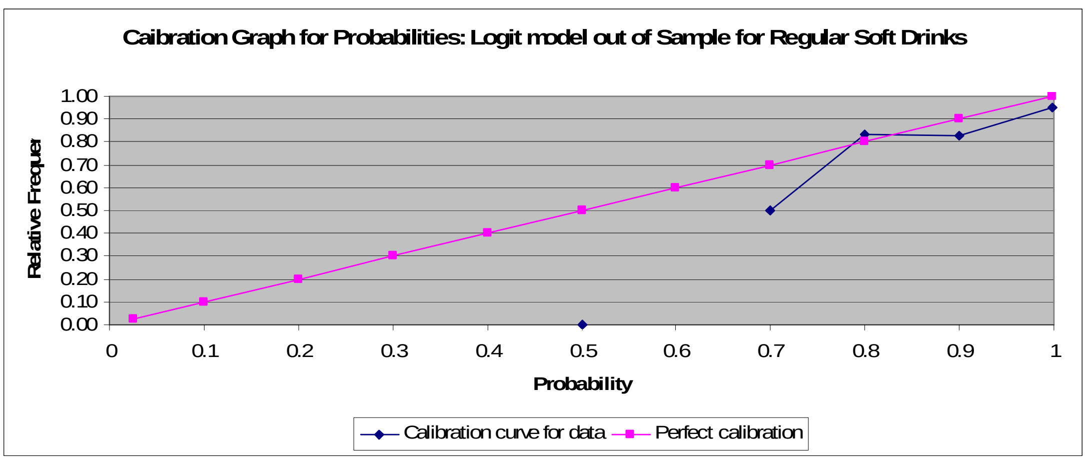

Figure 5.8: Calibration graph for probabilities: logit model out-of-sample for regular soft drinks

Tables 5.45 through 5.48 show the calculation of the *chi*-squared statistic to statistically test for calibration. According to the significance of the *chi*-squared test statistic, we fail to reject the null hypothesis that probabilities are well calibrated. That is to say, probit and logit model generated probabilities are well calibrated (both within-sample and out-of-sample) for the decision to purchase regular soft drinks.

Table 5.45: Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Regular Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	1	1	1.00	0.5	0.71	0.50
7	0.6	11	3	0.27	6.6	-1.40	1.96
8	0.7	60	33	0.55	42	-1.39	1.93
9	0.8	344	262	0.76	275.2	-0.80	0.63
10	0.9	1074	936	0.87	966.6	-0.98	0.97
11	0.999	2330	2209	0.95	2327.67	-2.46	6.05
						Chi-squared	**12.04**

Table 5.46: Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Regular Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5						
7	0.6	1	0	0.00	0.6	-0.77	0.60
8	0.7	11	4	0.36	7.7	-1.33	1.78
9	0.8	315	267	0.85	252	0.94	0.89
10	0.9	886	734	0.83	797.4	-2.25	5.04
11	0.999	2606	2472	0.95	2603.394	-2.58	6.63
						Chi-squared	**14.94**

Table 5.47 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Regular Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	3	0	0.00	1.5	-1.22	1.50
7	0.6	17	10	0.59	10.2	-0.06	0.00
8	0.7	73	45	0.62	51.1	-0.85	0.73
9	0.8	330	245	0.74	264	-1.17	1.37
10	0.9	976	858	0.88	878.4	-0.69	0.47
11	0.999	2421	2286	0.94	2418.579	-2.70	7.27
						Chi-squared	**11.34**

Table 5.48 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Regular Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	1	0	0.00	0.5	-0.71	0.50
7	0.6						
8	0.7	14	7	0.50	9.8	-0.89	0.80
9	0.8	348	291	0.84	278.4	0.76	0.57
10	0.9	813	674	0.83	731.7	-2.13	4.55
11	0.999	2643	2505	0.95	2640.357	-2.63	6.94
						Chi-squared	**13.36**

Diet Soft Drinks

Calibration graphs drawn for forecast probabilities generated through the decision to purchase diet soft drinks modeled using probit and logit models are depicted in Figures 5.9 through 5.12 (both within-sample and out-of-sample probabilities). Probit model generated within-sample probabilities are slightly over-confident. This result is clearly evident on Figure 5.9. Model generated calibration graph moves very close to the 45-degree line. According to the Figure 5.10, probit model generated out-of-sample probabilities are even better and show very small under-confidence around probability 0.30 and a very small over-confidence above probability 0.40. Also, the model generated calibration line moves very close to the 45-degree line. This result is indicative of good calibration of probabilities generated. Aforementioned graphical result is confirmed by the statistical result.

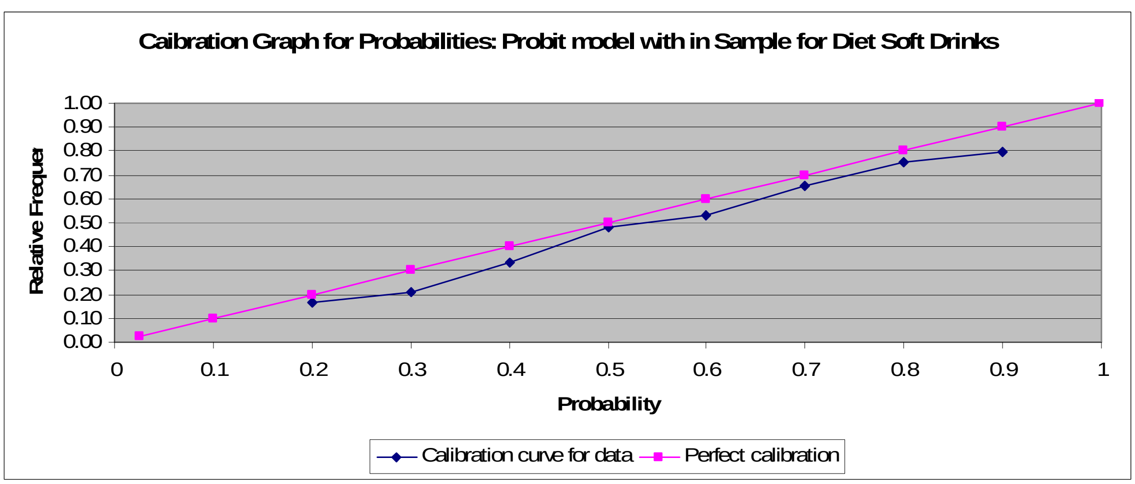

Figure 5.9: Calibration graph for probabilities: probit model within-sample for diet soft drinks

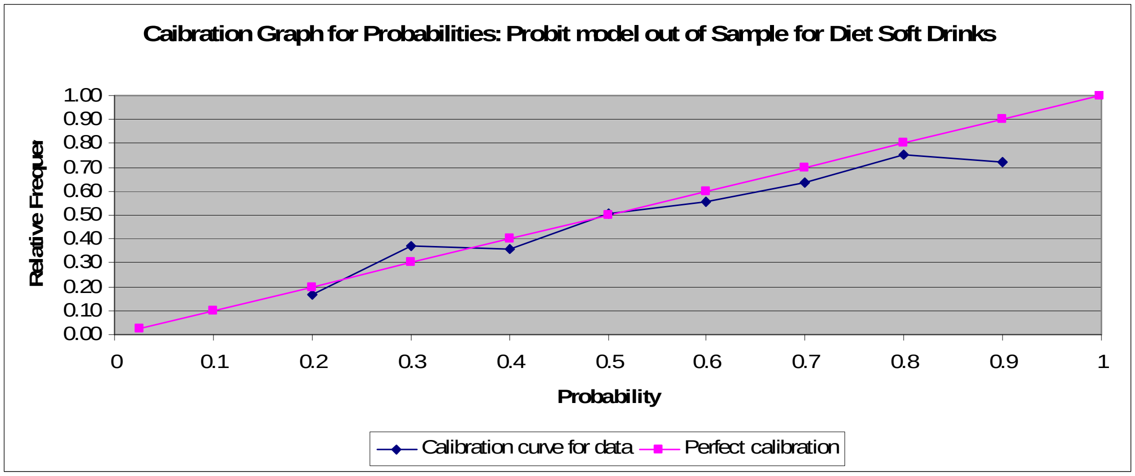

Figure 5.10: Calibration graph for probabilities: probit model out-of-sample for diet soft drinks

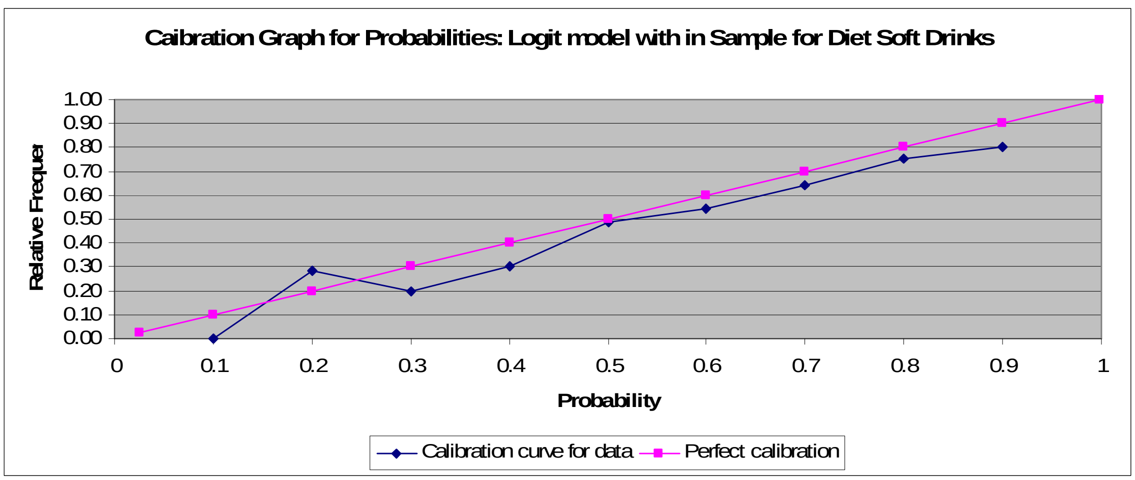

Figure 5.11: Calibration graph for probabilities: logit model within-sample for diet soft drinks

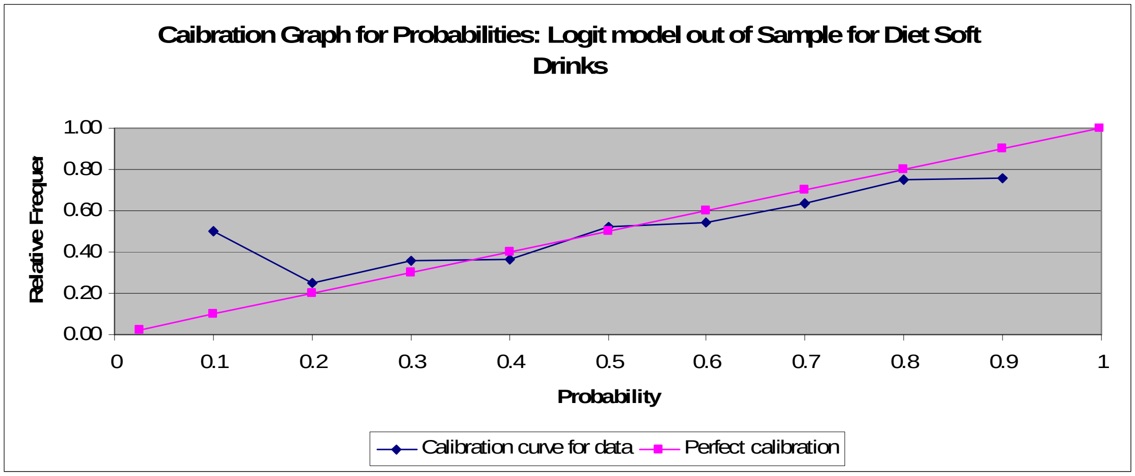

Figure 5.12: Calibration graph for probabilities: logit model out-of-sample for diet soft drinks

According to Tables 5.49 and 5.50, the calculated *chi*-squared statistic is less than the table *chi*-squared statistic value, thus failing to reject the null hypothesis of well calibration. In other words, probit model generated within-sample and out-of-sample probabilities for the decision to purchase diet soft drinks are well calibrated.

Calibration curve plotted for logit model generated within-sample probabilities show mixed results. They are slightly over-confident at low probabilities and slightly under-confident at probability 0.20. Over-confidence returns back for all probabilities greater than 0.30 and remain over-confident for the rest of the probabilities. Result is somewhat similar for logit model generated out-of-sample probabilities; however calibration curve shows a considerable under-confidence for low probabilities. We see consistently over-confident probabilities for higher probabilities, even though the deviation of the calibration curve from the 45-degree line is small.

Aforementioned result is supported by the statistical test on forecast probabilities and realized relative frequencies for logit model generated probabilities. According to Table 5.51 and 5.52, we see that the calculated *chi-squared* statistic is greater then the table value, indicating the rejection of the null hypothesis of perfect calibration. In other words, logit model generated probabilities for the decision to by diet soft drinks are not well calibrated (both within-sample and out-of-sample).

Table 5.49 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Diet Soft Drinks

Range j	Mid Point Pi	Frequency N	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2	6	1	0.17	1.2	-0.18	0.03
4	0.3	43	9	0.21	12.9	-1.09	1.18
5	0.4	115	38	0.33	46	-1.18	1.39
6	0.5	418	202	0.48	209	-0.48	0.23
7	0.6	480	255	0.53	288	-1.94	3.78
8	0.7	926	605	0.65	648.2	-1.70	2.88
9	0.8	1626	1220	0.75	1300.8	-2.24	5.02
10	0.9	205	163	0.80	184.5	-1.58	2.51
11	0.999						
						Chi-squared	**17.02**

Table 5.50 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Diet Soft Drinks

Range j	Mid Point Pi	Frequency N	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2	6	1	0.17	1.2	-0.18	0.03
4	0.3	51	19	0.37	15.3	0.95	0.89
5	0.4	64	23	0.36	25.6	-0.51	0.26
6	0.5	426	216	0.51	213	0.21	0.04
7	0.6	560	312	0.56	336	-1.31	1.71
8	0.7	941	598	0.64	658.7	-2.37	5.59
9	0.8	1667	1255	0.75	1333.6	-2.15	4.63
10	0.9	104	75	0.72	93.6	-1.92	3.70
11	0.999						
						Chi-squared	**16.87**

Table 5.51 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Diet Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1	1	0	0.00	0.1	-0.32	0.10
3	0.2	7	2	0.29	1.4	0.51	0.26
4	0.3	45	9	0.20	13.5	-1.22	1.50
5	0.4	119	36	0.30	47.6	-1.68	2.83
6	0.5	412	201	0.49	206	-0.35	0.12
7	0.6	484	263	0.54	290.4	-1.61	2.59
8	0.7	896	574	0.64	627.2	-2.12	4.51
9	0.8	1665	1256	0.75	1332	-2.08	4.34
10	0.9	190	152	0.80	171	-1.45	2.11
11	0.999						
						Chi-squared	**18.35**

Table 5.52 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Diet Soft Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1	2	1	0.50	0.2	1.79	3.20
3	0.2	4	1	0.25	0.8	0.22	0.05
4	0.3	53	19	0.36	15.9	0.78	0.60
5	0.4	63	23	0.37	25.2	-0.44	0.19
6	0.5	376	197	0.52	188	0.66	0.43
7	0.6	602	325	0.54	361.2	-1.90	3.63
8	0.7	955	608	0.64	668.5	-2.34	5.48
9	0.8	1649	1238	0.75	1319.2	-2.24	5.00
10	0.9	115	87	0.76	103.5	-1.62	2.63
11	0.999						
						Chi-squared	**21.21**

High-Fat Milk

Calibration graphs for forecast probabilities generated for the decision to purchase high-fat milk modeled through probit and logit model are shown in Figures 5.13 through 5.16. Probit and logit model generated within-sample forecast probabilities are slightly over-calibrated for all probabilities. Out-of-sample forecast probabilities show mixed results, where they are slightly under-confident for low probabilities and over-confident for high probabilities.

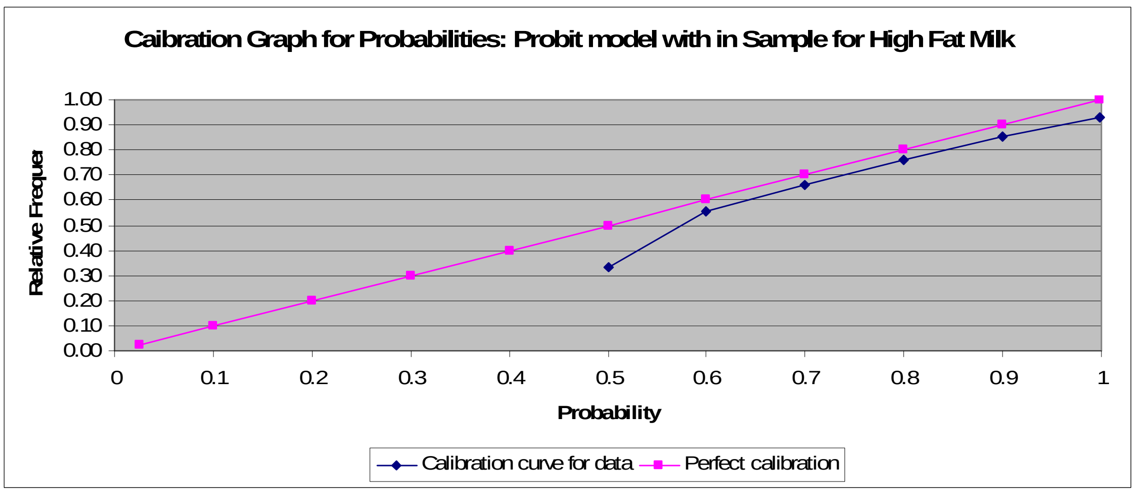

Figure 5.13: Calibration graph for probabilities: probit model within-sample for high-fat milk

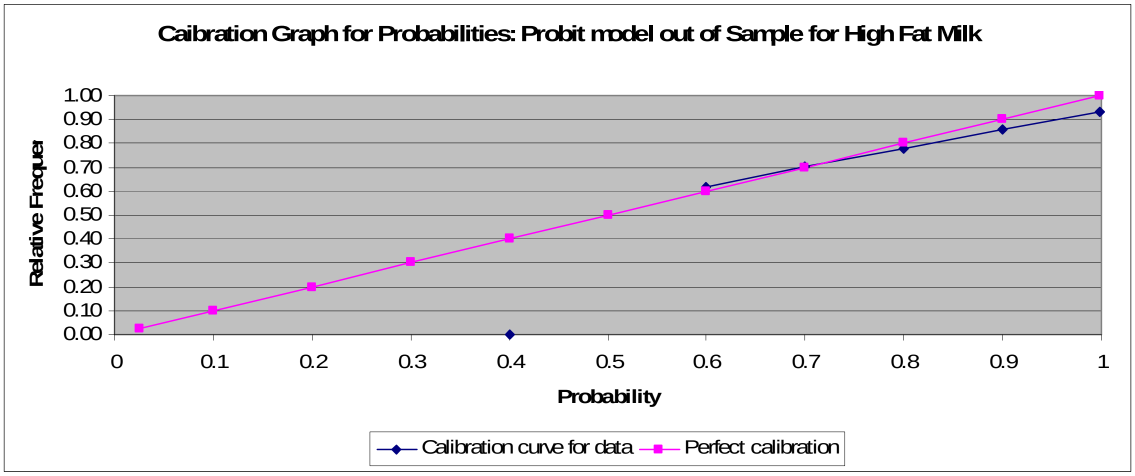

Figure 5.14: Calibration graph for probabilities: probit model out-of-sample for high-fat milk

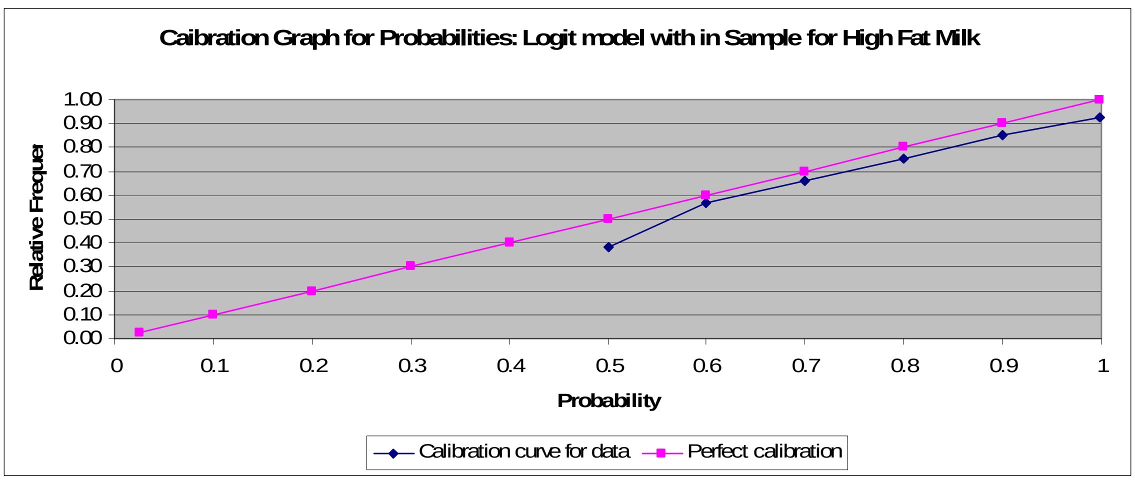

Figure 5.15: Calibration graph for probabilities: logit model within-sample for high-fat milk

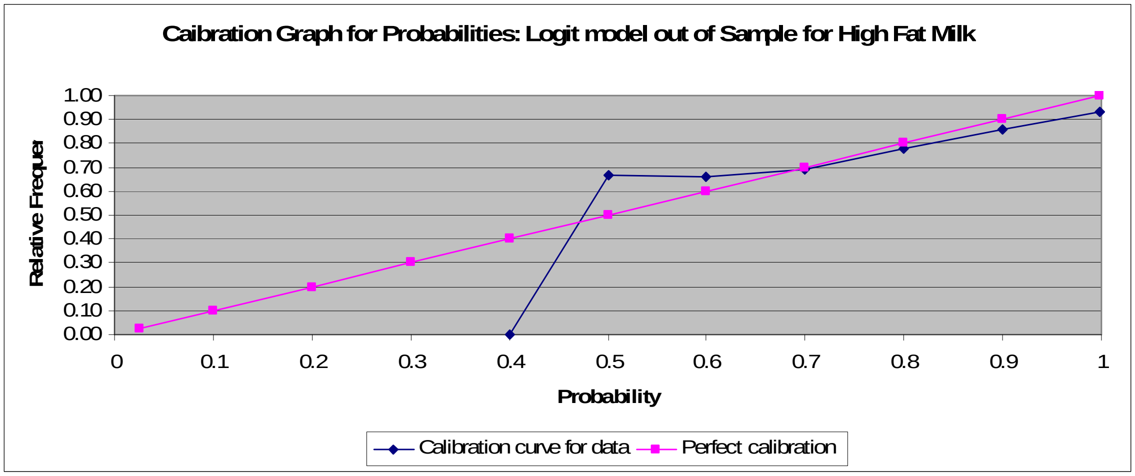

Figure 5.16: Calibration graph for probabilities: logit model out-of-sample for high-fat milk

According to the statistical tests shown in Table 5.53 through 5.56, the calculated *chi-squared* statistic is smaller than the critical table value, therefore, failing to reject the null hypothesis of well calibration. That is to say, probit and logit model generated forecast probabilities for the decision to purchase high-fat milk are well calibrated.

Table 5.53 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for High-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	9	3	0.33	4.5	-0.71	0.50
7	0.6	77	43	0.56	46.2	-0.47	0.22
8	0.7	310	205	0.66	217.0	-0.81	0.66
9	0.8	1051	797	0.76	840.8	-1.51	2.28
10	0.9	1704	1450	0.85	1533.6	-2.13	4.56
11	0.999	669	623	0.93	668.3	-1.75	3.07
						Chi-squared	**11.30**

Table 5.54 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for High-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	1	0	0.00	0.4	-0.63	0.40
6	0.5						
7	0.6	50	31	0.62	30	0.18	0.03
8	0.7	331	232	0.70	231.7	0.02	0.00
9	0.8	1157	898	0.78	925.6	-0.91	0.82
10	0.9	1646	1410	0.86	1481.4	-1.86	3.44
11	0.999	634	590	0.93	633.366	-1.72	2.97
						Chi-squared	**7.67**

Table 5.55: Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for High-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	13	5	0.38	6.5	-0.59	0.35
7	0.6	88	50	0.57	52.8	-0.39	0.15
8	0.7	301	199	0.66	210.7	-0.81	0.65
9	0.8	1027	775	0.75	821.6	-1.63	2.64
10	0.9	1716	1465	0.85	1544.4	-2.02	4.08
11	0.999	675	627	0.93	674.325	-1.82	3.32
						Chi-squared	**11.19**

Table 5.56: Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for High-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	1	0	0.00	0.4	-0.63	0.40
6	0.5	3	2	0.67	1.5	0.41	0.17
7	0.6	56	37	0.66	33.6	0.59	0.34
8	0.7	336	233	0.69	235.2	-0.14	0.02
9	0.8	1130	878	0.78	904	-0.86	0.75
10	0.9	1642	1405	0.86	1477.8	-1.89	3.59
11	0.999	651	606	0.93	650.349	-1.74	3.02
						Chi-squared	**8.29**

Low-Fat Milk

Figures 5.17 through 5.20, show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to purchase low-fat milk (both within-sample and out-of-sample forecast probabilities). For all scenarios, the calibration curve is very slightly over calibrated (over-confident) for all probabilities and as a result it is moving very close to the 45-degree line, probably showing good calibration. Preceding result is further confirmed through the statistical analysis performed on forecast probabilities.

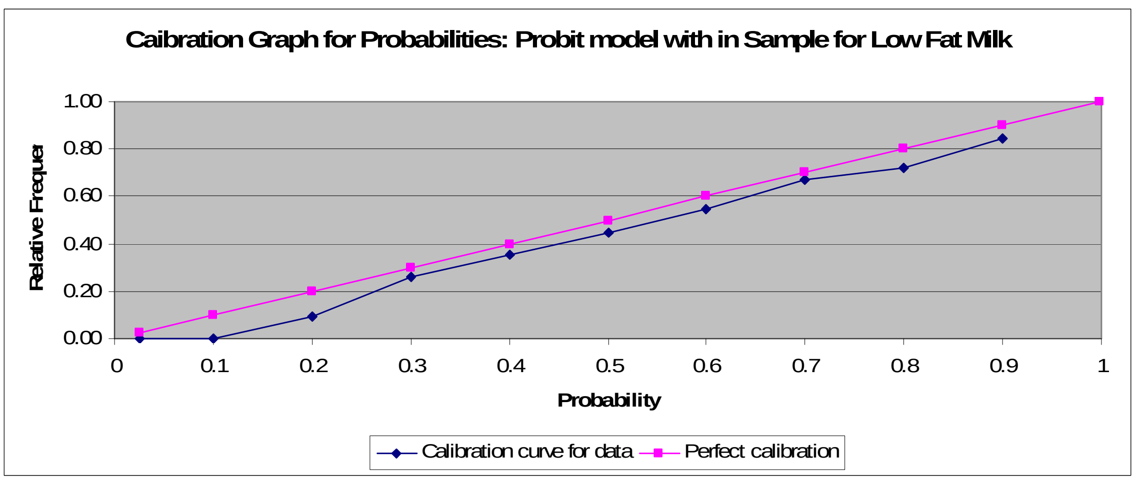

Figure 5.17: Calibration graph for probabilities: probit model within-sample for low-fat milk

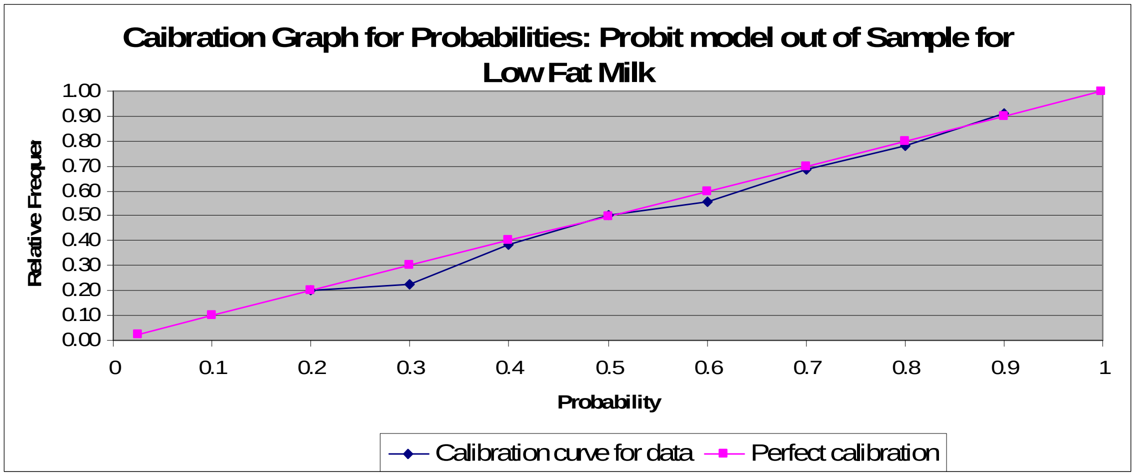

Figure 5.18: Calibration graph for probabilities: probit model out-of-sample for low-fat milk

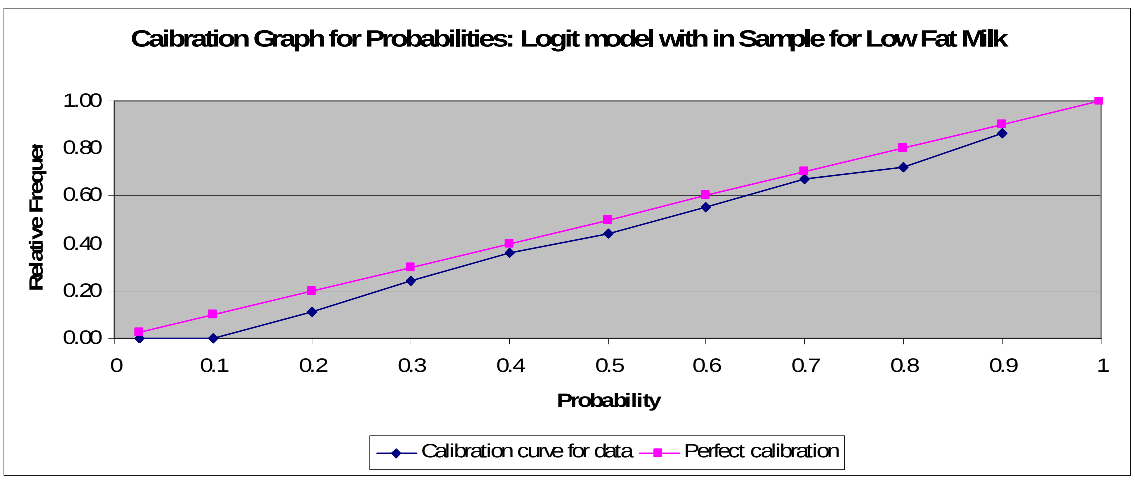

Figure 5.19: Calibration graph for probabilities: logit model within-sample for low-fat milk

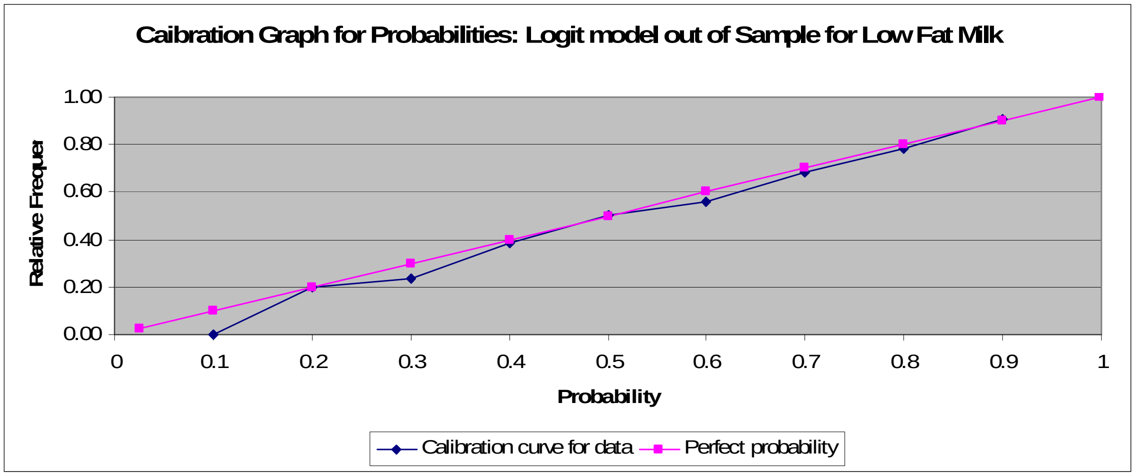

Figure 5.20: Calibration graph for probabilities: logit model out-of-sample for low-fat milk

Tables 5.57 through 5.60 show the *chi-square* test statistic calculation for forecast probabilities generated through probit and logit models. Calculated *chi-squared* test statistic values for all four scenarios are smaller than the table value at 5% significance level. Therefore, we fail to reject null hypothesis of well calibration. In other words, forecast probabilities generated through probit and logit models for the decision to purchase low-fat milk are well calibrated.

Table 5.57 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Low-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	2	0	0.00	0.2	-0.45	0.20
3	0.2	11	1	0.09	2.2	-0.81	0.65
4	0.3	38	10	0.26	11.4	-0.41	0.17
5	0.4	189	67	0.35	75.6	-0.99	0.98
6	0.5	427	190	0.44	213.5	-1.61	2.59
7	0.6	855	469	0.55	513	-1.94	3.77
8	0.7	1352	905	0.67	946.4	-1.35	1.81
9	0.8	887	641	0.72	709.6	-2.58	6.63
10	0.9	58	49	0.84	52.2	-0.44	0.20
11	0.999						
						Chi-squared	**17.03**

Table 5.58 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Low-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2	5	1	0.20	1	0	0
4	0.3	45	10	0.22	13.5	-0.95	0.91
5	0.4	182	70	0.38	72.8	-0.33	0.11
6	0.5	442	222	0.50	221	0.07	0.00
7	0.6	856	477	0.56	513.6	-1.61	2.61
8	0.7	1379	946	0.69	965.3	-0.62	0.39
9	0.8	864	673	0.78	691.2	-0.69	0.48
10	0.9	44	40	0.91	39.6	0.06	0.00
11	0.999						
						Chi-squared	**4.50**

Table 5.59 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Low-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	2	0	0.00	0.2	-0.45	0.20
3	0.2	9	1	0.11	1.8	-0.60	0.36
4	0.3	41	10	0.24	12.3	-0.66	0.43
5	0.4	191	69	0.36	76.4	-0.85	0.72
6	0.5	425	188	0.44	212.5	-1.68	2.82
7	0.6	849	467	0.55	509.4	-1.88	3.53
8	0.7	1353	904	0.67	947.1	-1.40	1.96
9	0.8	898	649	0.72	718.4	-2.59	6.70
10	0.9	51	44	0.86	45.9	-0.28	0.08
11	0.999						
						Chi-squared	**16.83**

Table 5.60 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Low-Fat Milk

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0		0.025	-0.16	0.03
2	0.1	1	0	0.00	0.1	-0.32	0.10
3	0.2	5	1	0.20	1	0.00	0.00
4	0.3	47	11	0.23	14.1	-0.83	0.68
5	0.4	179	69	0.39	71.6	-0.31	0.09
6	0.5	445	225	0.51	222.5	0.17	0.03
7	0.6	843	470	0.56	505.8	-1.59	2.53
8	0.7	1385	945	0.68	969.5	-0.79	0.62
9	0.8	870	679	0.78	696	-0.64	0.42
10	0.9	43	39	0.91	38.7	0.05	0.00
11	0.999						
						Chi-squared	**4.50**

Fruit Drinks

Figures 5.21 through 5.24 show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to purchase fruit drinks (both within-sample and out-of-sample forecast probabilities). Within-sample probit and logit model generated probabilities show a slight over-calibration for all probabilities generated. Out-of-sample generated probit and logit models show mixed results where they are under-calibrated for low probabilities and over-calibrated for higher probabilities.

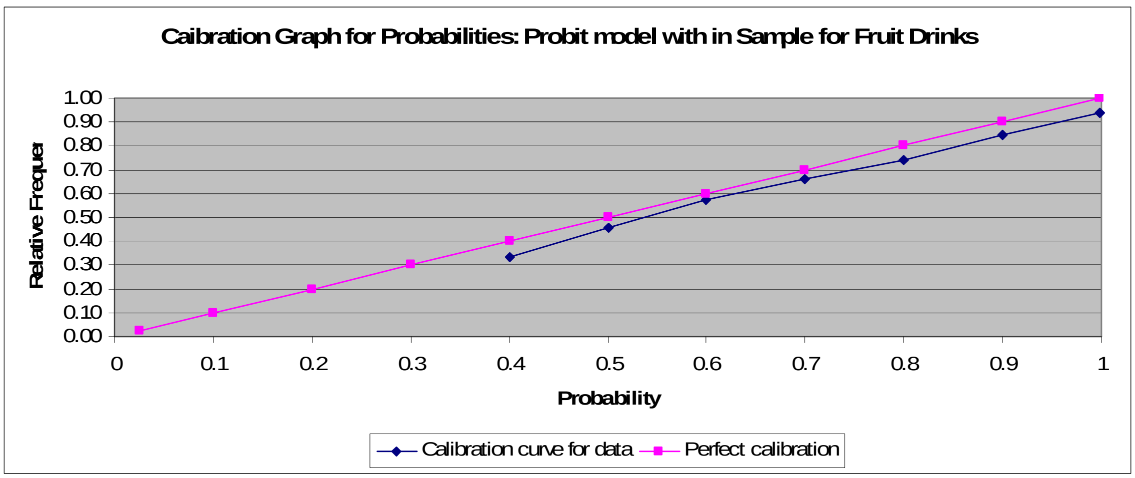

Figure 5.21: Calibration graph for probabilities: probit model within-sample for fruit drinks

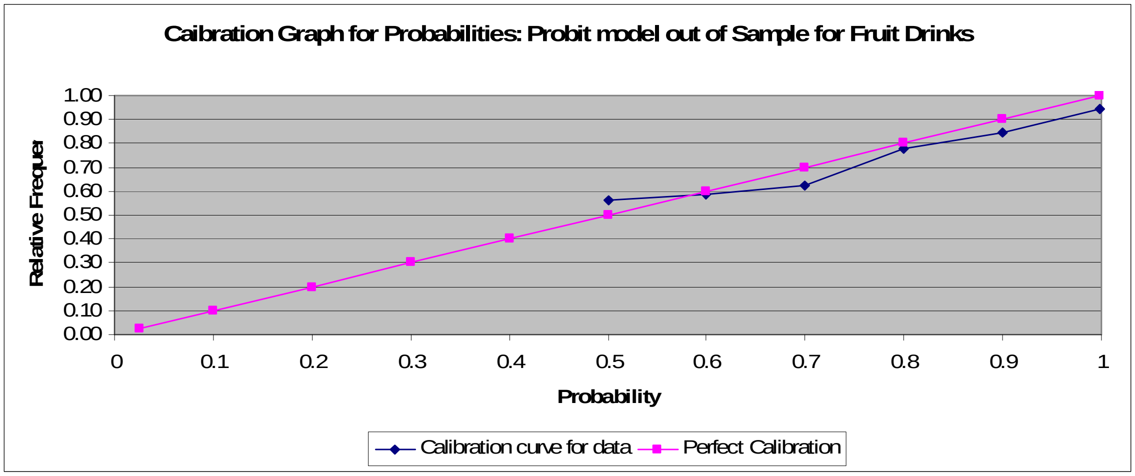

Figure 5.22: Calibration graph for probabilities: probit model out-of-sample for fruit drinks

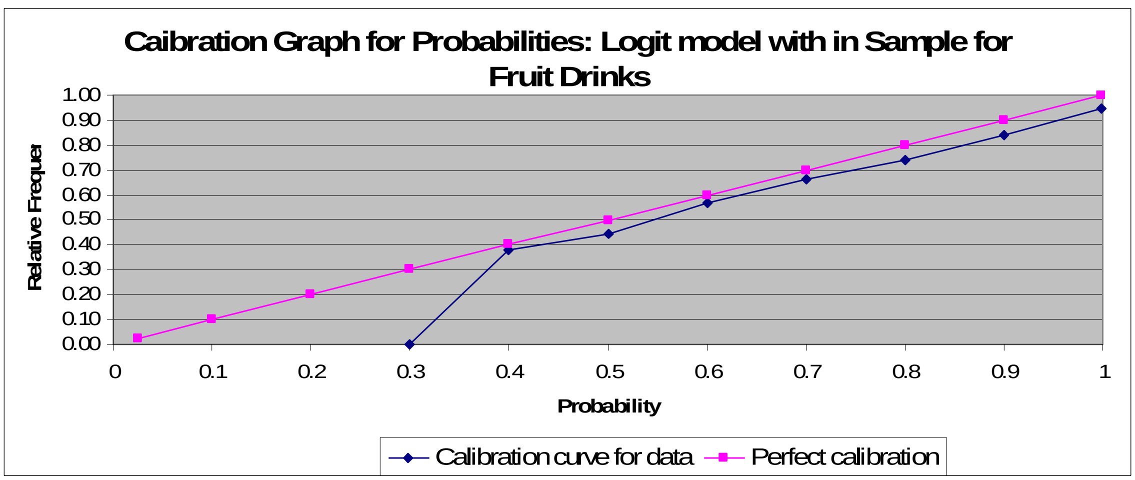

Figure 5.23: Calibration graph for probabilities: logit model within-sample for fruit drinks

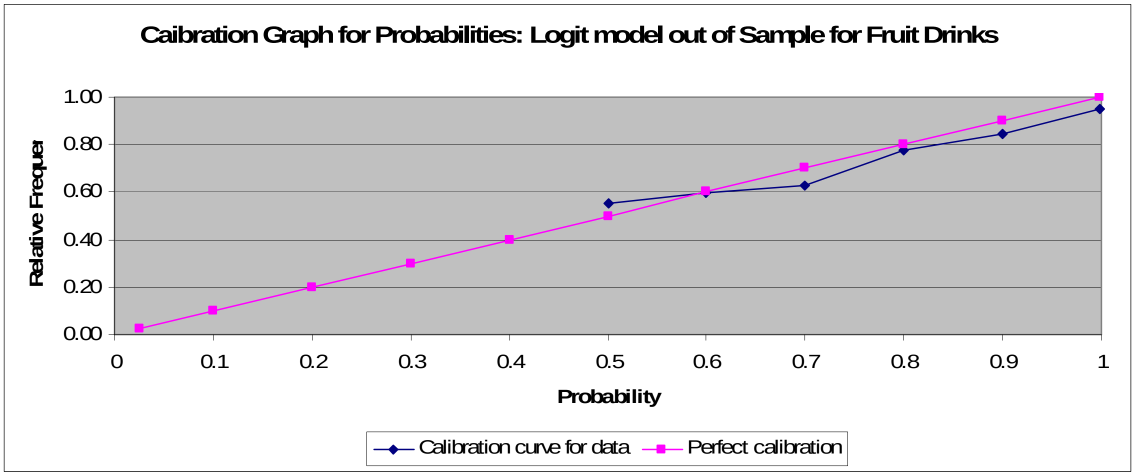

Figure 5.24: Calibration graph for probabilities: logit model out-of-sample for fruit drinks

Results from *chi-squared* tests for perfect calibration are shown in Tables 5.61 through 5.64. According to them, all calculated *chi-squared* test statistics are less than the *chi-squared* table value for degrees of freedom 10 and 95% significance level. That is to say, we fail to reject the null hypothesis of perfect calibration, indicating probit and logit model generated forecast probabilities for purchases of fruit drinks are well calibrated.

Table 5.61 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Fruit Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	42	14	0.33	16.8	-0.68	0.47
6	0.5	119	54	0.45	59.5	-0.71	0.51
7	0.6	374	214	0.57	224.4	-0.69	0.48
8	0.7	796	527	0.66	557.2	-1.28	1.64
9	0.8	920	680	0.74	736	-2.06	4.26
10	0.9	1051	891	0.85	945.9	-1.79	3.19
11	0.999	518	486	0.94	517.482	-1.38	1.92
						Chi-squared	**12.46**

Table 5.62 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Fruit Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	64	36	0.56	32	0.71	0.50
7	0.6	363	213	0.59	217.8	-0.33	0.11
8	0.7	514	320	0.62	359.8	-2.10	4.40
9	0.8	1597	1245	0.78	1277.6	-0.91	0.83
10	0.9	1002	845	0.84	901.8	-1.89	3.58
11	0.999	279	264	0.95	278.721	-0.88	0.78
						Chi-squared	**10.20**

Table 5.63 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Fruit Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3	1	0	0.00	0.3	-0.55	0.30
5	0.4	50	19	0.38	20	-0.22	0.05
6	0.5	119	53	0.45	59.5	-0.84	0.71
7	0.6	365	208	0.57	219	-0.74	0.55
8	0.7	767	508	0.66	536.9	-1.25	1.56
9	0.8	917	679	0.74	733.6	-2.02	4.06
10	0.9	1122	946	0.84	1009.8	-2.01	4.03
11	0.999	479	453	0.95	478.521	-1.17	1.36
						Chi-squared	**12.62**

Table 5.64 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Fruit Drinks

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	65	36	0.55	32.5	0.61	0.38
7	0.6	369	219	0.59	221.4	-0.16	0.03
8	0.7	506	316	0.62	354.2	-2.03	4.12
9	0.8	1565	1213	0.78	1252	-1.10	1.21
10	0.9	1059	897	0.85	953.1	-1.82	3.30
11	0.999	255	242	0.95	254.745	-0.80	0.64
						Chi-squared	**9.68**

Fruit Juices

Figures 5.25 through 5.28 show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to purchase fruit juices (forecast probabilities are generated for both within-sample and out-of-sample scenarios). Calibration graphs generated for within-sample probabilities show under-confidence for low probability values and over-confidence for probabilities beyond 0.40 for probit model and 0.70 for logit model generated probabilities respectively. Calibration graphs associated with out-of-sample forecast probabilities show a consistent vary small over-confidence whole throughout for all probability values.

Above graphical result is confirmed by the *chi-squared* test performed taking forecast probabilities generated through probit and logit models and realized relative frequencies.

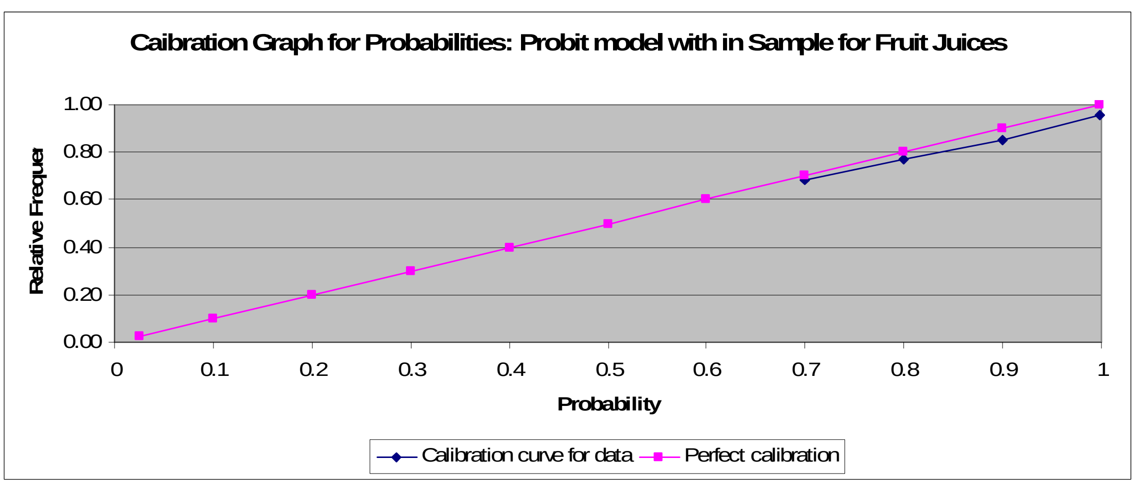

Figure 5.25: Calibration graph for probabilities: probit model within-sample for fruit juices

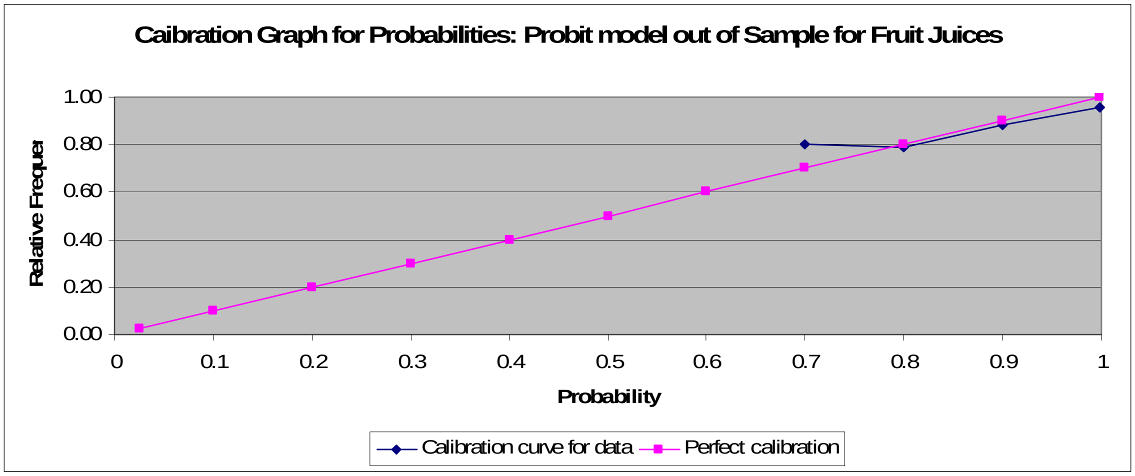

Figure 5.26: Calibration graph for probabilities: probit model out-of-sample for fruit juices

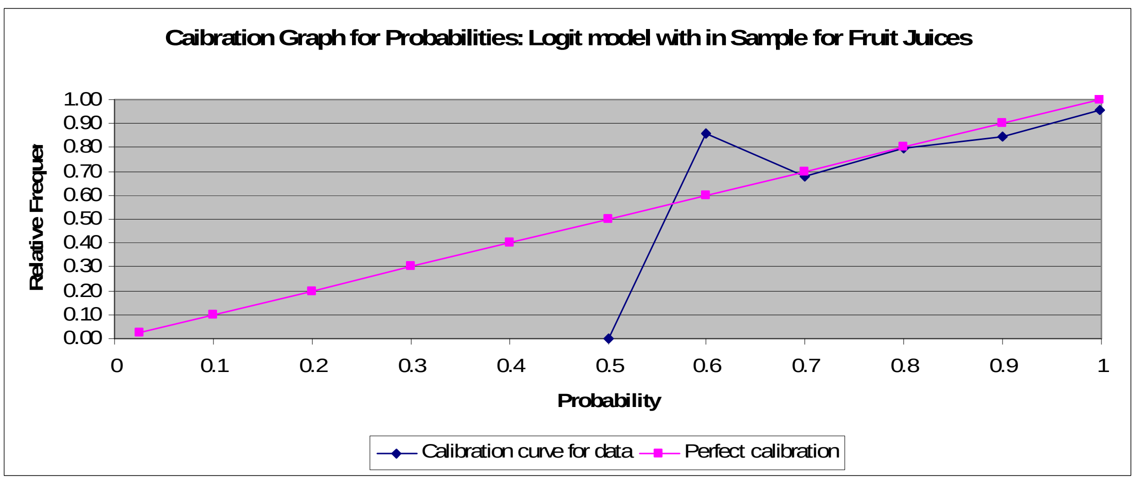

Figure 5.27: Calibration graph for probabilities: logit model within-sample for fruit juices

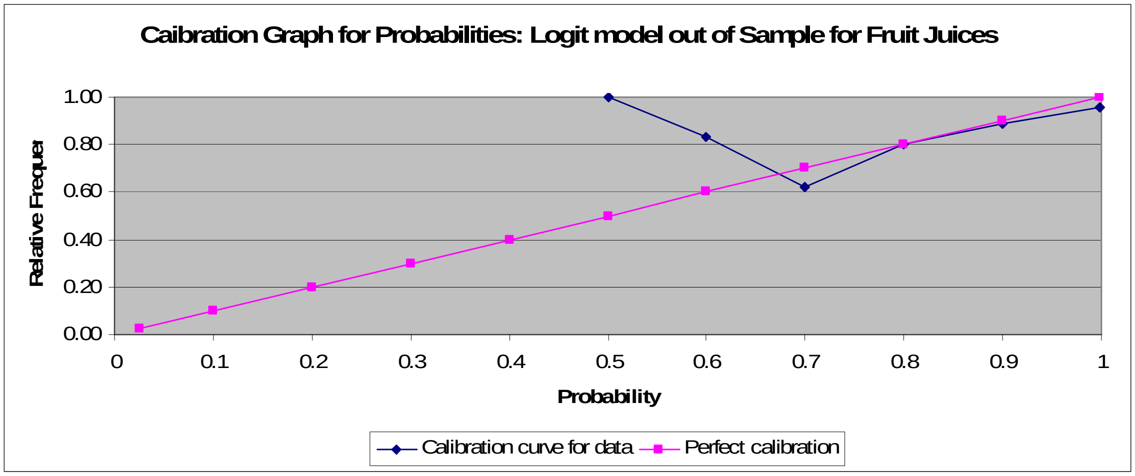

Figure 5.28: Calibration graph for probabilities: logit model out-of-sample for fruit juices

According to calculation shown in Tables 5.65 through 5.68, calculated *chi-squared* statistics are smaller than table *chi-squared* value for degrees of freedom 10 and at 95% significance level, indicating well calibrated probabilities.

<u>*Bottled Water*</u>

Figures 5.29 through 5.32 show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to buy bottled water (both within-sample and out-of-sample forecast probabilities). Calibration graphs generated for within-sample forecast probabilities show slight under calibrated probabilities for low probabilities and consistent small over calibration for higher probabilities. Even though we observe mixed results, calibration graph is very close to 45-degree line of perfect calibration. Above result is confirmed further through the *chi-squared* test performed taking forecast probabilities and realized relative frequencies.

Table 5.65: Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Fruit Juices

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5						
7	0.6						
8	0.7	19	13	0.68	13.3	-0.08	0.01
9	0.8	113	87	0.77	90.4	-0.36	0.13
10	0.9	668	568	0.85	601.2	-1.35	1.83
11	0.999	3009	2876	0.96	3005.991	-2.37	5.62
						Chi-squared	**7.59**

Table 5.66: Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Fruit Juices

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5						
7	0.6						
8	0.7	15	12	0.80	10.5	0.46	0.21
9	0.8	109	86	0.79	87.2	-0.13	0.02
10	0.9	669	590	0.88	602.1	-0.49	0.24
11	0.999	3007	2877	0.96	3003.993	-2.32	5.37
						Chi-squared	**5.84**

Table 5.67: Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Fruit Juices

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	1	0	0.00	0.5	-0.71	0.50
7	0.6	7	6	0.86	4.2	0.88	0.77
8	0.7	34	23	0.68	23.8	-0.16	0.03
9	0.8	114	91	0.80	91.2	-0.02	0.00
10	0.9	594	503	0.85	534.6	-1.37	1.87
11	0.999	3063	2925	0.95	3059.937	-2.44	5.95
						Chi-squared	**9.12**

Table 5.68: Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Fruit Juices

Range J	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4						
6	0.5	1	1	1.00	0.5	0.71	0.50
7	0.6	6	5	0.83	3.6	0.74	0.54
8	0.7	21	13	0.62	14.7	-0.44	0.20
9	0.8	107	86	0.80	85.6	0.04	0.00
10	0.9	592	524	0.89	532.8	-0.38	0.15
11	0.999	3077	2940	0.96	3073.923	-2.42	5.83
						Chi-squared	**7.22**

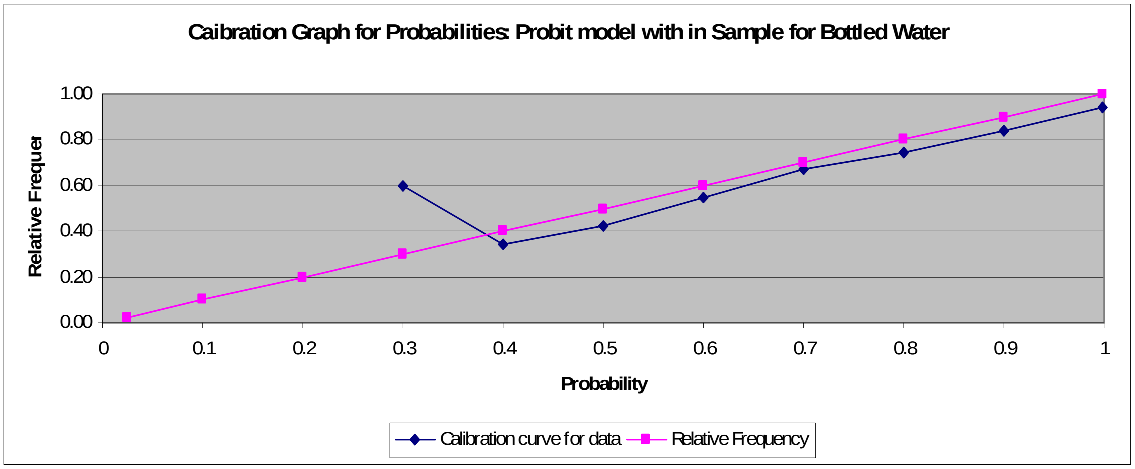

Figure 5.29: Calibration graph for probabilities: probit model within-sample for bottled water

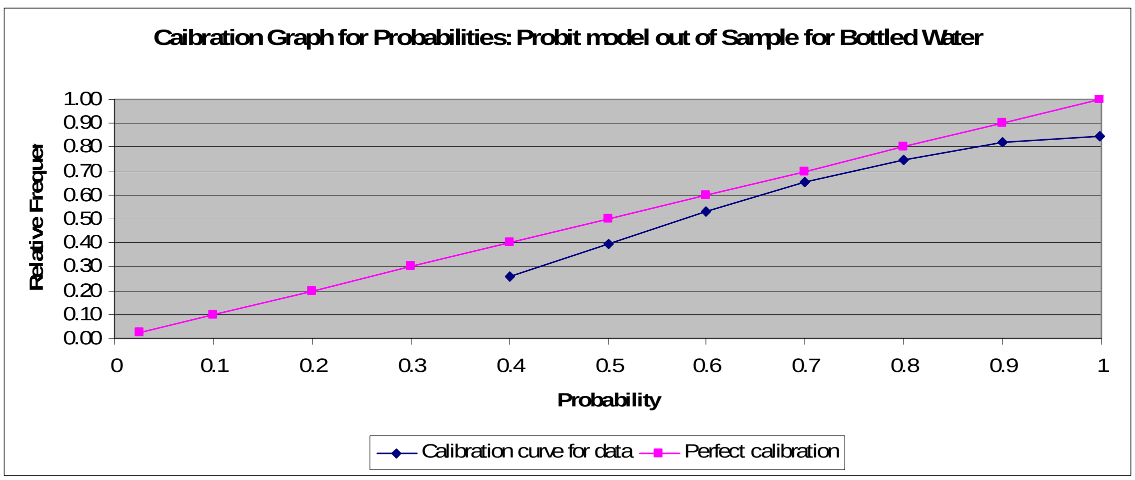

Figure 5.30: Calibration graph for probabilities: probit model out-of-sample for bottled water

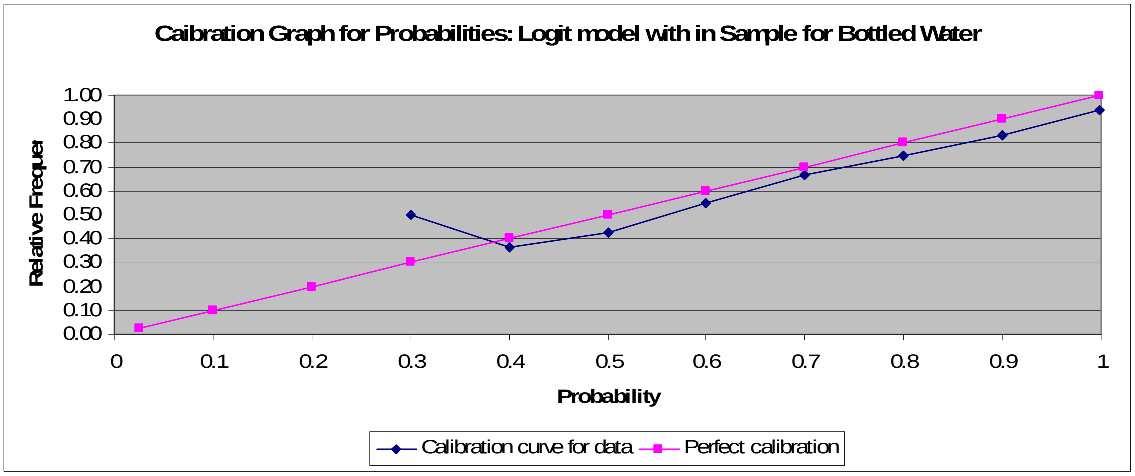

Figure 5.31: Calibration graph for probabilities: logit model within-sample for bottled water

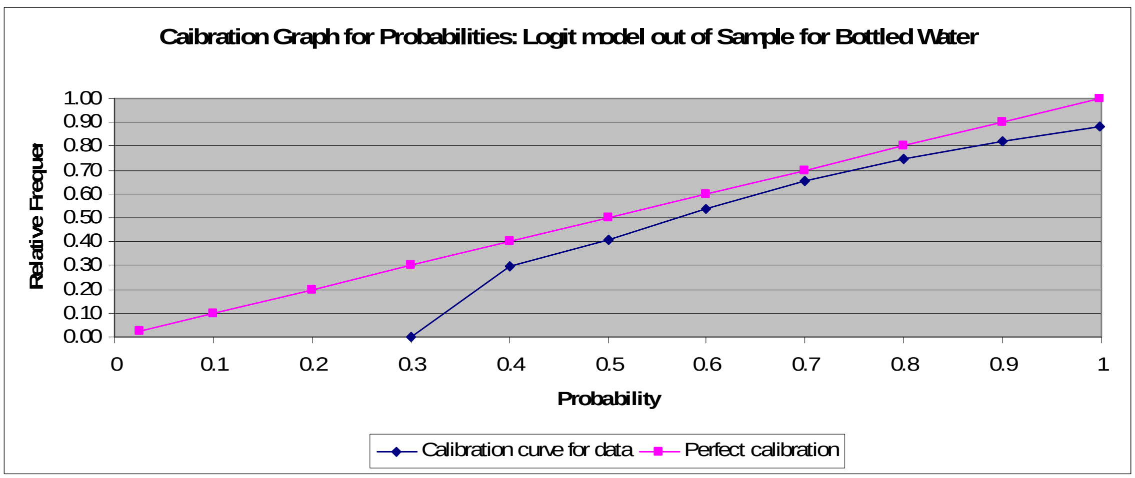

Figure 5.32: Calibration graph for probabilities: logit model out-of-sample for bottled water

Chi-squared test calculation is shown in Table 5.69 through 5.72. According to *chi-squared* test, we fail to reject the null hypothesis of well calibration. That is to say, forecast probabilities generated through probit and logit models for within-sample data are well calibrated.

However, according to the *chi-squared* statistic calculated for out-of-sample forecast probabilities, we reject the null hypothesis of well calibration. That is to say, probit and logit model generated forecast probabilities for out-of-sample data are not well calibrated. This result is evident when one look at the calibration graph generated for such probabilities. Calibration curve lies consistently below the 45-degree line indicating consistent over-confidence in forecast probabilities.

Coffee

Figures 5.33 through 5.36 show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to purchase coffee (both within-sample and out-of-sample forecast probabilities). Calibration graphs generated for within-sample forecast probabilities show mixed results indicating a slight under-confidence for probabilities below forecast probability 0.4 and a small over-confidence in forecast probabilities above 0.4 probability level.

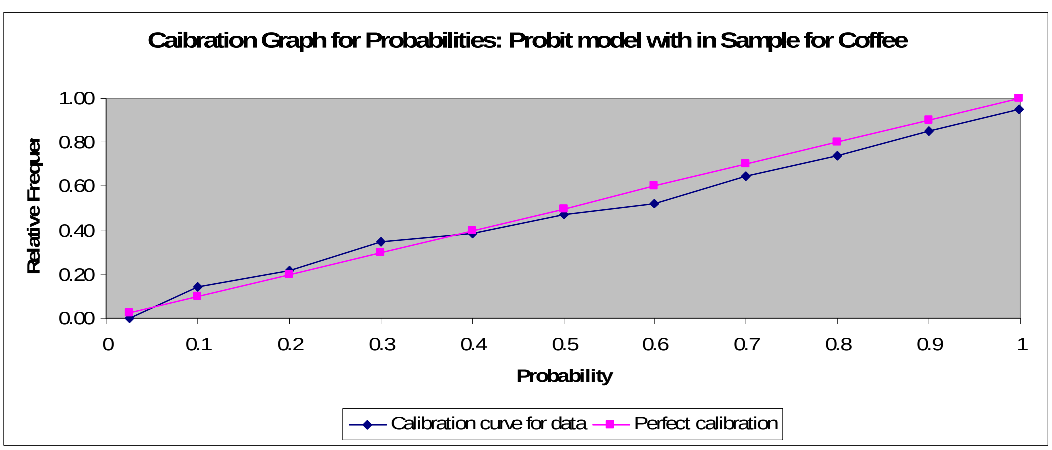

Figure 5.33: Calibration graph for probabilities: probit model within-sample for coffee

Table 5.69 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Bottled Water

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3	5	3	0.60	1.5	1.22	1.50
5	0.4	52	18	0.35	20.8	-0.61	0.38
6	0.5	156	66	0.42	78	-1.36	1.85
7	0.6	560	308	0.55	336	-1.53	2.33
8	0.7	783	525	0.67	548.1	-0.99	0.97
9	0.8	1413	1053	0.75	1130.4	-2.30	5.30
10	0.9	780	653	0.84	702	-1.85	3.42
11	0.999	71	67	0.94	70.929	-0.47	0.22
						Chi-squared	**15.97**

Table 5.70 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Bottled Water

Range J	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	27	7	0.26	10.8	-1.16	1.34
6	0.5	96	38	0.40	48	-1.44	2.08
7	0.6	394	210	0.53	236.4	-1.72	2.95
8	0.7	1036	677	0.65	725.2	-1.79	3.20
9	0.8	1535	1147	0.75	1228	-2.31	5.34
10	0.9	679	558	0.82	611.1	-2.15	4.61
11	0.999	52	44	0.85	51.948	-1.10	1.22
						Chi-squared	**20.75**

Table 5.71 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Bottled Water

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3	6	3	0.50	1.8	0.89	0.80
5	0.4	55	20	0.36	22	-0.43	0.18
6	0.5	161	69	0.43	80.5	-1.28	1.64
7	0.6	553	305	0.55	331.8	-1.47	2.16
8	0.7	763	509	0.67	534.1	-1.09	1.18
9	0.8	1414	1058	0.75	1131.2	-2.18	4.74
10	0.9	817	681	0.83	735.3	-2.00	4.01
11	0.999	51	48	0.94	50.949	-0.41	0.17
						Chi-squared	**14.89**

Table 5.72 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Bottled Water

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3	1	0	0.00	0.3	-0.55	0.30
5	0.4	27	8	0.30	10.8	-0.85	0.73
6	0.5	106	43	0.41	53	-1.37	1.89
7	0.6	391	210	0.54	234.6	-1.61	2.58
8	0.7	1013	661	0.65	709.1	-1.81	3.26
9	0.8	1533	1144	0.75	1226.4	-2.35	5.54
10	0.9	706	578	0.82	635.4	-2.28	5.19
11	0.999	42	37	0.88	41.958	-0.77	0.59
						Chi-squared	**20.06**

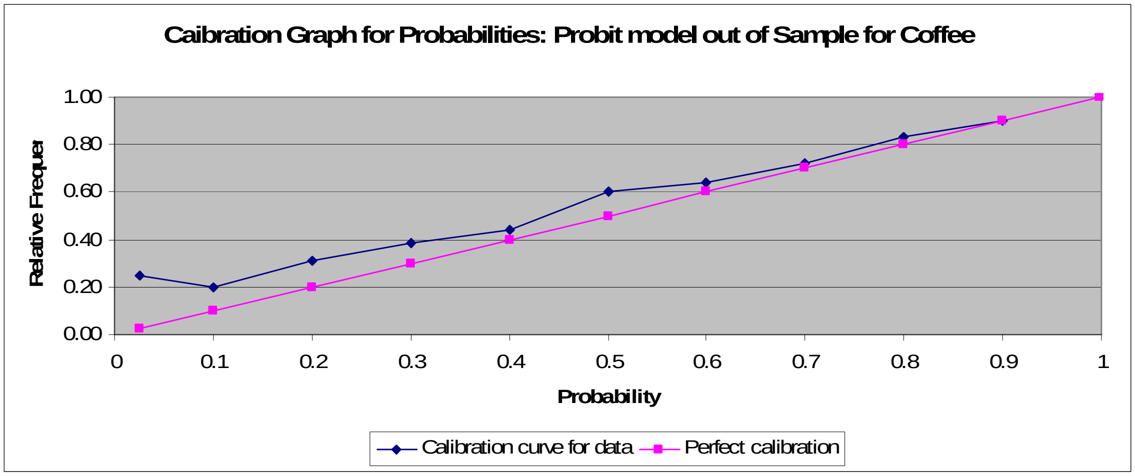

Figure 5.34: Calibration graph for probabilities: probit model out-of-sample for coffee

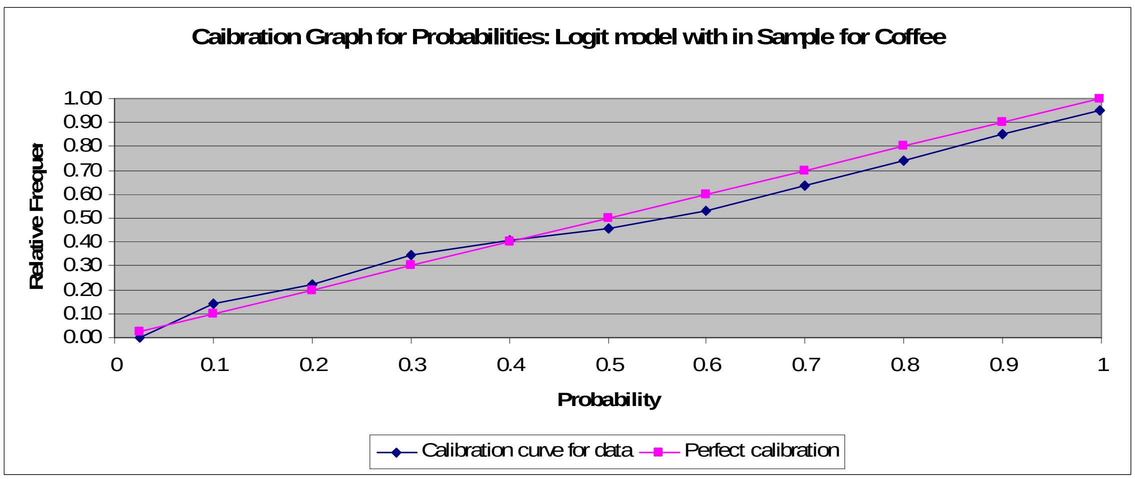

Figure 5.35: Calibration graph for probabilities: logit model within-sample for coffee

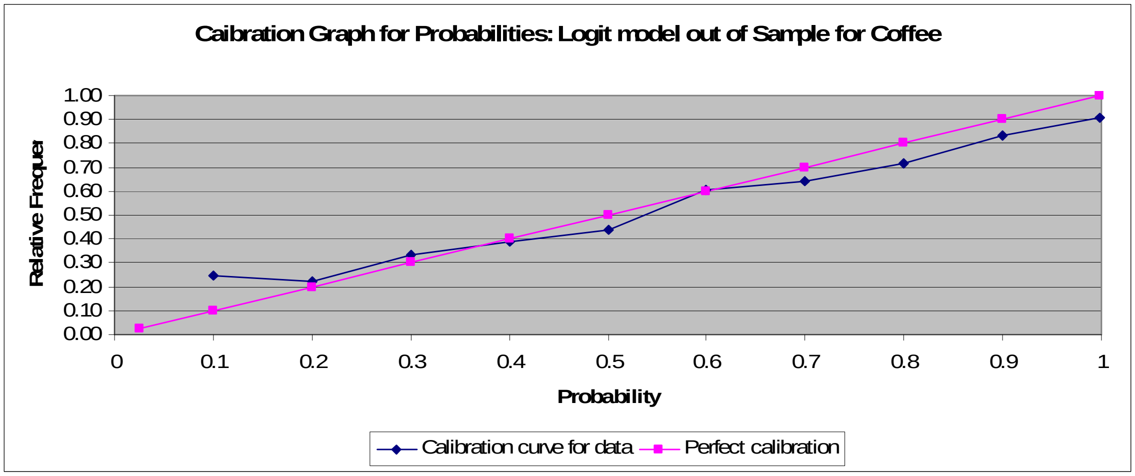

Figure 5.36: Calibration graph for probabilities: logit model out-of-sample for coffee

Aforementioned result is supported by the *chi-squared* test statistic shown in Tables 5.73 through 5.76. According to that, probit and logit model generated within-sample forecast probabilities are well calibrated (calculated *chi-squared* test statistic is smaller than the *chi-squared* table value at degrees of freedom 10 and 95% significance level, thereby failing to reject the null hypothesis of well calibration).

Calibration curves drawn for out-of-sample forecast probabilities show consistent under-confidence and lies above the 45-degree well calibration line for all probabilities. According to the *chi-squared* statistic, these probabilities are not well calibrated (see Tables 5.74 and 5.76).

Table 5.73 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Coffee

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	14	2	0.14	1.4	0.51	0.26
3	0.2	37	8	0.22	7.4	0.22	0.05
4	0.3	60	21	0.35	18	0.71	0.50
5	0.4	115	44	0.38	46	-0.29	0.09
6	0.5	179	84	0.47	89.5	-0.58	0.34
7	0.6	341	177	0.52	204.6	-1.93	3.72
8	0.7	564	365	0.65	394.8	-1.50	2.25
9	0.8	799	591	0.74	639.2	-1.91	3.63
10	0.9	1047	891	0.85	942.3	-1.67	2.79
11	0.999	663	629	0.95	662.337	-1.30	1.68
						Chi-squared	**15.33**

Table 5.74 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Coffee

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1	4	1	0.25	0.4	0.95	0.90
3	0.2	30	6	0.20	6	0.00	0.00
4	0.3	81	25	0.31	24.3	0.14	0.02
5	0.4	129	50	0.39	51.6	-0.22	0.05
6	0.5	219	97	0.44	109.5	-1.19	1.43
7	0.6	331	199	0.60	198.6	0.03	0.00
8	0.7	554	355	0.64	387.8	-1.67	2.77
9	0.8	780	564	0.72	624	-2.40	5.77
10	0.9	1057	877	0.83	951.3	-2.41	5.80
11	0.999	634	572	0.90	633.366	-2.44	5.95
						Chi-squared	**22.69**

Table 5.75 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Coffee

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025	1	0	0.00	0.025	-0.16	0.03
2	0.1	14	2	0.14	1.4	0.51	0.26
3	0.2	41	9	0.22	8.2	0.28	0.08
4	0.3	70	24	0.34	21	0.65	0.43
5	0.4	113	46	0.41	45.2	0.12	0.01
6	0.5	179	82	0.46	89.5	-0.79	0.63
7	0.6	322	170	0.53	193.2	-1.67	2.79
8	0.7	546	348	0.64	382.2	-1.75	3.06
9	0.8	804	595	0.74	643.2	-1.90	3.61
10	0.9	1110	947	0.85	999	-1.65	2.71
11	0.999	620	589	0.95	619.38	-1.22	1.49
						Chi-squared	**15.09**

Table 5.76 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Coffee

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1	4	1	0.25	0.4	0.95	0.90
3	0.2	40	9	0.23	8	0.35	0.13
4	0.3	81	27	0.33	24.3	0.55	0.30
5	0.4	132	51	0.39	52.8	-0.25	0.06
6	0.5	221	97	0.44	110.5	-1.28	1.65
7	0.6	313	190	0.61	187.8	0.16	0.03
8	0.7	527	338	0.64	368.9	-1.61	2.59
9	0.8	774	555	0.72	619.2	-2.58	6.66
10	0.9	1148	954	0.83	1033.2	-2.46	6.07
11	0.999	579	524	0.91	578.421	-2.26	5.12
						Chi-squared	**23.50**

Tea

Figures 5.37 through 5.38 show calibration graphs drawn for forecast probabilities generated through probit and logit models for the decision to purchase tea (both within-sample and out-of-sample forecast probabilities). Within-sample generated forecast probabilities show consistent over-confidence while out-of-sample generated forecast probabilities show some under-confidence for forecast probabilities below 0.50 and over-confidence for forecast probabilities above 0.50.

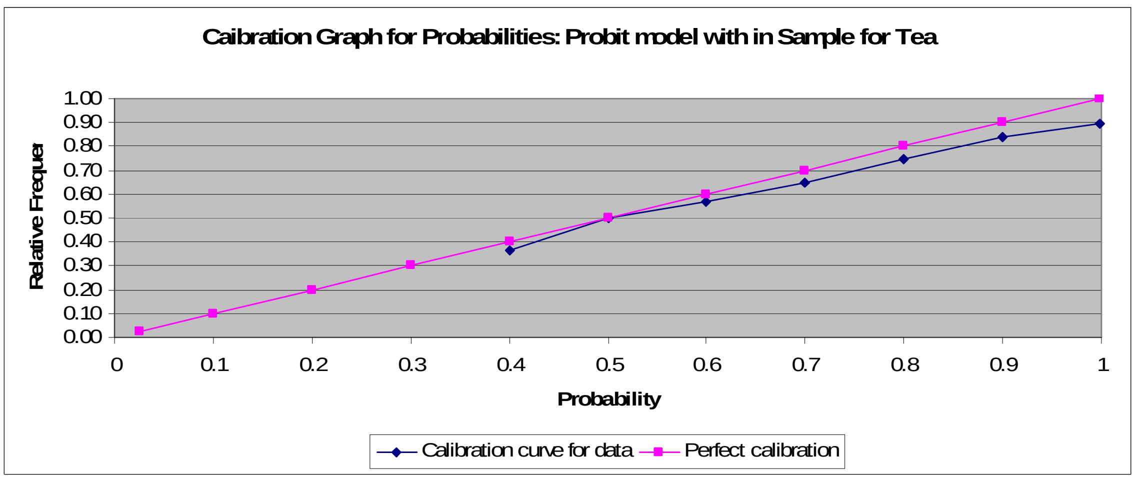

Figure 5.37: Calibration graph for probabilities: probit model within-sample for tea

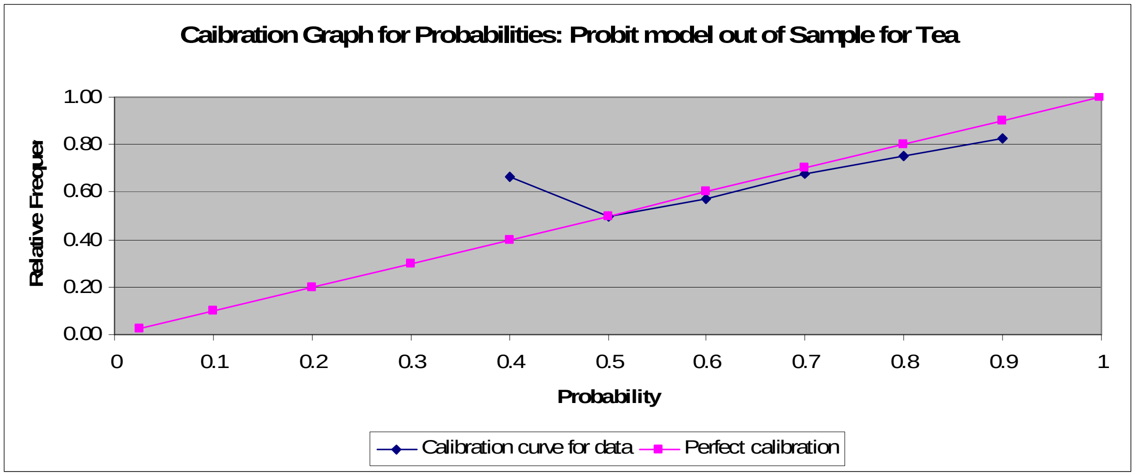

Figure 5.38: Calibration graph for probabilities: logit model out-of-sample for tea

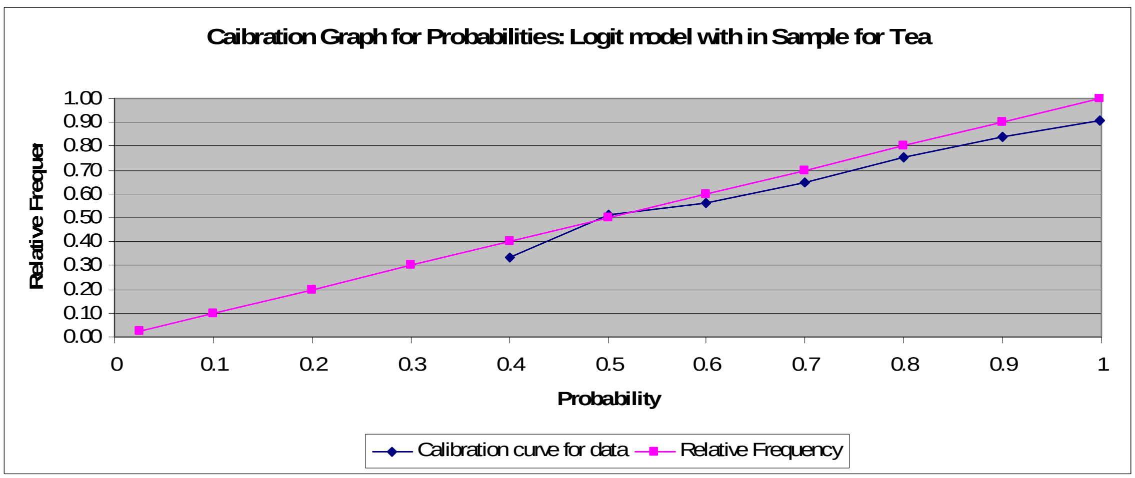

Figure 5.39: Calibration graph for probabilities: logit model within-sample for tea

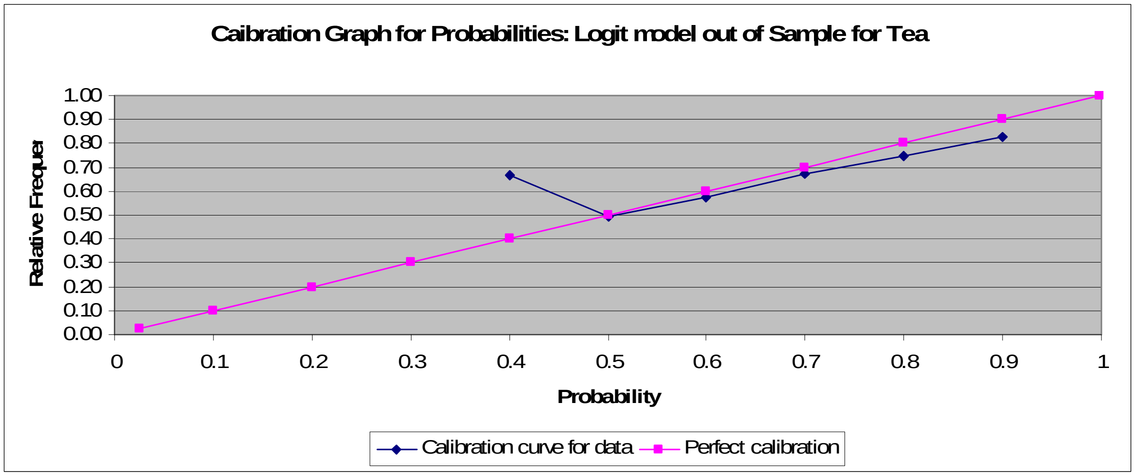

Figure 5.40: Calibration graph for probabilities: logit model out-of-sample for tea

Tables 5.77 through 5.80 show the calculated *chi-squared* statistics taking forecast probabilities and realized relative frequencies. According to them, probit and logit model generated forecast probabilities are well calibrated for within-sample and out-of-sample data for tea.

Table 5.77 Chi-squared Test Statistic for Calibration: Probit Model Within-Sample Probabilities for Tea

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	11	4	0.36	4.4	-0.19	0.04
6	0.5	128	64	0.50	64	0.00	0.00
7	0.6	342	195	0.57	205.2	-0.71	0.51
8	0.7	959	621	0.65	671.3	-1.94	3.77
9	0.8	1460	1095	0.75	1168	-2.14	4.56
10	0.9	891	748	0.84	801.9	-1.90	3.62
11	0.999	29	26	0.90	28.971	-0.55	0.30
						Chi-squared	**12.80**

Table 5.78 Chi-squared Test Statistic for Calibration: Probit Model Out-of-Sample Probabilities for Tea

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	3	2	0.67	1.2	0.73	0.53
6	0.5	121	60	0.50	60.5	-0.06	0.00
7	0.6	255	146	0.57	153	-0.57	0.32
8	0.7	991	670	0.68	693.7	-0.90	0.81
9	0.8	1497	1121	0.75	1197.6	-2.21	4.90
10	0.9	952	786	0.83	856.8	-2.42	5.85
11	0.999						
						Chi-squared	**12.42**

Table 5.79 Chi-squared Test Statistic for Calibration: Logit Model Within-Sample Probabilities for Tea

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	15	5	0.33	6	-0.41	0.17
6	0.5	127	65	0.51	63.5	0.19	0.04
7	0.6	339	191	0.56	203.4	-0.87	0.76
8	0.7	940	609	0.65	658	-1.91	3.65
9	0.8	1477	1108	0.75	1181.6	-2.14	4.58
10	0.9	901	756	0.84	810.9	-1.93	3.72
11	0.999	21	19	0.90	20.979	-0.43	0.19
						Chi-squared	**13.09**

Table 5.80 Chi-squared Test Statistic for Calibration: Logit Model Out-of-Sample Probabilities for Tea

Range j	Mid Point Pi	Frequency n	Purchase d=1	Relative Frequencies Rho=d/n	Expected e=n*Pi	Test statistic z=(d-e)/e*0.5	z-squared
1	0.025						
2	0.1						
3	0.2						
4	0.3						
5	0.4	3	2	0.67	1.2	0.73	0.53
6	0.5	122	60	0.49	61	-0.13	0.02
7	0.6	257	148	0.58	154.2	-0.50	0.25
8	0.7	969	654	0.67	678.3	-0.93	0.87
9	0.8	1522	1138	0.75	1217.6	-2.28	5.20
10	0.9	946	783	0.83	851.4	-2.34	5.50
11	0.999						
						Chi-squared	**12.37**

Probability Resolution and Resolution Graphs (Covariance Graphs)

In the following sections we discuss the theoretical development and empirical analysis with respect to resolution (sorting) of probabilities generated through probit and logit models in the decision to purchase non-alcoholic beverages by U.S households in calendar year 2003. A graphical and a regression analysis are performed.

Theoretical Development

Resolution is a metric of goodness of sorting power of a forecasting model. In our work, it is the model's ability to sort probabilities into two classes, such as probabilities associated with events that occurred versus probabilities associated with events that did not occur. Say for example our model is designed to give out probabilities associated with an event that occurs (say probability of purchase of a given non-alcoholic beverage). We would like to see high probabilities associated with the events that occurred (in our study high probabilities should be associated with all those events where a purchase of a given non-alcoholic beverage occurred) and low probabilities associated with all those events that did not occur (in our study low probabilities must be associated with all those events where a purchase of a given non-alcoholic beverage did not occur). Furthermore, for a perfect sorting model, we would like to see probability 1 associated with all those events that occur and probability 0 associated with all those events that do not occur. In other words, according to Yates (1982), events that are assigned probabilities close to 1 occur frequently, whereas those assigned probabilities near 0 occur rarely.

This information can be used to plot a *resolution graph (covariance graph)* where probabilities are plotted in *y*-axis and outcome index is on *x*-axis (outcome index is a zero (0) one (1) type index where zero is associated with an event that did not occur and one is associated with an event that did occur).

Sanders (1963) explained the concept of *resolution* in his partition of Brier Score into *validity* (we call it calibration now) and *sharpness* (we call it *resolution* or *sorting* power now). He further stated that *"forecaster can minimize the sharpness contribution to his overall score only by recognizing nearly certain instances as often as possible"* (Sanders, 1963). That is to say, in issuing subjective probabilities, if a forecaster issues probability 1 for all events that occur and probability 0 for all those events that do not occur, his sharpness is perfect or he issues perfectly sorted probabilities. The same can be true with a model that issues objective probability forecasts such as qualitative choice models we use in our study. Such a model (or a forecaster) not only issues well sorted probabilities, but also they are well calibrated.

However, it is imperative to understand that well calibration does not necessarily mean good resolution or sorting power. Dawid (1986) explains this as follows. He uses an example from weather forecasting (these are subjective probability forecasts). Suppose that we observe an alternating weather pattern as dry, wet, dry, wet and so on. Let two forecasters offer probabilities for getting wet weather. Forecaster 1 issues probability 0.5 for all cases and forecaster 2 issues probabilities as 0,1,0,1,……The question is, who is well calibrated and who is well resolved (or does a better sorting of probabilities). Both forecasters are well calibrated. However, forecaster 2 does a perfect forecast. In other words, when he forecasts zero probability for wet weather, the observed event is a dry day and when he forecasts probability one for wet weather, the observed event is a wet day. Therefore, forecaster 2's probabilities are well calibrated and well resolved. However, forecaster 1's probabilities are not well sorted or resolved, even though they were well calibrated. Lesson we learn from above exercise is that, calibration measures how good a forecaster or a model at corresponding issued probabilities with realized outcome after the fact and it does not address the issue of sorting aspect at all. Dawid (1986) further states that it is unreasonable in general to expect for perfect sorting, because, perfect sorting is equivalent to an absolutely correct or an absolutely incorrect categorical forecasting.

Murphy (1972a and 1972b) partitioned the Brier Score into reliability (calibration) and resolution (sorting power); scalar partition in the 1972a paper and a vector partition in the 1972b paper. He used a sample of weather forecasts to compare and contrast scalar and vector partitions of the probability score (Brier score). He neither did develop a resolution graph nor a resolution regression. Murphy (1973) extended his 1972 work and partitioned the Brier score into a new set of 3 parts, thus, a measure of uncertainty, a measure of reliability and a measure of resolution. Please see the equation 2.30 for such a partition. According to equation 2.30, the resolution component is different from his 1972 work; however, it essentially explained the sorting power of the model (the probability score measure or the Brier score). However, again, he did not develop a resolution graph or a resolution regression to explain the concept further. In our study we do not develop Sanders (1963) or Murphy (1972a or 1972b) type decompositions to understand probability resolution, rather we use a different approach. Our method first will plot a resolution graph and then regress forecast probabilities on an outcome index to see the statistical validity of the resolution graph.

Data Analysis and Discussion

In our resolution regression (this is also called covariance regression in the literature), we would like to see an intercept terms that is statistically not different from zero and a slope coefficient that is statistically not different from one. This finding will correspond with perfect resolution (or sorting of probabilities). Any deviation of slope from one and intercept from zero would be characterized by not-so-good resolved probabilities. We also plot the resolution graph where forecast probabilities are plotted on *y*-axis and outcome index on *x*-axis. In explaining the goodness of sorting of probabilities, we concentrate on the mean values of those forecast probabilities associated with outcome index zero and one. Dispersion (variance) of above forecast probabilities are taken up in the next section (section 5.5).

Beverage-by-beverage discussion on resolution of forecast probabilities is as follows.

<u>*Isotonics*</u>

Figures 5.41 through 5.44 show resolution graphs (covariance graphs) plotted taking forecast probabilities and outcome indexes for within-sample and out-of-sample probability forecasts. These forecasts are generated for the decision to purchase isotonics modeled through probit and logit models. According to them, outcome index zero is modestly associated with low probabilities, even though it shows a large dispersion. The

mean forecast probability associated with zero outcome index is about 0.20, which is low enough to say that we observe a good sorting behavior for forecast probabilities that are associated with zero outcome index. However, we would like to observe large probability values associated with outcome index 1, which we do not observe in this analysis. The mean of the forecast probability that is associated with outcome index 1 is about 0.29. It should have been high (close to one) if we were to observe good probability sorting behavior. Overall, resolution graph for isotonics is upward sloping, however relatively very flat compared the 45 degree perfect sorting line.

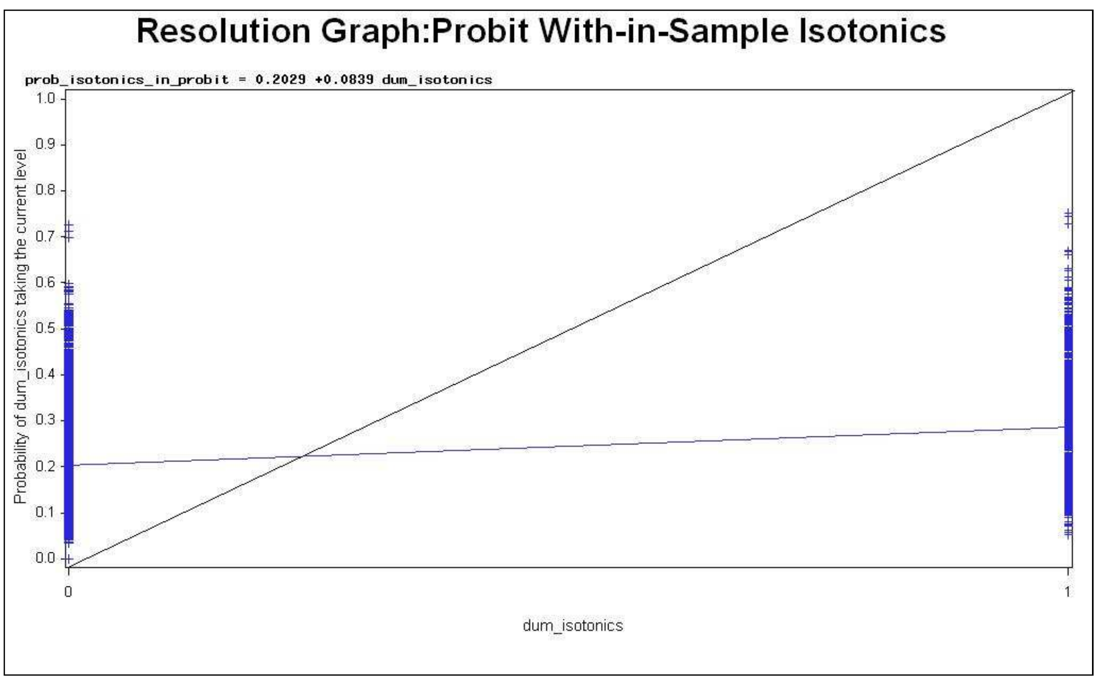

Figure 5.41: Resolution graph probabilities and outcome index: probit model within-sample for isotonics

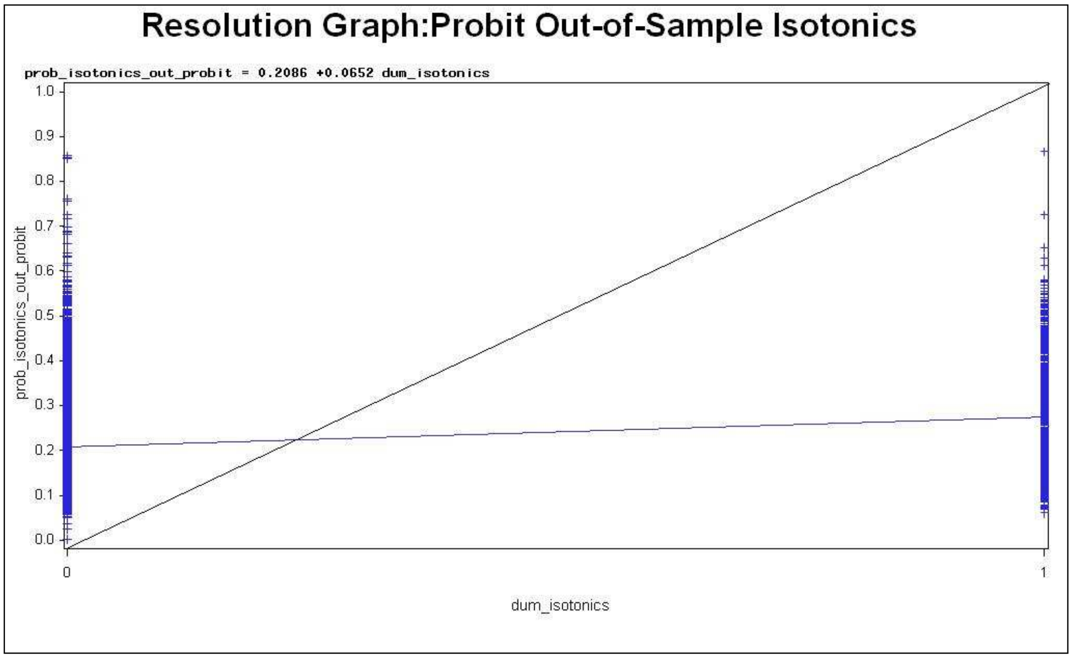

Figure 5.42: Resolution graph probabilities and outcome index: probit model out-of-sample for isotonics

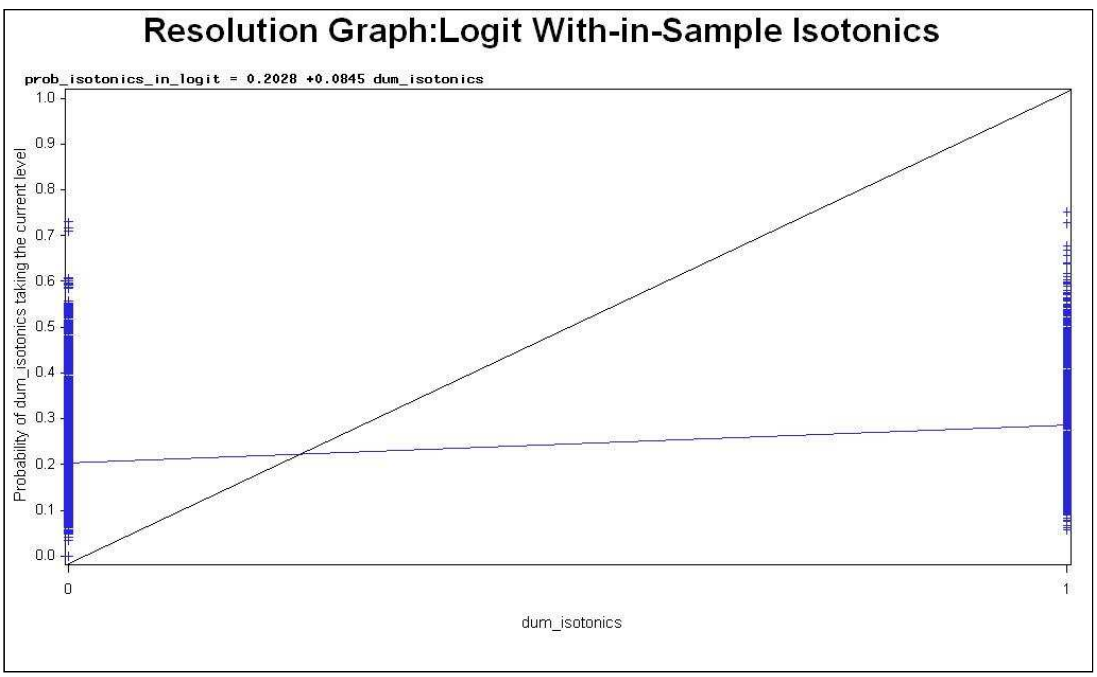

Figure 5.43: Resolution graph probabilities and outcome index: logit model within-sample for isotonics

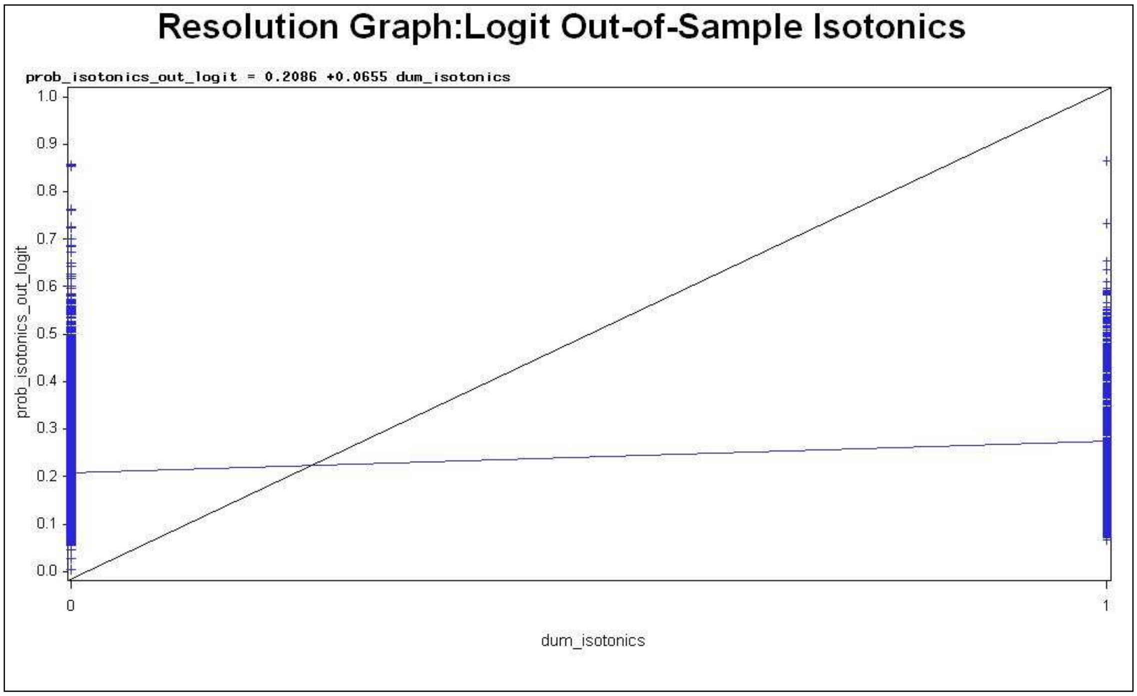

Figure 5.44: Resolution graph probabilities and outcome index: logit model out-of-sample for isotonics

Resolution regression (covariance regression) results, as depicted in the Appendix 4, confirm above graphical outcome. Intercept coefficient is 0.20, representing the mean of forecast probabilities associated with outcome index zero and slope coefficient is 0.08 for within-sample regression and 0.06 for out-of-sample regression. Both coefficients are statistically significant at 5% level rejecting null hypotheses of perfect resolution. For perfect forecast probability resolution we must observe intercept coefficient significantly not different from zero and slope parameter significantly not different from one.

Regular Soft Drinks

Figures 5.45 through 5.48 show resolution graphs plotted taking forecast probabilities and outcome indexes for within-sample and out-of-sample probability forecasts for the decision to purchase regular soft drinks by U.S households in calendar year 2003. According to above figures, we observe high probabilities associated with outcome indexes both zero and one. It should be noted that we expected to have high probabilities associated with outcome index one (event where a purchase of regular soft drink occurred) and to support that contention we observe a mean probability value of 0.91. This observation is a good thing where the model sorts forecast probabilities associated with events that have outcome index one more correctly. However, model does not sort forecast probabilities associated with outcome index zero well. Model offers a high mean probability (about 0.84) for events associated with outcome index zero, even though we expected to observe a low mean probability value. Therefore, we can state that the model does not sort probabilities associated with outcome index zero well.

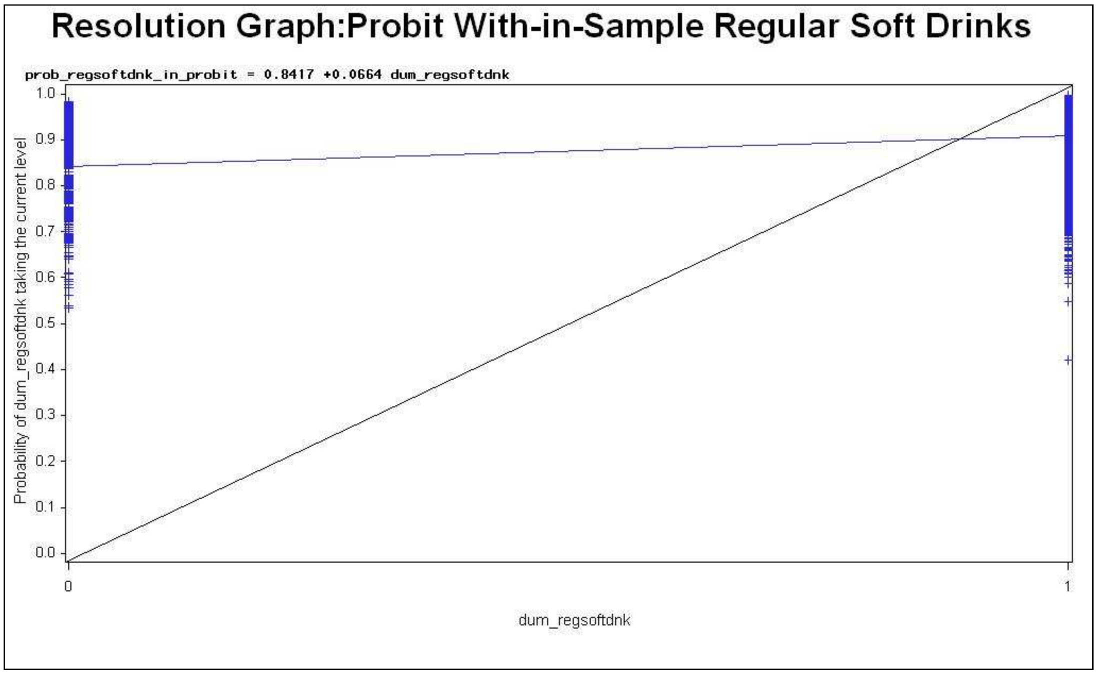

Figure 5.45: Resolution graph probabilities and outcome index: probit model within-sample for regular soft drinks

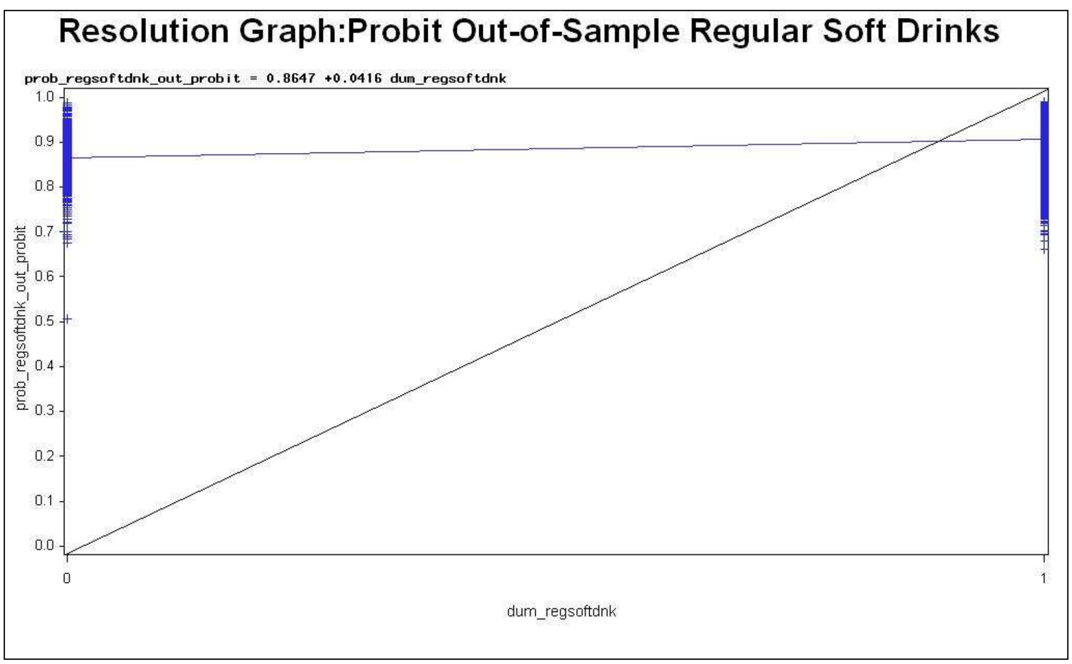

Figure 5.46: Resolution graph probabilities and outcome index: probit model out-of-sample for regular soft drinks

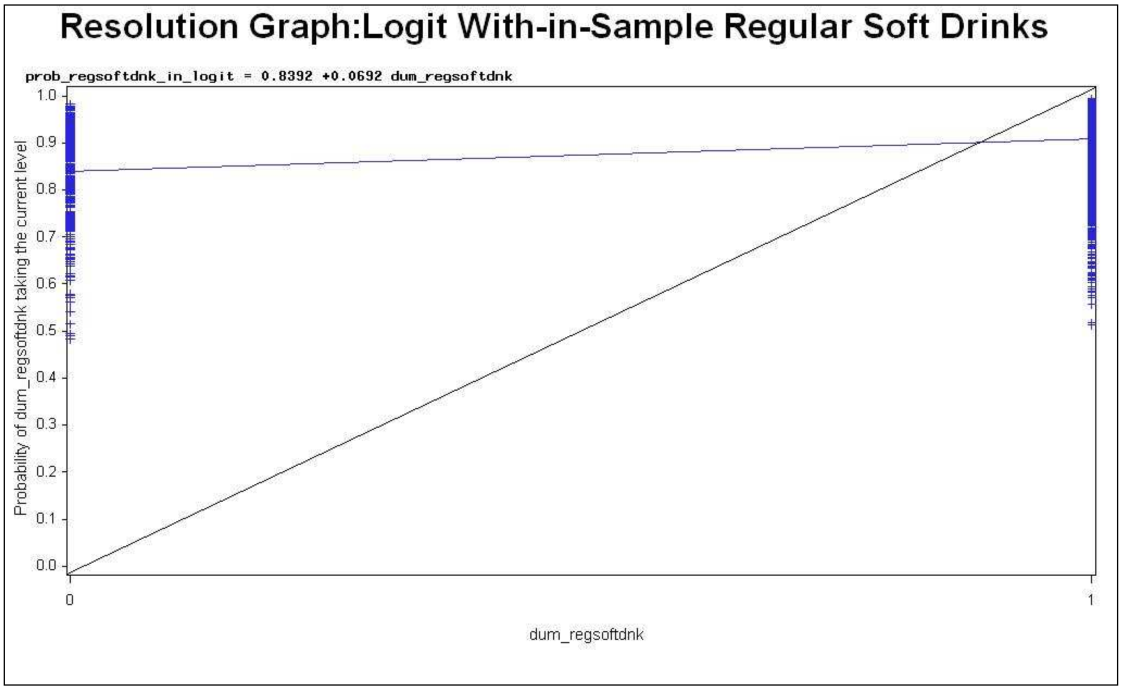

Figure 5.47: Resolution graph probabilities and outcome index: logit model within-sample for regular soft drinks

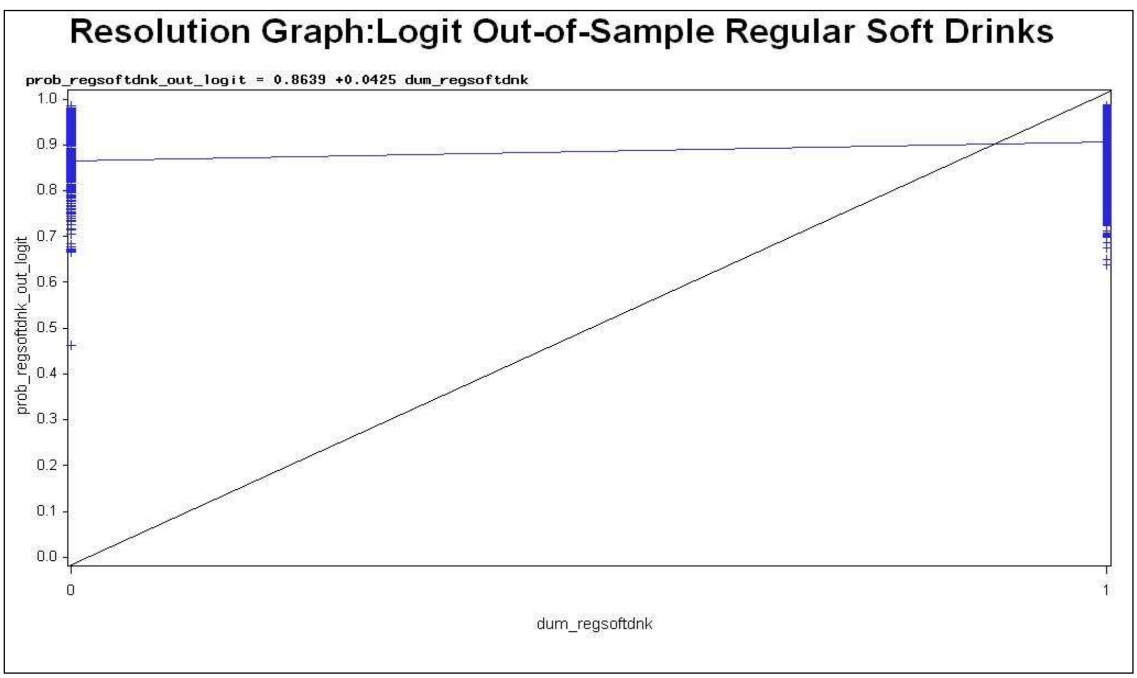

Figure 5.48: Resolution graph probabilities and outcome index: logit model out-of-sample for regular soft drinks

Aforementioned graphical result is supported by the covariance regressions (see in the Appendix 4). Intercept coefficients of covariance regressions show the mean probability value associated with events with outcome index zero and it is statistically significant at 5% level. This would reject the null hypothesis of perfect sorting of probabilities. Also, the calculated slope coefficients are significantly different from one for both within-sample and out-of-sample regressions indicating poor sorting of probabilities. Nevertheless, models do have some sorting power and it is indicative of upward sloping resolution graph, even though it is relatively flat compared to 45-degree perfect sorting line.

Diet Soft Drinks

Figures 5.49 through 5.52 show resolution graphs plotted for within-sample and out-of-sample probability forecasts for the decision to purchase diet soft drinks. We observed high probabilities associated with outcome index 1 and on average it was 0.68 for within-sample probabilities and 0.67 for out-of-sample probabilities. We also observed high probabilities associated with outcome index 0, averaging 0.61. However, we expected to have low probabilities associated with outcome index zero, indicating better probability sorting power.

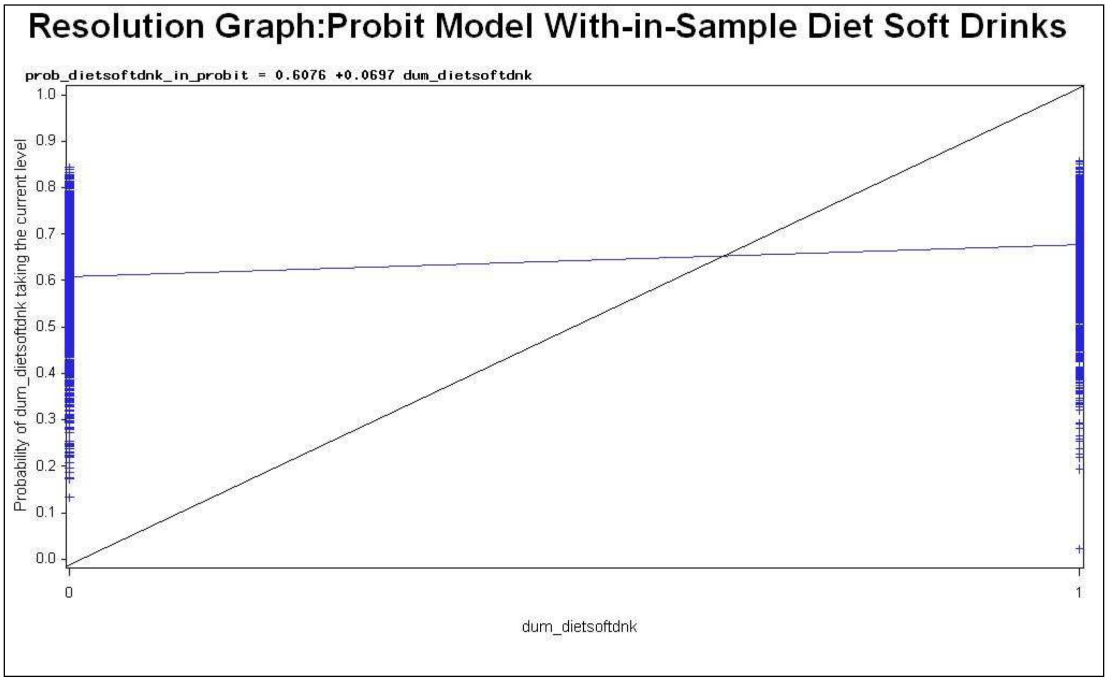

Figure 5.49: Resolution graph probabilities and outcome index: probit model within-sample for diet soft drinks

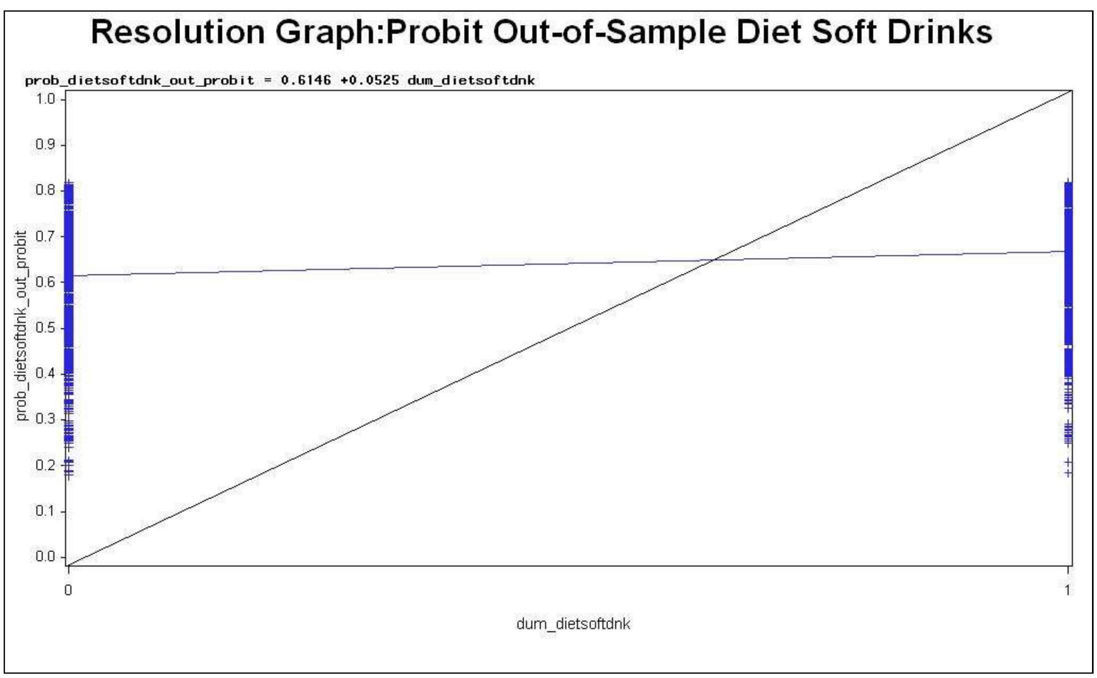

Figure 5.50: Resolution graph probabilities and outcome index: probit model out-of-sample for diet soft drinks

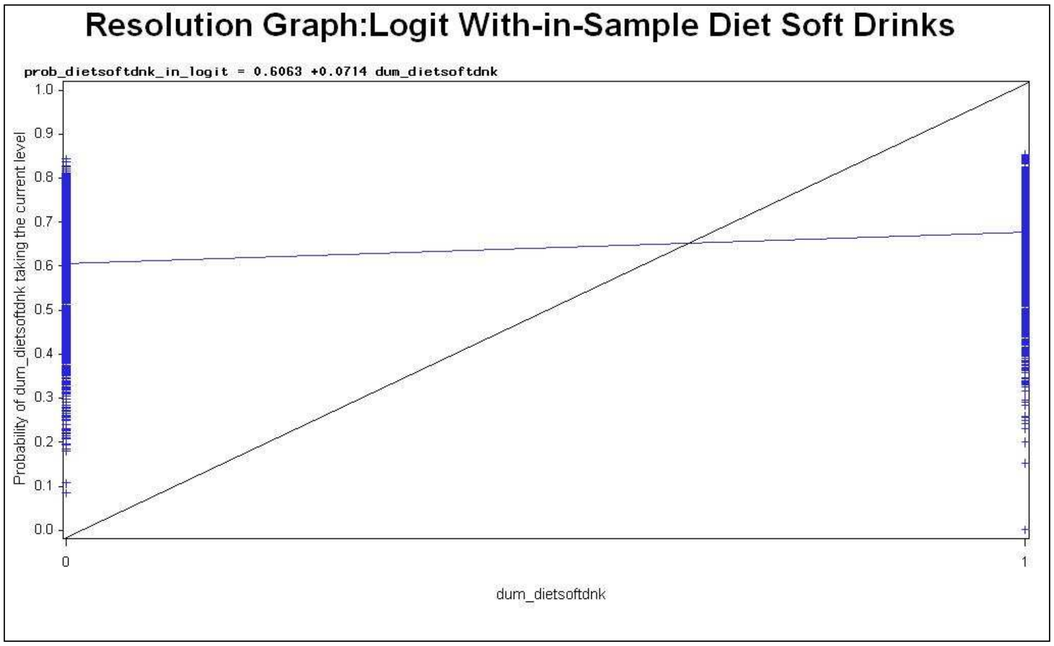

Figure 5.51: Resolution graph probabilities and outcome index: logit model within-sample for diet soft drinks

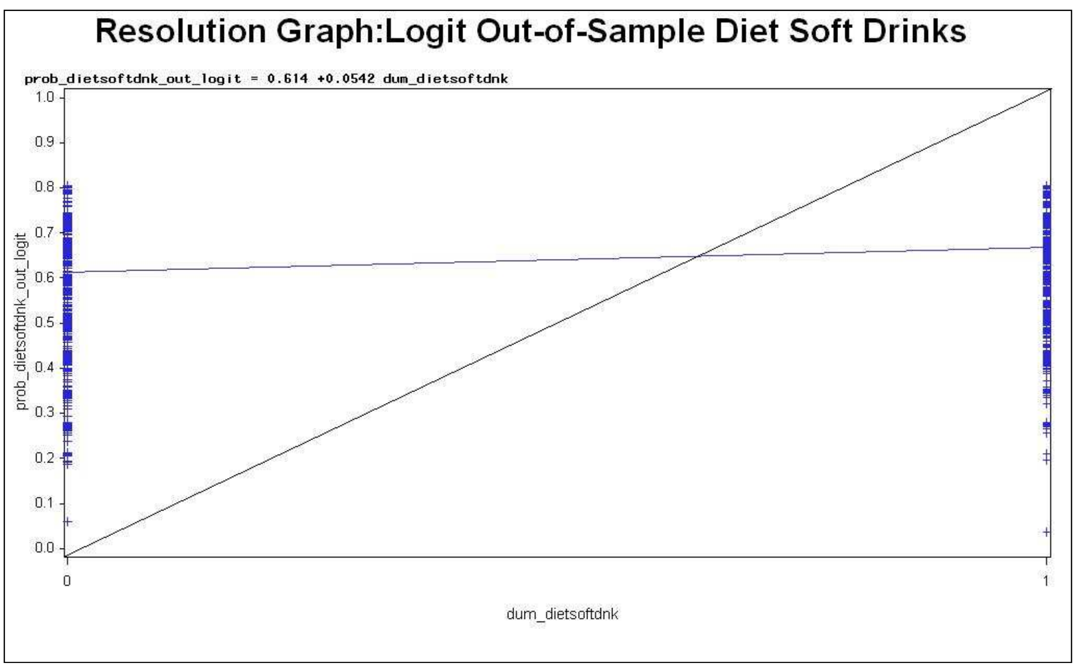

Figure 5.52: Resolution graph probabilities and outcome index: logit model out-of-sample for diet soft drinks

Aforementioned result also was seen through resolution regressions. Regression results from covariance regressions for forecast probabilities generated for the decision to purchase diet soft drinks are shown in the Appendix 4. The calculated intercept coefficient is 0.60 and 0.61 for within-sample and out-of-sample probabilities respectively. It is the mean of the forecast probabilities associated with outcome index zero. Intercept coefficients are statistically different from zero at 5% level, indicating poor sorting of probabilities. The slope coefficient is about 0.06 and significantly different from one, also indicating poor sorting of probabilities. The resolution graph is however upward sloping, even through very flat compared to the 45-degree perfect sorting line.

High-Fat Milk

Figures 5.53 through 5.56 show resolution graphs plotted taking forecast probabilities and outcome indexes for within-sample and out-of-sample probability forecasts for high-fat milk. According to them, we observe high probabilities associated with outcome indexes both zero and one. High probabilities associated with outcome index one is what we expected to have and the mean probability for those probabilities associated with outcome index 1 is 0.83 and 0.82 for within-sample and out-of-sample forecasts respectively. However, we expected to have low probabilities associated with zero outcome indexes, which we did not observe. Mean probability associated with zero outcome index is about 0.77. That is to say, the model did not sort the probabilities associated with zero outcome index well, even though it did a better job sorting probabilities associated with outcome index one.

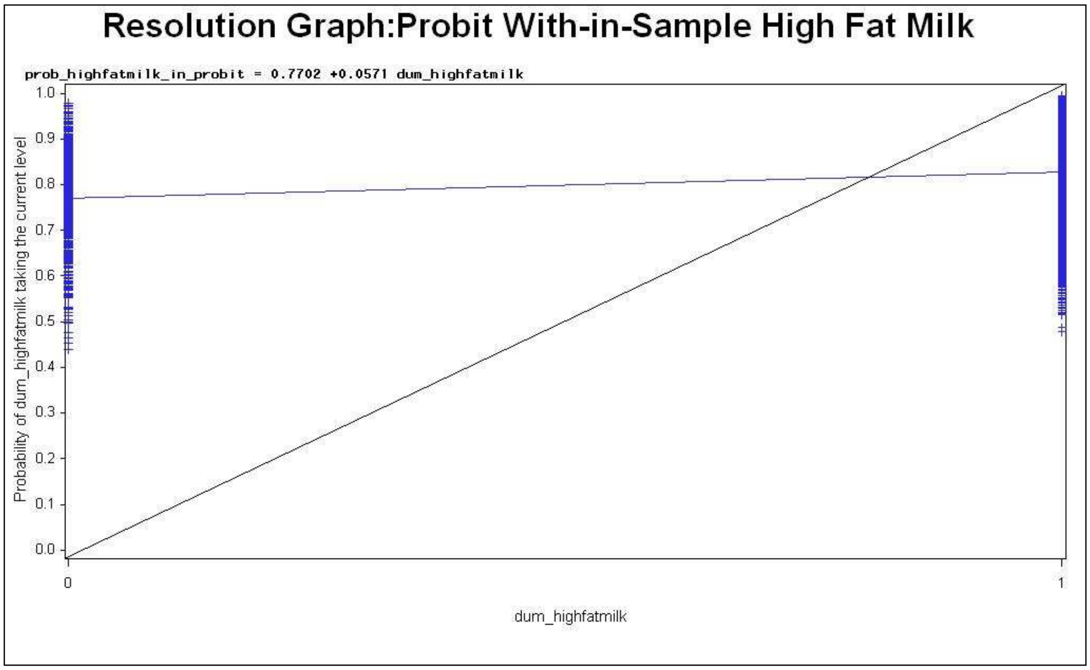

Figure 5.53: Resolution graph probabilities and outcome index: probit model within-sample for high-fat milk

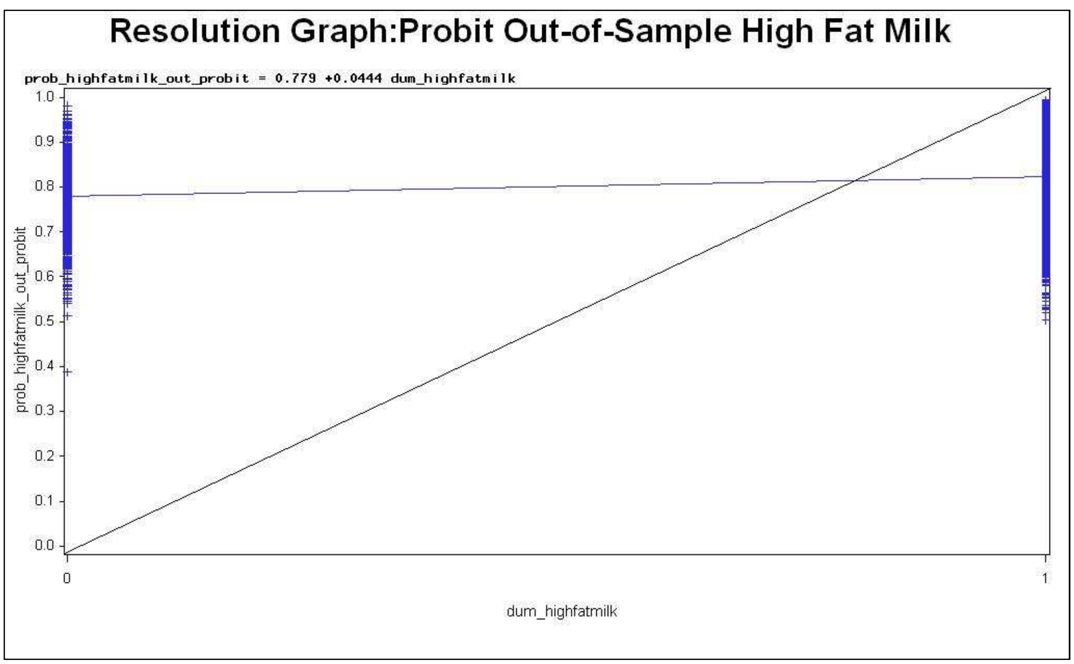

Figure 5.54: Resolution graph probabilities and outcome index: probit model out-of-sample for high-fat milk

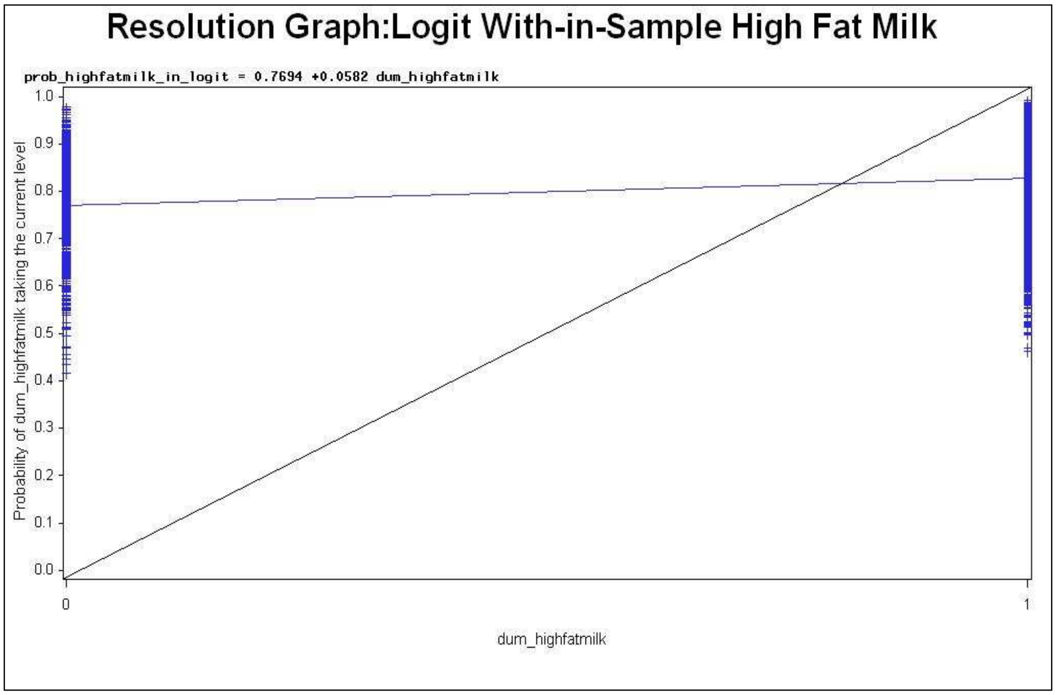

Figure 5.55: Resolution graph probabilities and outcome index: logit model within-sample for high-fat milk

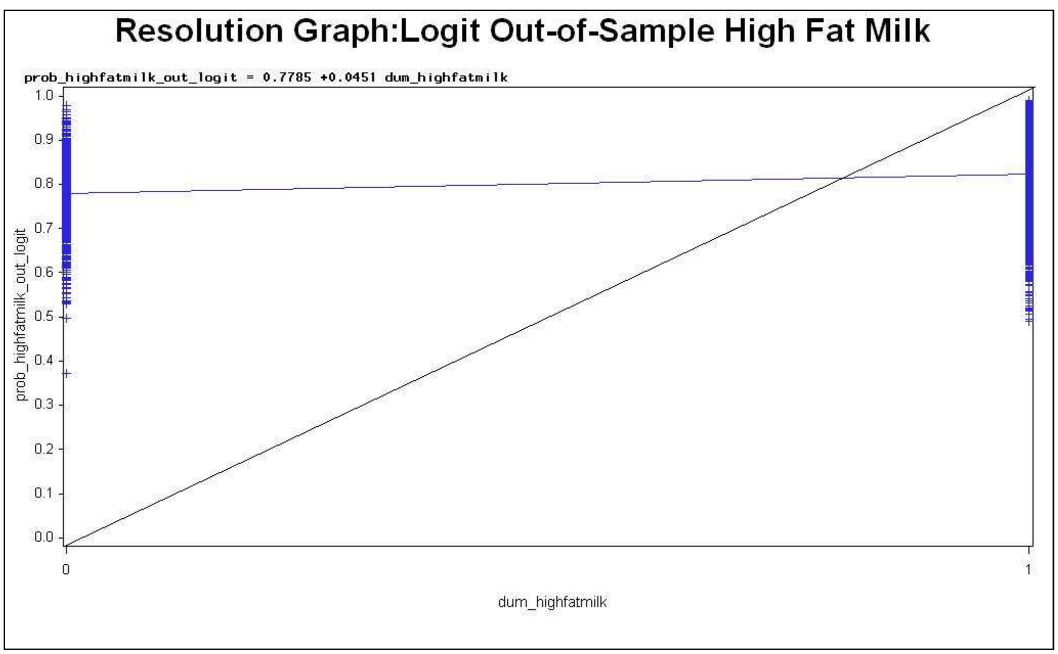

Figure 5.56: Resolution Graph Probabilities and Outcome Index: Logit Model Out-of-Sample for High-Fat Milk

Results from graphical analysis are supported by covariance regressions shown in the Appendix 4. According to them, intercept coefficients are statistically different from zero and slope parameters are statistically different from 1, both results indicating sub-optimal sorting power of the models (both within-sample and out-of-sample). Nevertheless, resolution graph is upward sloping, even though is relatively flat, indicating some degree of sorting power of the models.

Low-Fat Milk

Figures 5.57 through 5.60 show resolution graphs plotted for within-sample and out-of-sample probability forecasts for the decision to purchase low-fat milk. According to them the mean forecast probability associated with outcome index 1 is 0.63 for within-sample and out-of-sample probabilities, indicating acceptable level of probability sorting. However, we also find a high mean probability level (0.57) associated with zero outcome indexes as well. Latter result is not very supportive of good sorting behavior of models, as we expect to have low probabilities (mostly close to zero) to associate with zero outcome index.

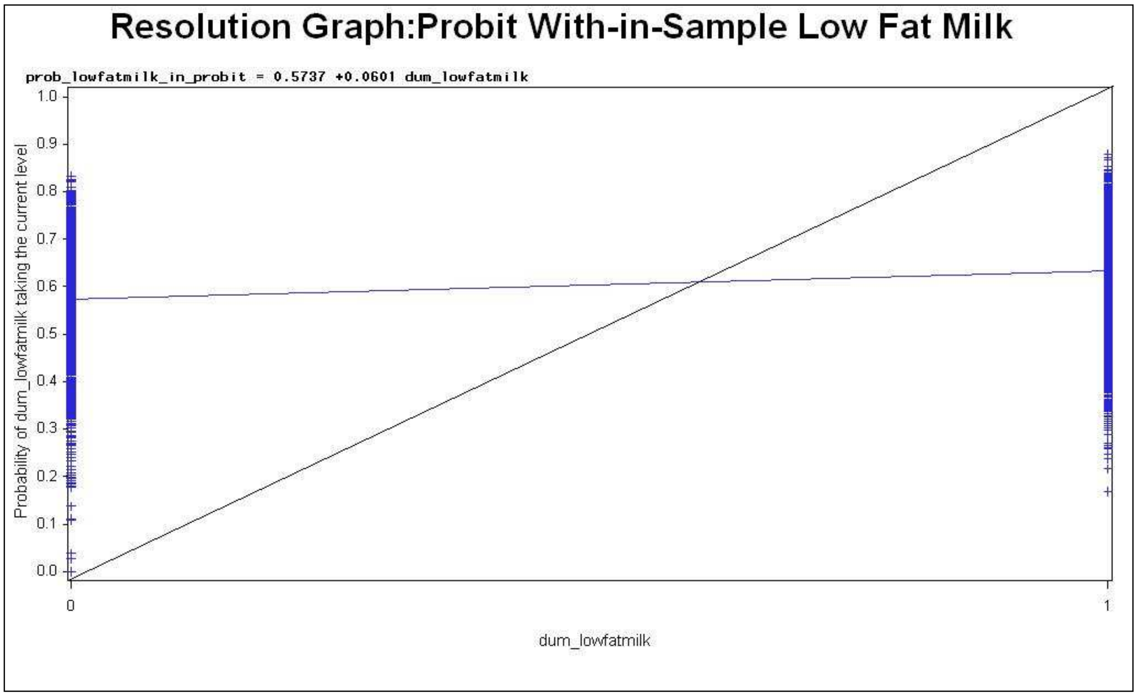

Figure 5.57: Resolution graph probabilities and outcome index: probit model within-sample for low-fat milk

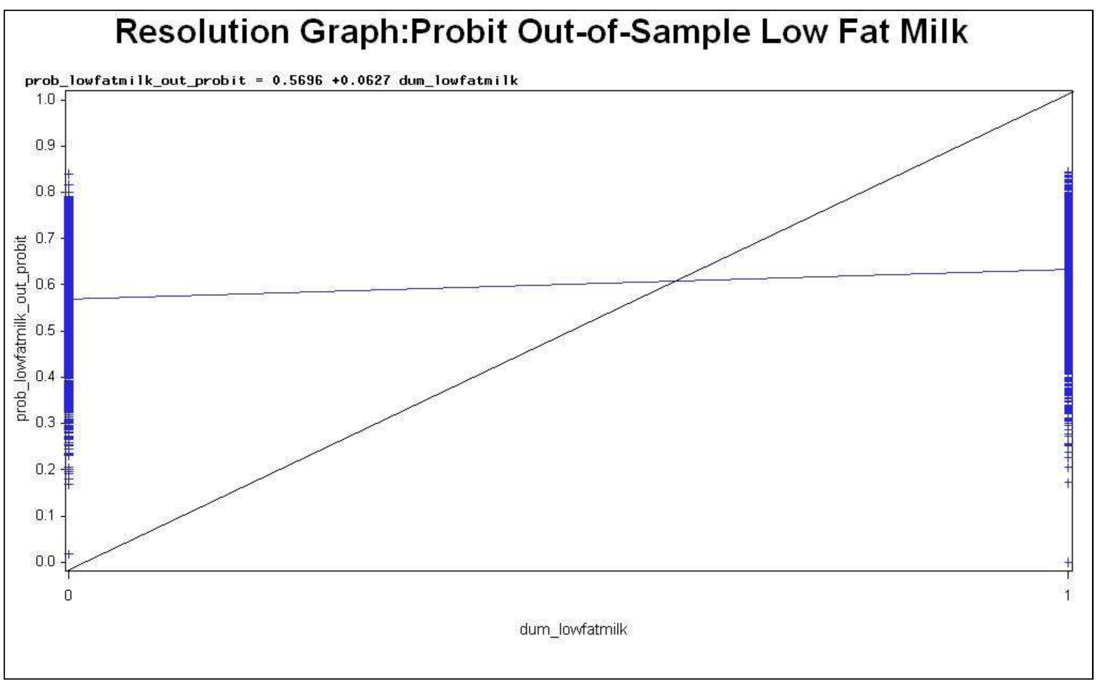

Figure 5.58: Resolution graph probabilities and outcome index: probit model out-of-sample for low-fat milk

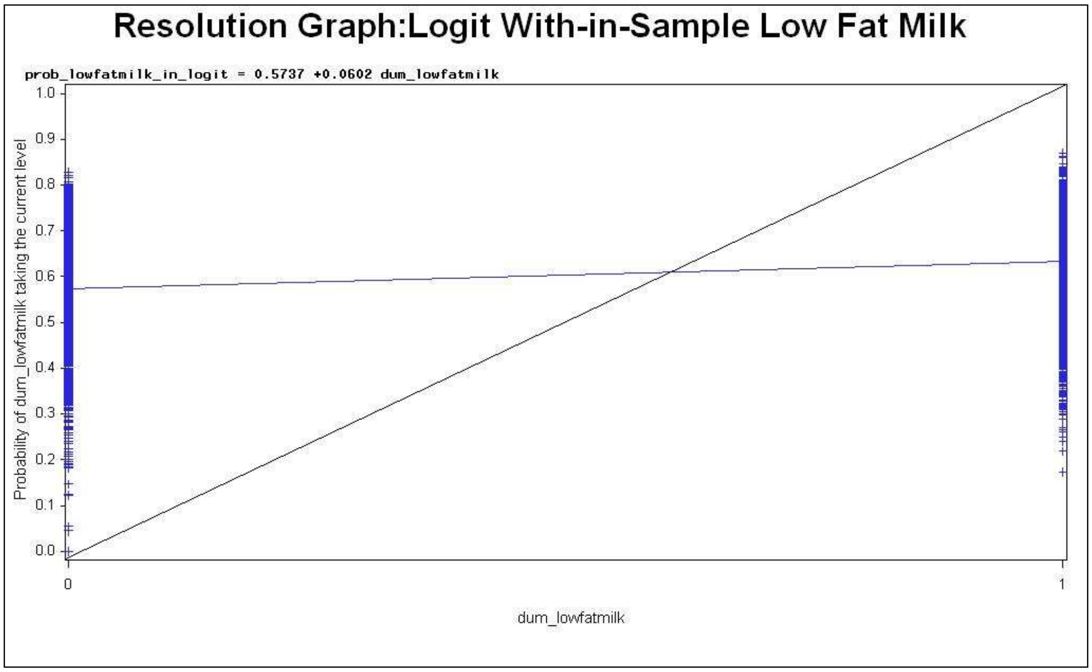

Figure 5.59: Resolution graph probabilities and outcome index: logit model within-sample for low-fat milk

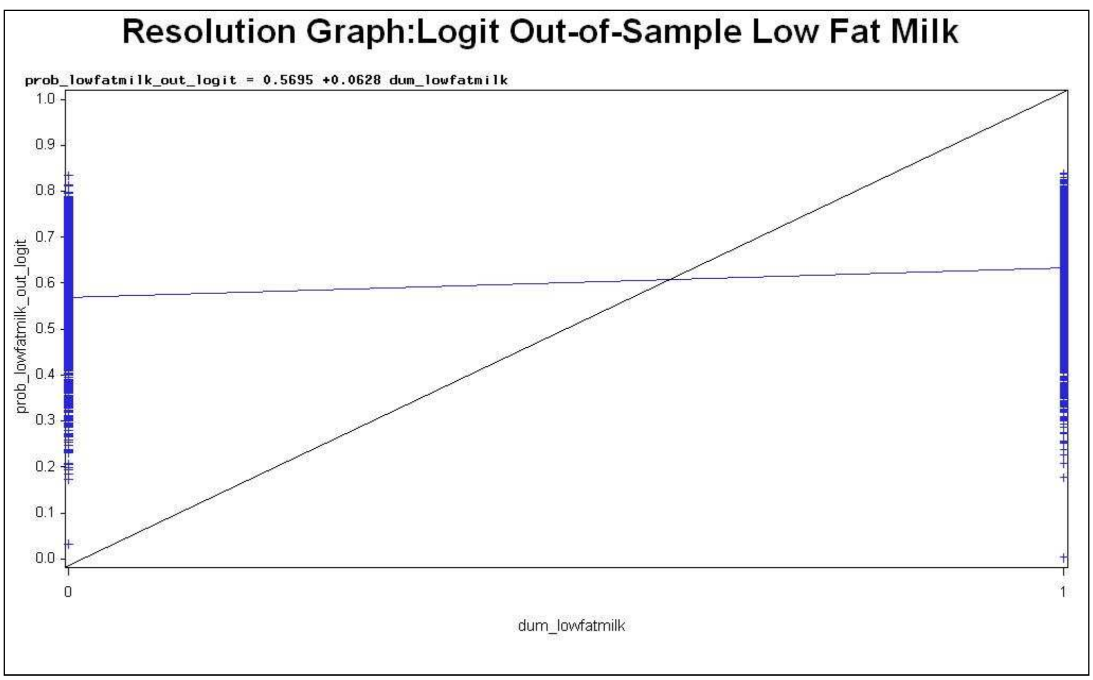

Figure 5.60: Resolution graph probabilities and outcome index: logit model out-of-sample for low-fat milk

Aforementioned graphical result is supported by the covariance regressions shown in the Appendix 4. Both intercept and slope coefficients are statistically not different from zero and one respectively at 5% significance level, indicating sub optimal sorting power of the model. However, the upward sloping calibration curve is indicative of some degree of sorting power.

Fruit Drinks

Figure 5.61 through 5.64 show resolution graphs for within-sample and out-of-sample probability forecasts for the decision to purchase fruit drinks. Mean forecast probability associated with outcome index 1 is 0.77 and it is high as we expected indicating good sorting power of models for forecast probabilities associated with outcome indexes 1. However, we did not observe low probabilities associated with outcome index zero (the mean probability for such forecasts were 0.68), indicating underperforming sorting behavior of the model for probabilities associated with zero outcome index. This result is supported by the resolution regressions shown in the Appendix 4. According to them, intercept coefficient is statistically different from zero and slope coefficient is significantly different from one, indicating sub optimal sorting behavior of forecast probabilities.

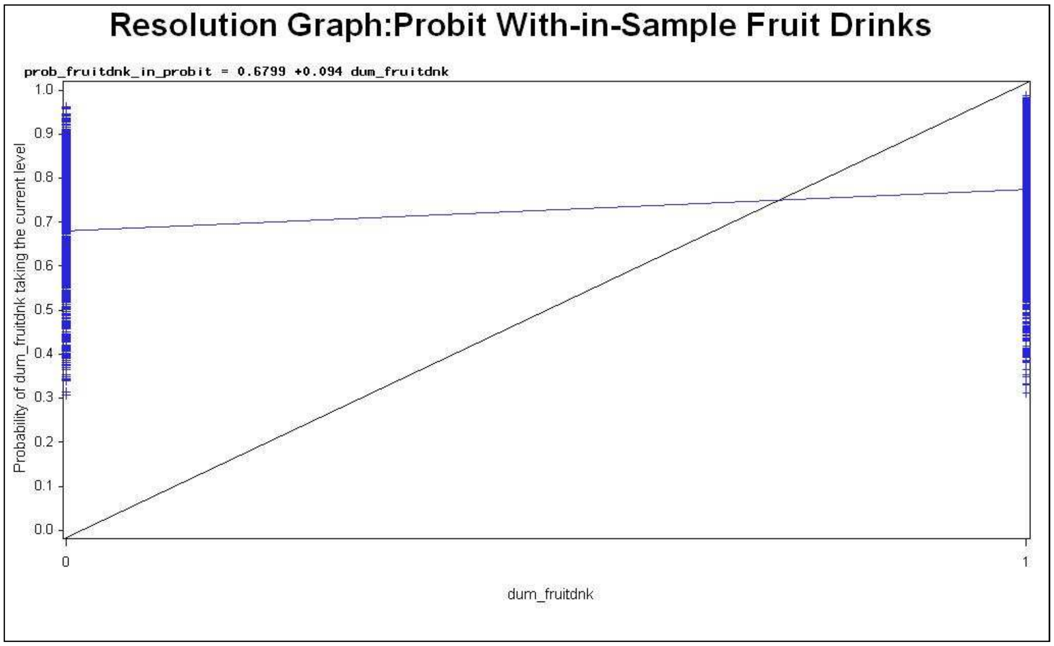

Figure 5.61: Resolution graph probabilities and outcome index: probit model within-sample for fruit drinks

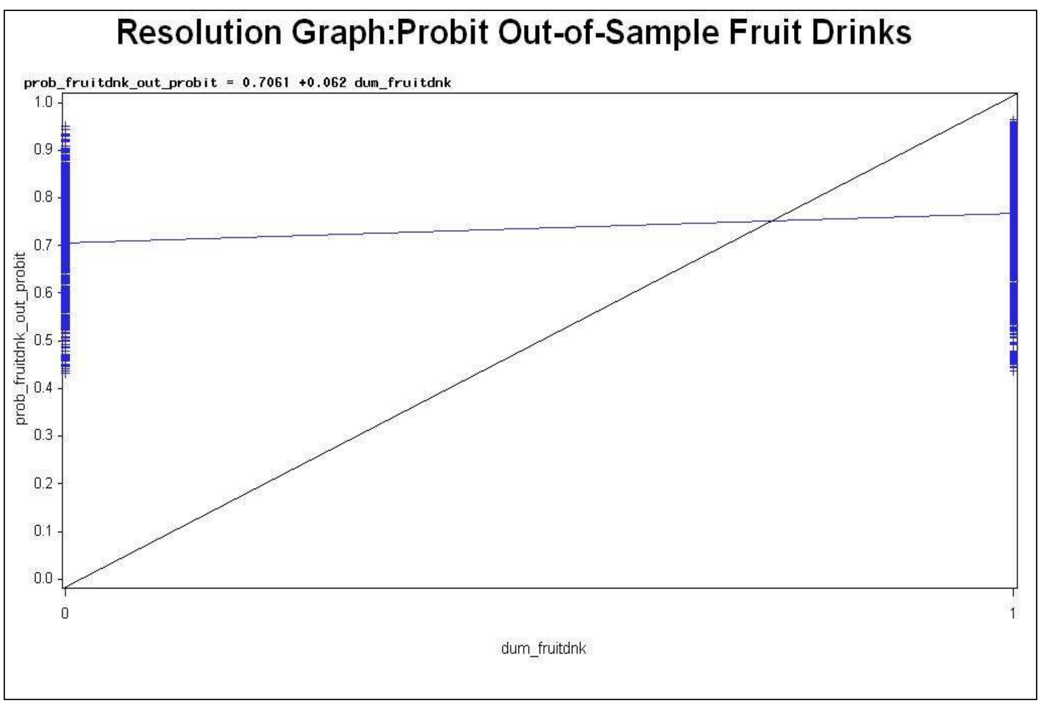

Figure 5.62: Resolution graph probabilities and outcome index: probit model out-of-sample for fruit drinks

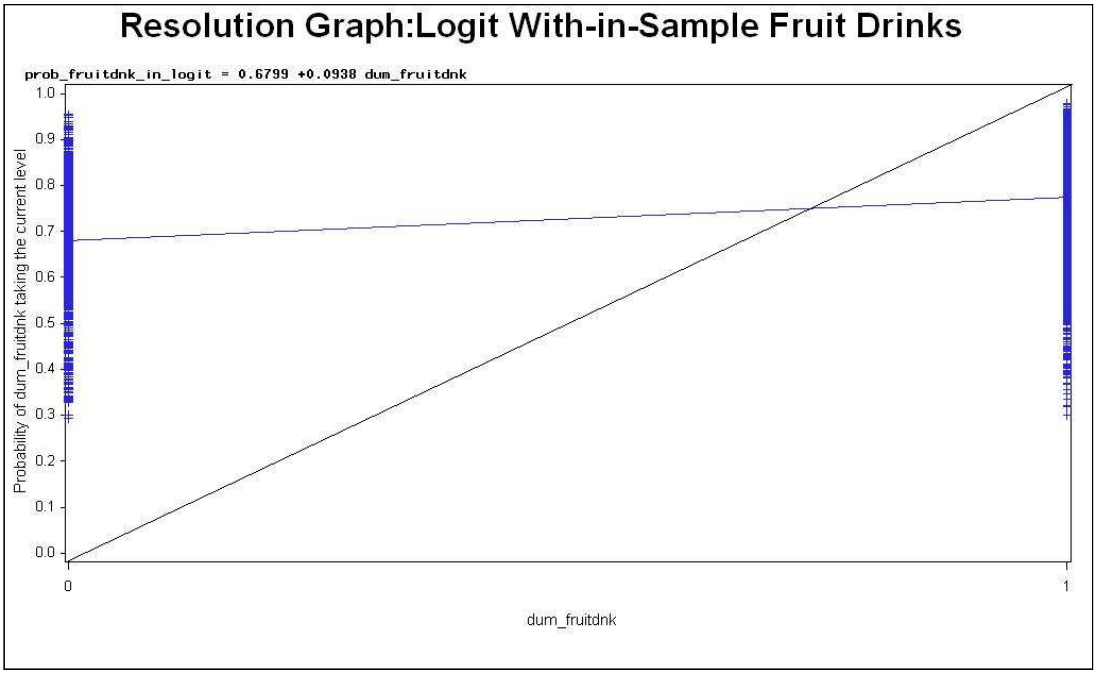

Figure 5.63: Resolution graph probabilities and outcome index: logit model within-sample for fruit drinks

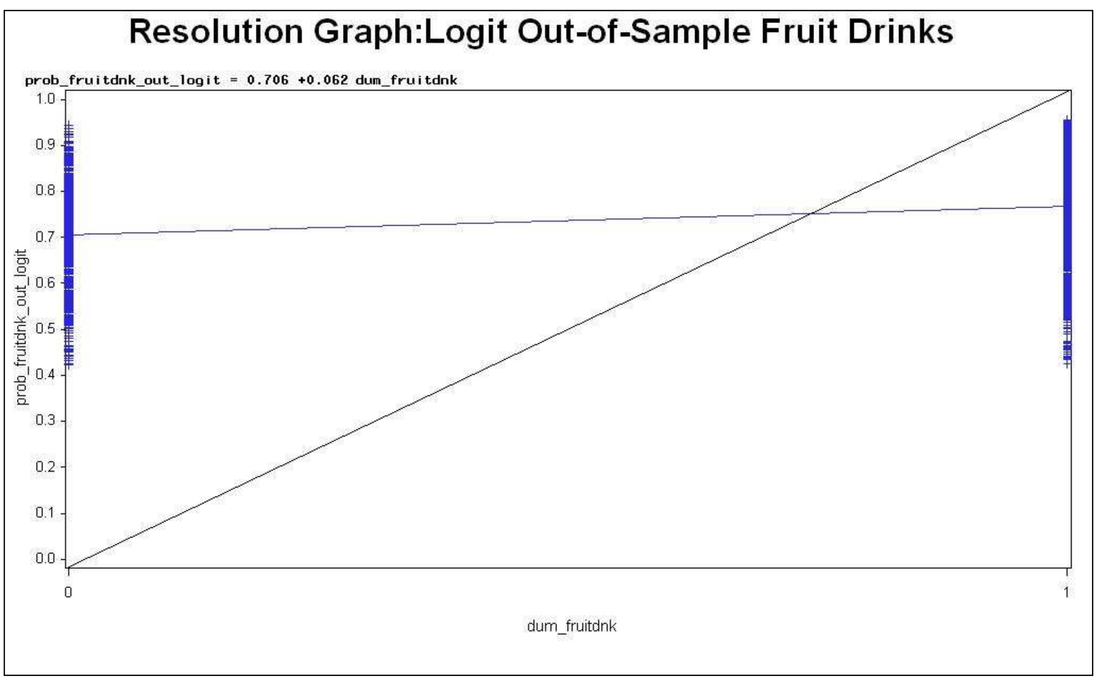

Figure 5.64: Resolution graph probabilities and outcome index: logit model out-of-sample for fruit drinks

Fruit Juices

Figure 5.65 through 5.68 show resolution graphs for within-sample and out-of-sample probability forecasts for the decision to buy fruit juices. We observe high mean forecast probability associated with outcome index 1. It is 0.93 and has a very low dispersion of probabilities. Above high probability associated with outcome index one is indicative of proper sorting behavior of the models for events where a purchase did occur. However, we also observe high mean probability associated with zero outcome indexes as well; which is indicative of not-so-good sorting behavior.

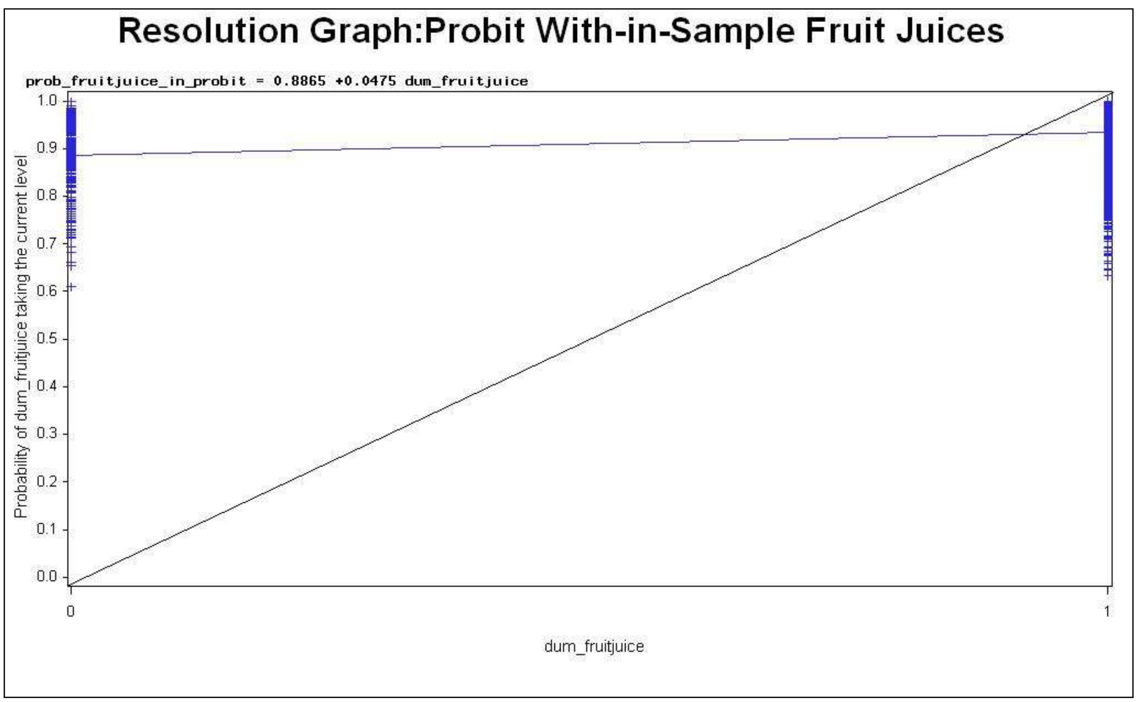

Figure 5.65: Resolution graph probabilities and outcome index: probit model within-sample for fruit juices

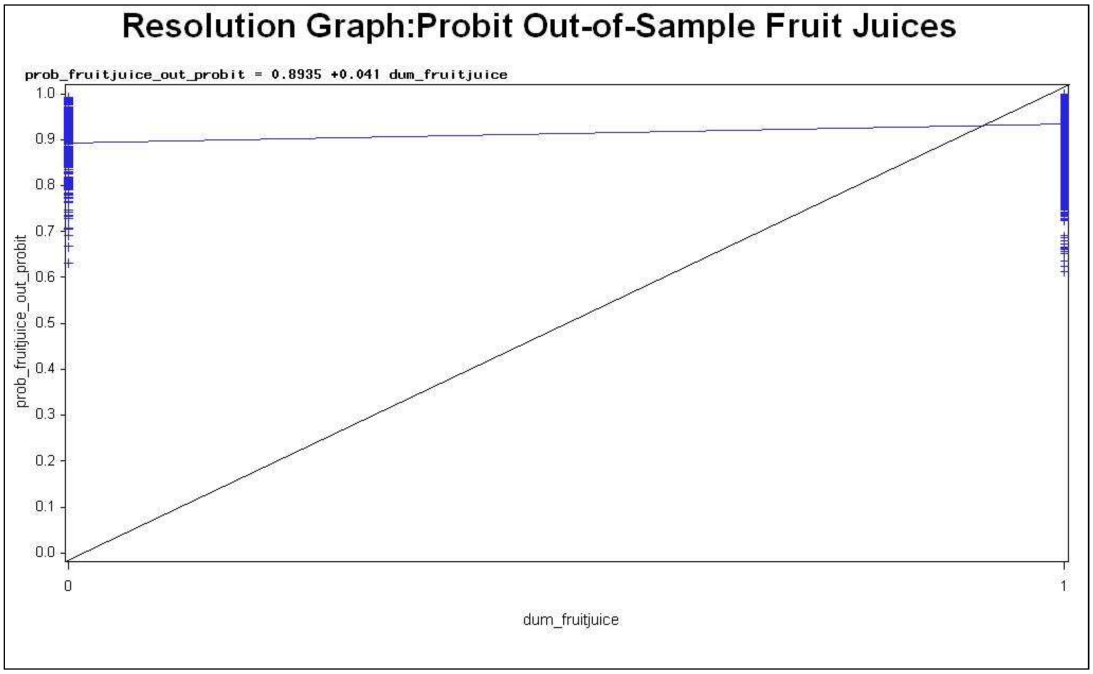

Figure 5.66: Resolution graph probabilities and outcome index: probit model out-of-sample for fruit juices

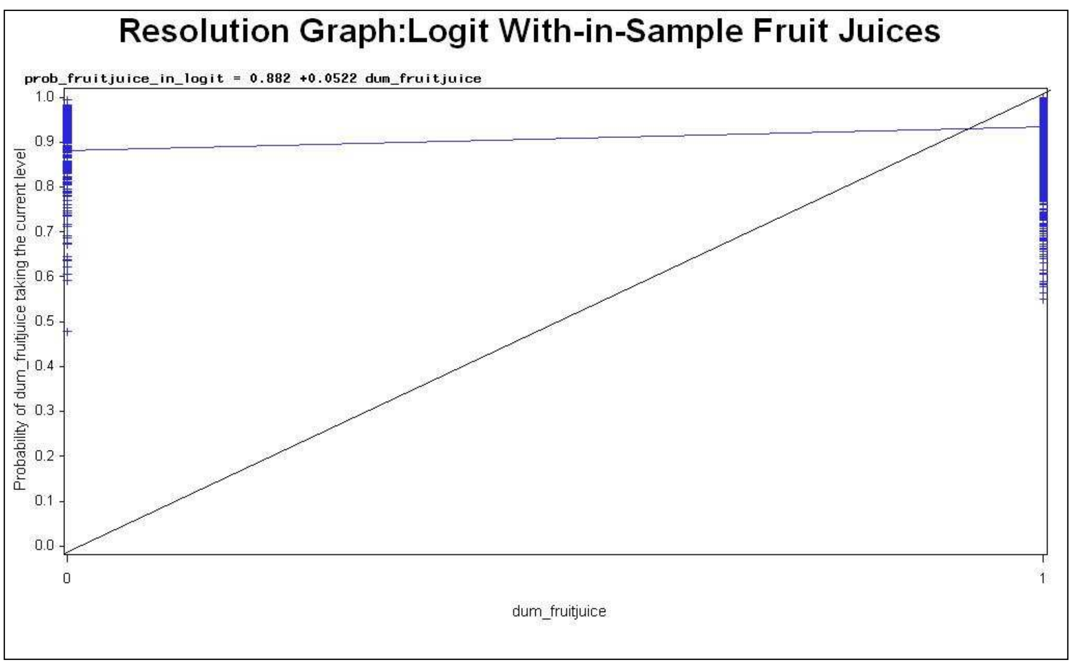

Figure 5.67: Resolution graph probabilities and outcome index: logit model within-sample for fruit juices

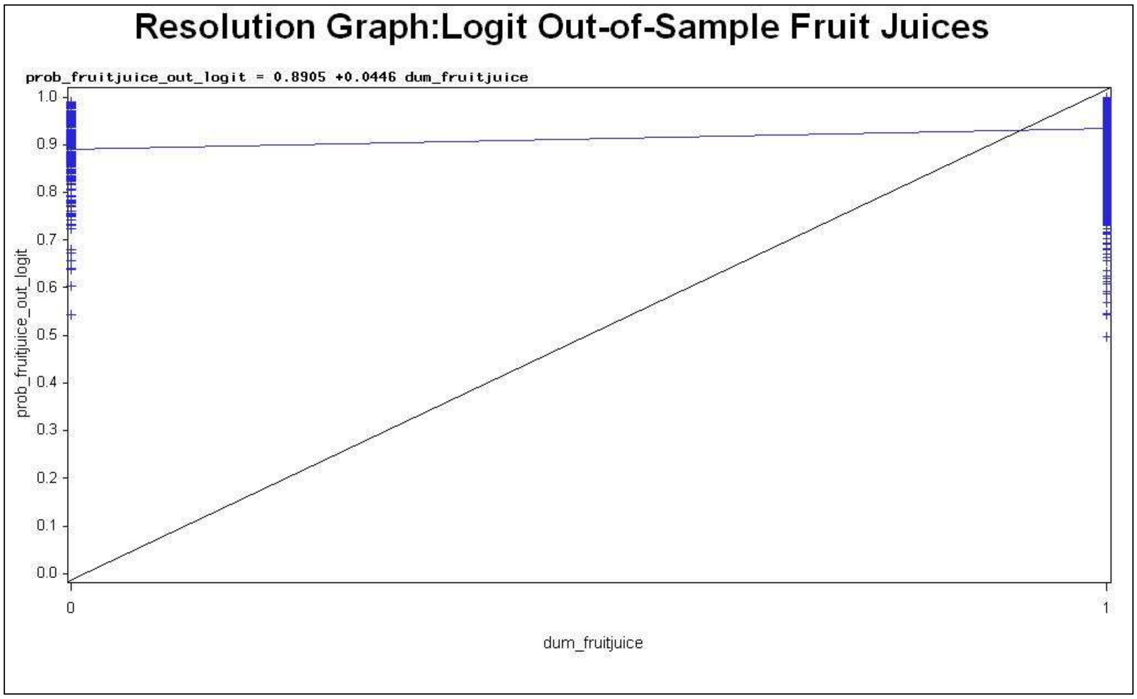

Figure 5.68: Resolution graph probabilities and outcome index: logit model out-of-sample for fruit juices

Aforementioned graphical result is supported by covariance regressions depicted in the Appendix 4. Even though we observe an upward sloping resolution graph for forecast probabilities for fruit juice, it is relatively very flat compared to the 45-degree perfect sorting line. Calculated intercept and slope coefficients are statistically different from zero and one respectively indicating sub optimal sorting behavior of models.

Bottled Water

Figures 5.69 through 5.72 show resolution graphs plotted for within-sample and out-of-sample probability forecasts for the decision to buy bottled water by U.S households during calendar year 2003. We observe high probabilities associated with outcome index 1 and on average the forecast probability was 0.72. This result is indicative of proper sorting of probabilities associated with events where a purchase did occur. However, we did not observe low probabilities associated with outcome index zero as expected. The mean probability value for those probabilities associated with outcome index zero is 0.66. This result is not supportive of proper sorting behavior of forecasting models.

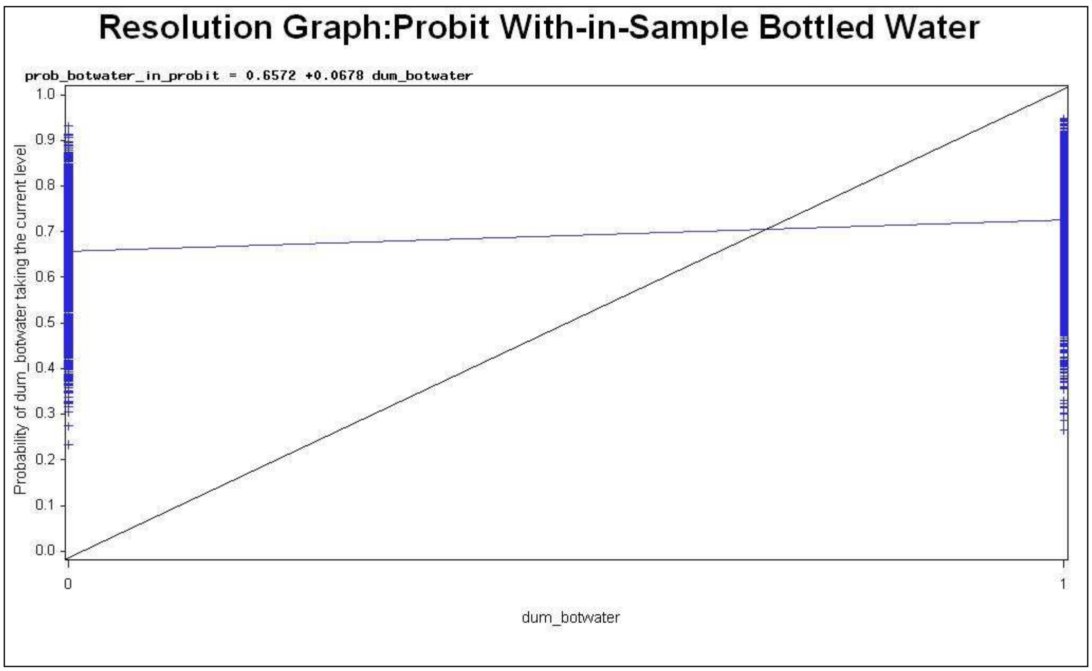

Figure 5.69: Resolution graph probabilities and outcome index: probit model within-sample for bottled water

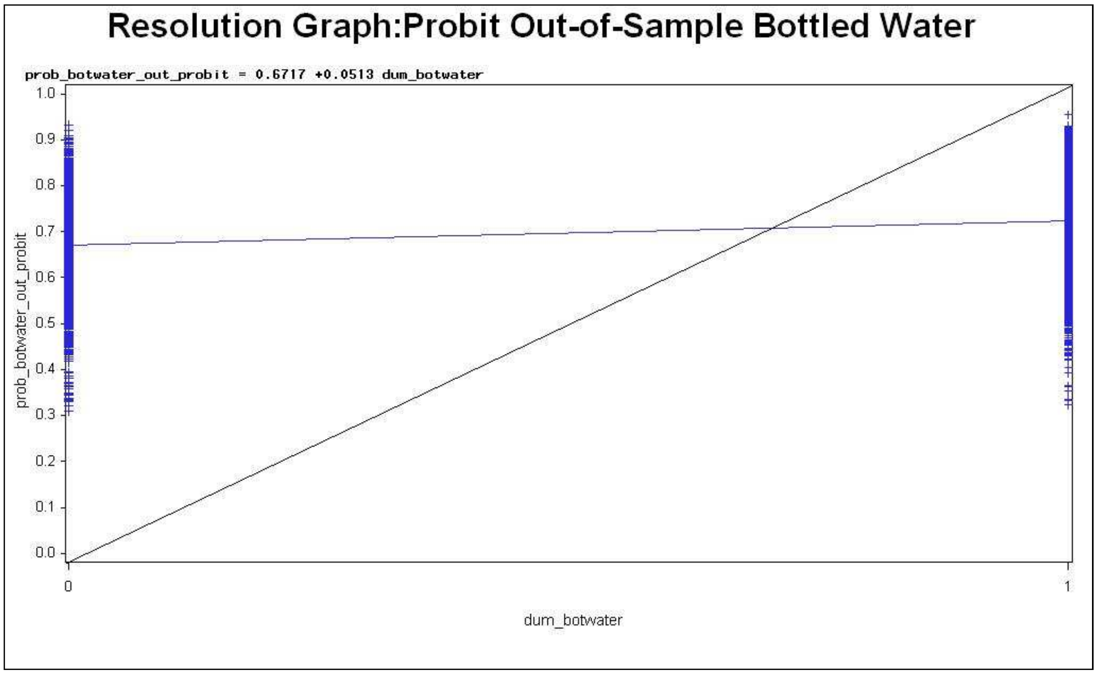

Figure 5.70: Resolution graph probabilities and outcome index: probit model out-of-sample for bottled water

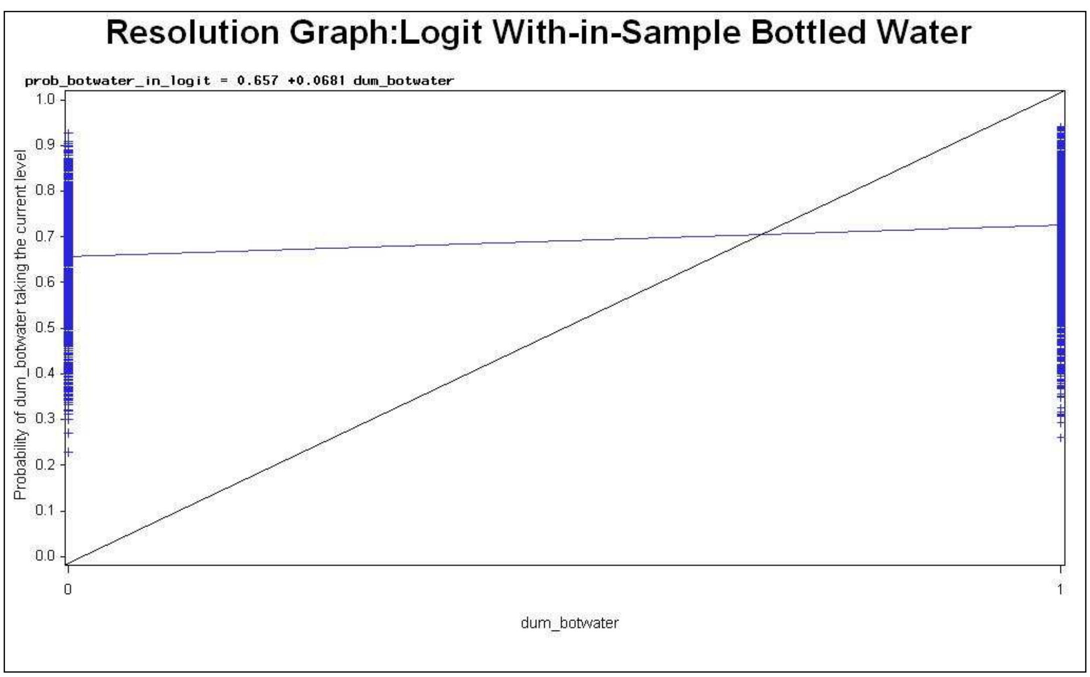

Figure 5.71: Resolution graph probabilities and outcome index: logit model within-sample for bottled water

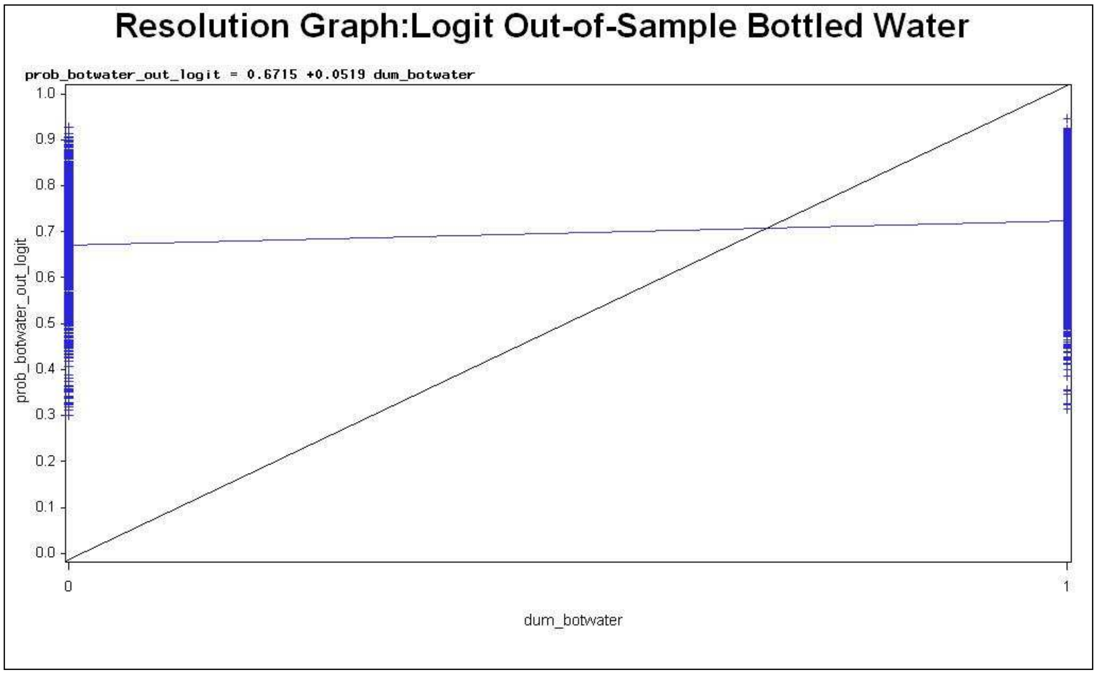

Figure 5.72: Resolution graph probabilities and outcome index: logit model out-of-sample for bottled water

The covariance regressions for forecast probabilities and outcome indexes for bottled water are shown in the Appendix 4. According to them, we observe that both intercept and slope coefficients are statistically different from zero and one respectively. Therefore, we conclude that models do not sort probabilities well, in particular those associated with outcome index zero.

Coffee

Figures 5.73 through 5.76 show resolution graphs plotted for within-sample and out-of-sample probability forecasts for the decision to buy coffee. Mean probability associated with outcome index 1 is about 0.78. Above result is indicative of good sorting behavior of probabilities associated with purchases that did occur. However, those probabilities show a large dispersion around the mean. On the other hand, the mean probability associated with outcome index zero is about 0.62, which is probably higher than we expected. Also, we observe a large dispersion in those probabilities around the mean value.

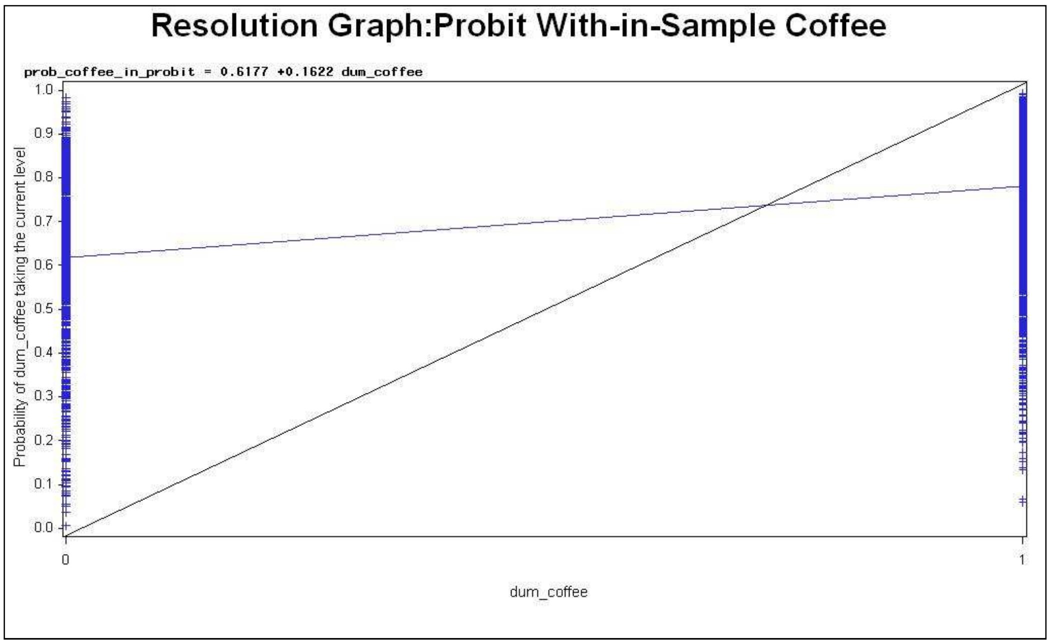

Figure 5.73: Resolution graph probabilities and outcome index: probit model within-sample for coffee

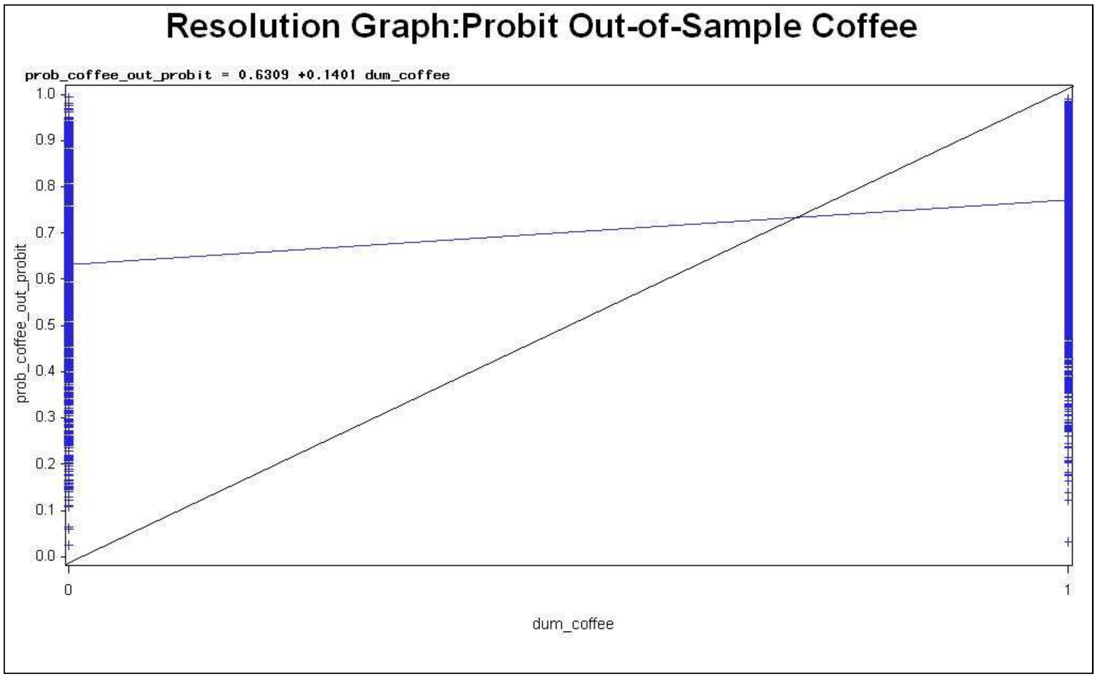

Figure 5.74: Resolution graph probabilities and outcome index: probit model out-of-sample for coffee

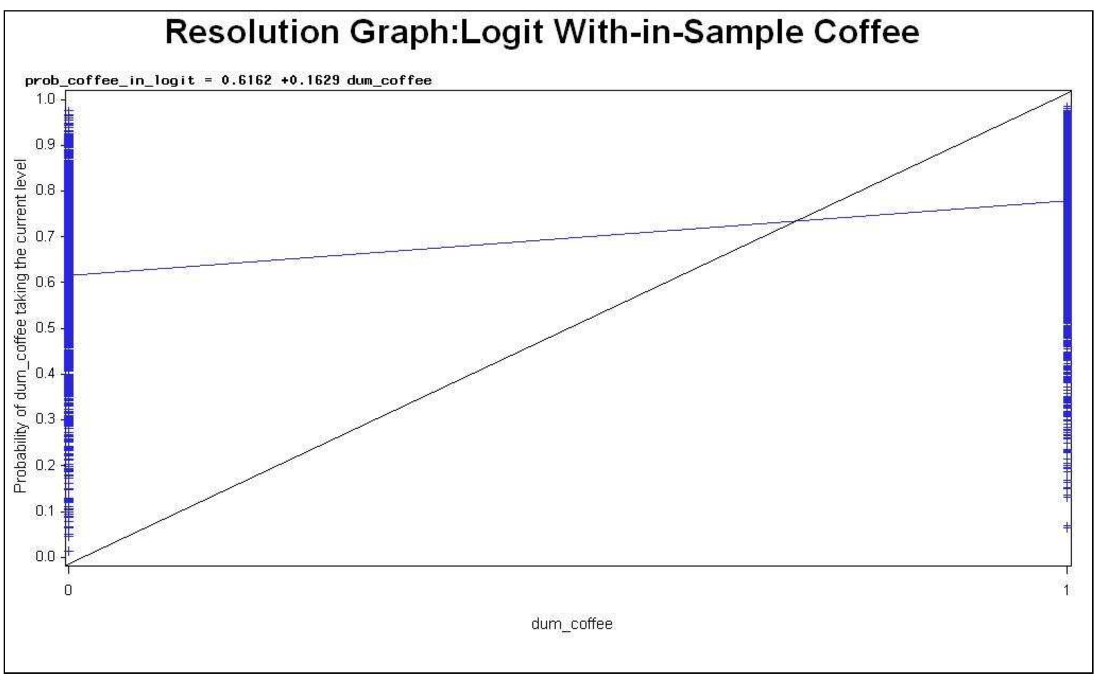

Figure 5.75: Resolution graph probabilities and outcome index: logit model within-sample for coffee

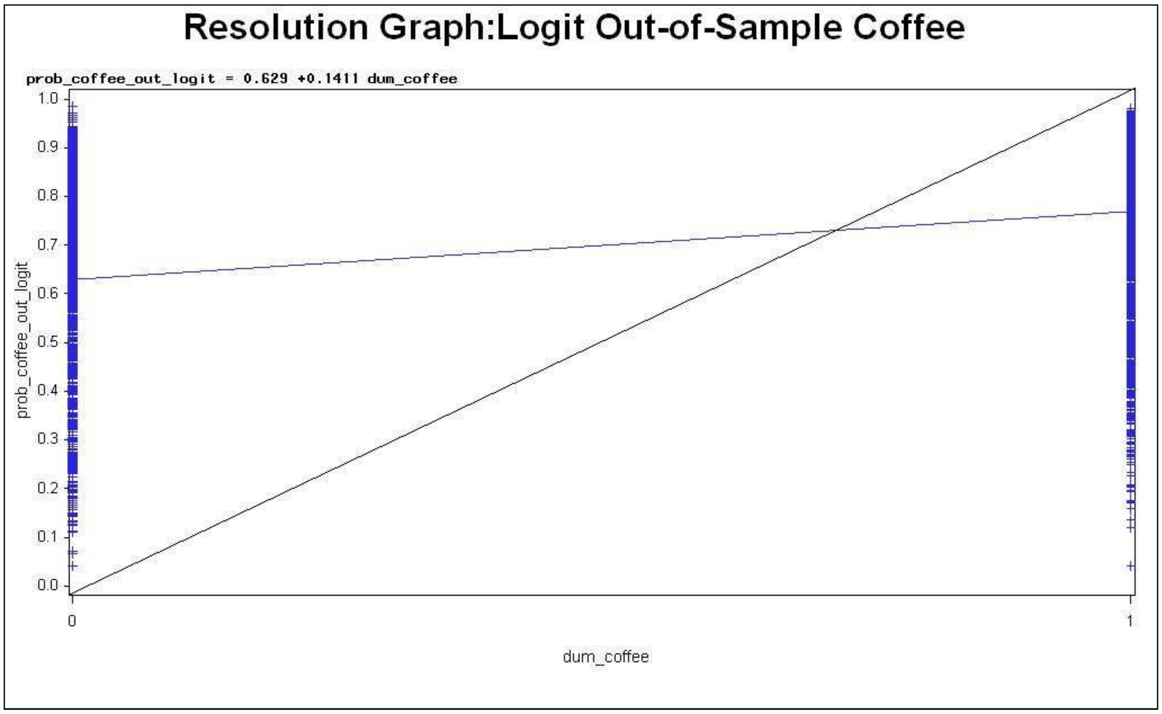

Figure 5.76: Resolution graph probabilities and outcome index: logit model out-of-sample for coffee

The covariance regression for forecast probabilities and outcome indexes for coffee is shown in the Appendix 4. According to them, we reject the null hypothesis of perfect sorting at 5% significance level in terms of both intercept and slope coefficients.

Tea

Figures 5.77 through 5.80 show resolution graphs plotted for within-sample and out-of-sample probability forecasts for the decision to buy tea. We observe high mean probability associated with outcome index one (which is 0.73). This result is indicative of good sorting behavior of probabilities that are associated with an event where tea was purchased. However, on the other hand, we do not observe low probabilities associated with outcome index zero.

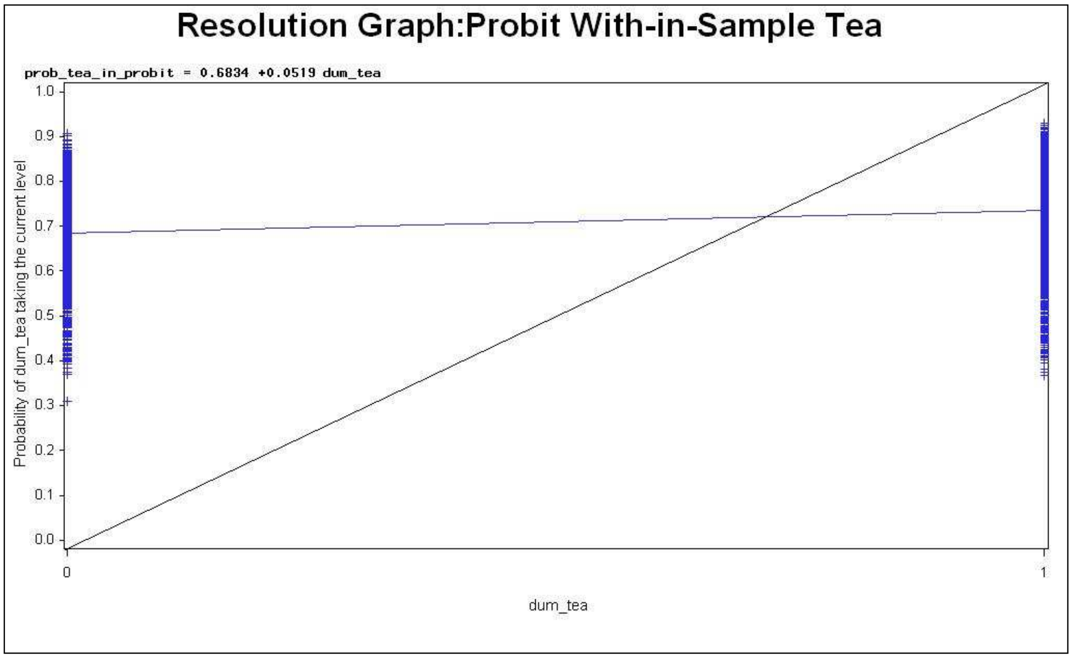

Figure 5.77: Resolution graph probabilities and outcome index: probit model within-sample for tea

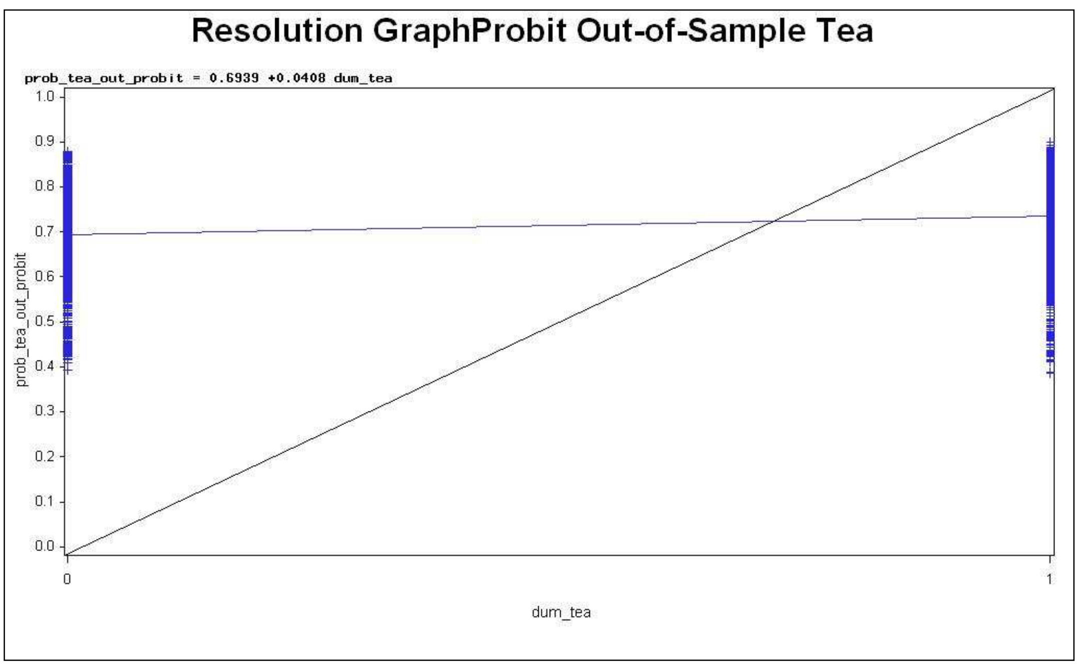

Figure 5.78: Resolution graph probabilities and outcome index: probit model out-of-sample for tea

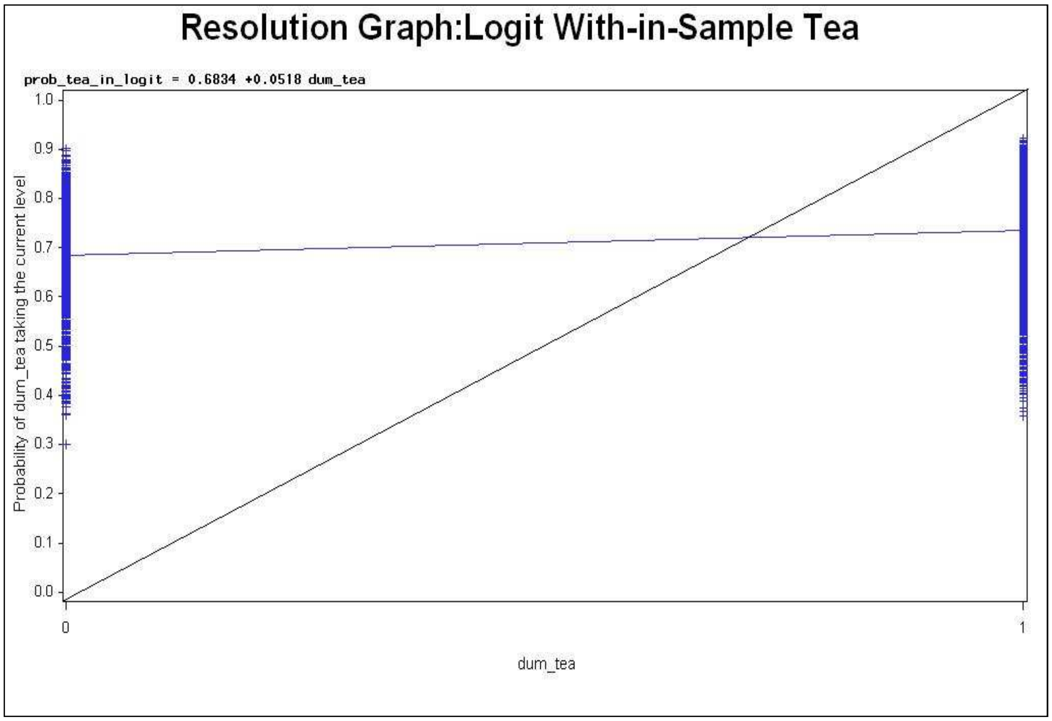

Figure 5.79: Resolution graph probabilities and outcome index: logit model within-sample for tea

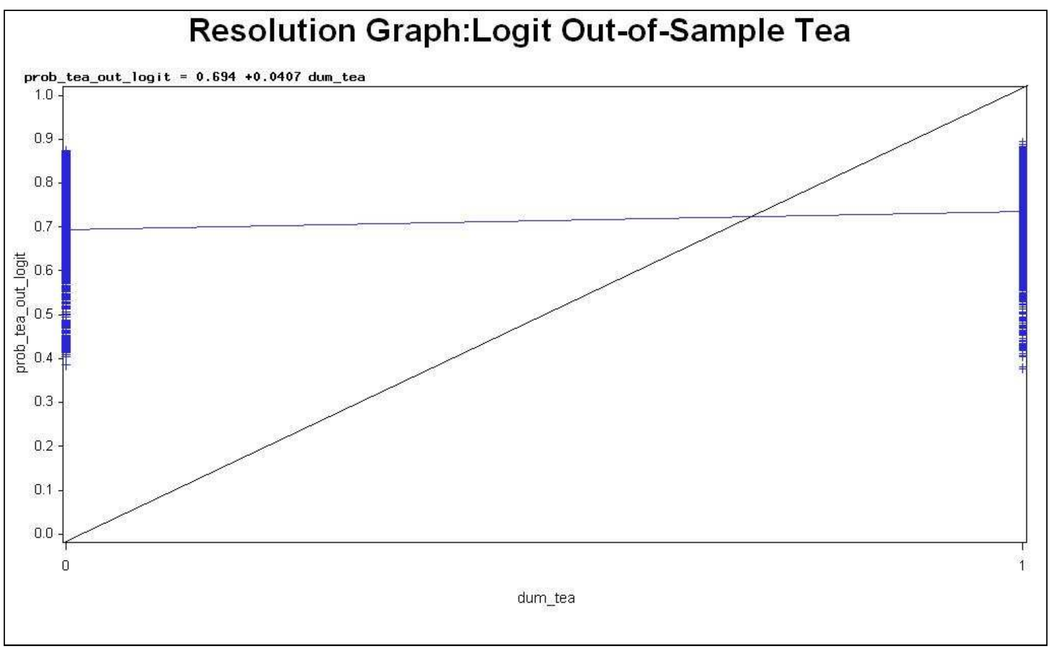

Figure 5.80: Resolution graph probabilities and outcome index: logit model out-of-sample for tea

Aforementioned graphical result is supported by results for resolution regression shown in the Appendix 4. According to them, we reject the null hypothesis of well sorting behavior. Significance of slope and intercept coefficient from aforementioned regressions would testify the graphical result.

The Brier Score and the Yates Partition of the Brier Score

In this section we explain the model/theoretical development of the Brier score and the Yates partition to the Brier score and their empirical applications to forecast probabilities generated through probit and logit models. These probit and logit models are used in the analysis of factors affecting the decision to purchase non-alcoholic beverages by a sample of U.S households in the calendar year 2003.

Theoretical Development

Following account on the Brier score and the Yates partition of the Brier score (BS) (also known as a variant of mean probability score; $\overline{PS}$) is borrowed from Brier (1950), Yates (1982), Yates and Curley (1985) and Yates (1988). According to Yates (1982), by far the most widely used rule for summarizing *external correspondence*[23] is the Brier score. The Brier score and the Yates partition of the Brier score can be formulated for a single-event and a multiple-event case. A single-event situation is where when one considers only one side of an event that has two probability partitions. For example, say a purchase decision by a consumer where he can buy or not-buy a given product. Two probability partitions would be, low probabilities for *not-buy* event (probability of zero or close to zero) and large probabilities for *buy* events (probability of

[23] The extent to which probabilistic forecasts do anticipate the events at issue is called external correspondence (Yates, 1982)

one or close to one). When a single event is considered, we may use the event associated with either *buy* or *not-buy*. Say, if we used probabilities associated with event *buy*, the Brier score value of other half that is associated with *not-buy* can be recovered from the inherent symmetry of probabilities of the two sided event. In other words, if we consider both sides of a two sided event in evaluating probabilities using the Brier score, the calculated Brier score is as twice as much large as the value one can obtain if only one side of probabilities are used to calculate the Brier score for a two sided event.

A multiple event situation is where when one consider *i*th side of an event that has *j*th probability partitions (where $j>2$). For example, consider a situation where we have three probability partitions such as three employment categories and their predictions. Employment categories would be, employed in public sector, private sector and not employed. If a model issues probabilities for each of above employment categories, during evaluation process using the Brier score, we have to use probabilities associated with all three sides of the event in the Brier score formula. If we use only one side of the event in evaluating probabilities, unlike in the two sided event considered above, we cannot use the symmetry condition to recover Brier score values.

Brier (1950) indicated that Brier score can be applied to single-event and multiple-event cases when evaluating probabilities. Furthermore, Yates (1982) shows single event covariance decomposition of the Brier score and Yates (1988) shows the extension of that for a multiple event case. It is important to note that, in contrast to Sanders (1963) and Murphy (1972a and 1972b) decompositions, Yates (1982) covariance decomposition of the Brier score can be applied to either continuous or discrete forecasts (Yates, 1982). In the following sections below, we discuss the single and multiple event covariance decomposition of the Brier score in detail.

Single Event Covariance Decomposition of the Brier Score

Let f represent the probabilistic forecast for an event that the forecaster is trying to predict (in our analysis, probabilities are generated using qualitative choice models). Let d represent the outcome index where, $d = 1$ if the event occurs and $d = 0$ if the event does not occur. As shown in equation 5.4, the probability score *(PS)* is formally defined as the squared difference between f and d:

(5.4) $PS(f, d) = (f - d)^2$

The *PS* clearly has following bounds from above an below $0 \leq PS \leq 1$ respectively. More specifically, *PS* reaches a minimum of zero when the forest is perfect, i.e. $f = d = 1$. PS is maximum at 1 when either the forecaster is absolutely certain that the event will occur, when in fact it does not occur in reality; i.e. $f = 1, d = 0$,or the forecaster is certain that the event will not occur, when in fact it does occur in reality, i.e. $f = 0, d = 1$.

Over N occasions, indexed by $i = 1, \ldots.., N$, the mean of the PS ($\overline{PS}$ or the Brier score) is given by:

(5.5) $\overline{PS}(f, d) = \frac{1}{N} \sum_{i=1}^{N} (f_i - d_i)^2$

Sanders (1963) and Murphy (1972a, 1972b, 1973) have decomposed the Brier score into various components including measures of calibration and resolution. However, Yates (1982), Yates and Curley (1985), and Yates (1988) further decomposed Brier score into its variance and covariance components allowing for additional analysis. His formulation called *"covariance decomposition"* is given as follows:

(5.6)[24] $\overline{PS}(f,d) = Var(d) + MinVar(f) + Scat(f) + Bias^2 - 2 * Cov(f,d)$

The various components of $\overline{PS}$ on the right hand side of equation 5.6 have following definitions and interpretations. *Var(d)* represents the variance of the outcome index and defined as:

(5.7) $Var(d) = \bar{d}(1-\bar{d})$

where

(5.8) $\bar{d} = \frac{1}{N}\sum_{i=1}^{N} d_i$

Equation 5.8 shows the relative frequency or the "base rate" with which the target event occurs, where the target event for our analysis would be the decision to *buy* a given non-alcoholic beverage. This decision is completely out of control of the forecaster (in our analysis the forecaster is the qualitative choice model), hence the *Var(d)* is not determined through our model. The remaining terms reflect the factors that are under the forecaster's control. Thus we want to minimize, $Scat(f)$ and $Bias^2$, while maximizing $Cov(f,d)$ for an allowable minimum variance ($MinVar(f)$) to obtain the lowest $\overline{PS}$ (more about allowable $MinVar(f)$ will be discussed later in the chapter). It should be noted that our objective is to minimize the $\overline{PS}$ in evaluating probabilities, because the

[24] Please refer to the appendix to Chapter VI for the derivation of covariance decomposition of the mean probability score (the Brier score)

lower the Brier score (mean probability score), the higher the ability of the model to correctly classify probabilities.

Bias is defined as follows:

(5.9) $Bias = (\bar{f} - \bar{d})$

where

(5.10) $\bar{f} = \frac{1}{N}\sum_{i=1}^{N} f_i$

In the equation 5.7, $\bar{f}$ is the mean of the probabilities generated from the model. Bias is sometimes labeled calibration-in-the-large (Yates, 1988) or the mean probability judgment reported for the target event. It reflects the overall miscalibration of the forecast, i.e. how much the probability assessments are too high or too low. The square of the bias, which is what actually appears in the covariance decomposition (equation 5.3), reflects the calibration error regardless of the direction (+ or -) of the error. We ought to minimize the $Bias(f, d)$ in trying to achieve a lower mean probability score, which is desirable.

The $Cov(f, d)$ term is defined as follows:

(5.11) $Cov(f, d) = [slope][Var(d)]$

The slope is defined as the difference between the means of conditional probability of events that actually occurred and conditional probability of events that actually did not occur. Algebraically the slope is defined as follows:

(5.12) $Slope = (\bar{f}_1 - \bar{f}_0)$

where

(5.13) $$\bar{f}_1 = \frac{1}{N_1}\sum_{j=1}^{N_1} f_{1j}$$

(5.14) $$\bar{f}_0 = \frac{1}{N_0}\sum_{j=1}^{N_0} f_{0j}$$

Here $\bar{f}_1$ represents the conditional mean probability forecast for event under consideration over the N_1 occurrences for which the event actually occurs; $\bar{f}_0$ represents the conditional mean probability for event under consideration over the N_0 occurrences that the event does not occur, with $N = N_1 + N_0$. The maximum value that Slope can have is 1, which occurs when the forecaster always reports (or model reports) $f = 1$ when the target event is going to occur and $f = 0$ when it is not. Furthermore, *slope* is the gradient of the regression line when probabilities generated through the model are regressed on outcome indexes. For a perfect forecast, all the probabilities associated with events that do not occur must have probabilities equal to zero and all probabilities associated with events that did occur must have probabilities equal to one, resulting in a slope equal to one. Therefore, it makes sense for *slope* to contribute to mean probability score negatively. In other words, steeper the *slope*, the more appropriate the classification of probabilities for events that occurred and that did not occur (high probabilities for event that occurred and lower probabilities for events that did not occur, the smaller the Brier score the better).

Covariance between the probabilities generated through the model and outcome index $Cov(f, d)$ is the heart of the forecasting problem (Yates, 1988). It reflects the model's ability to make distinctions between individual occasions in which the event occurs or does not occur. In other words, it represents how responsive the forecast is to information related to the event. Our objective with respect to minimum variance is that the model needs to maximize the value associated with the $Cov(f,d)$ to achieve a lower mean probability score.

Scatter is defined as the mean of the weighted variances of probabilities associated with events that occurred and that did not occur. The algebraic representation of scatter is depicted in the equation 5.15 below:

$$(5.15) \quad Scat(f) = \frac{1}{N}[N_1 Var(f_1) + N_0 Var(f_0)]$$

where

$$(5.16) \quad Var(f_1) = \frac{1}{N_1}\sum_{i=1}^{N_1}(f_{1i} - \bar{f}_1)^2$$

and

$$(5.17) \quad Var(f_0) = \frac{1}{N_0}\sum_{i=1}^{N_0}(f_{0i} - \bar{f}_0)^2$$

$Var(f_1)$ is the conditional variance of the probabilities generated from the model associated with the events on those N_1 occasions when the event actually occurred and $Var(f_0)$ is the conditional variance of the probabilities generated from the model associated with the events on those N_0 occasions when the event actually did not occur. $Var(f_1)$ and $Var(f_0)$ measure variability in model generated probabilities which is unrelated to whether or not the target event occurs. Scatter can be interpreted as an index of overall noise contained in model generated probabilities. It is expected that the Scatter will be minimized to achieve a lower mean probability score.

$MinVar(f)$ is defined as follows:

(5.18) $MinVar(f) = Var(f) - Scat(f)$

where $Var(f)$ is the variance of the entire collection of probabilities generated for the target event. Minimum variance can also be shown as follows:

(5.19) $MinVar\ (f) = (\bar{f}_1 - \bar{f}_0)^2[\bar{d}(1-\bar{d})]$

which contains the elements of the covariance of judgments and outcome indexes (Yates, 1988). To give more perspective to the relationship between minimum variance and overall variance of the probabilities generated through the models, we can rearrange the equation 5.18 as follows:

(5.20) $Var(f) = MinVar(f) + Scat(f)$

Minimum variance can also be defined as the variance of probabilities on top of scatter that contributes toward the overall variance, i.e. $Var(f)$.

Since $Var(f)$ contributes to the Brier score positively, one would want to minimize it. That is to say, in the equation 5.20, we have to minimize the components in the right hand side, i.e. $MinVar(f)$ and $Scat(f)$. It would make sense to minimize $Scat(f)$ of probabilities as lower the $Scat(f)$ the tighter the distribution of probabilities around conditional means of probabilities for events that actually occurred and events that did not occur the better the model's ability to sort probabilities for events that occurred versus events that did not occur. However, it would not make sense to minimize the $MinVar(f)$ in trying to minimize the overall variance of the probabilities generated. This is clear when one looks at the equation 5.19. $MinVar(f)$ is a function of *Slope* and variance of index variable, where the latter is not determined through the model that we used to generate probabilities. The only manipulatable component is the *Slope*, which is a function of conditional probabilities. What is desired is to have a maximum slope of one at the extreme in minimizing the Brier score. However, in trying to minimize the $Var(f)$, if one minimizes the $MinVar(f)$, it will eliminate the slope, which is not desirable. Therefore, we need to have some *Slope*, hence some $MinVar(f)$ in the model, in minimizing $Var(f)$ and trying to achieve the minimum Brier score. Therefore, $MinVar(f)$ essentially reflects the *maximum allowable model variability* (or amount of model variability that must be tolerated) which is required to minimize the $Var(f)$, hence the Brier score.

Since $Cov(f,d)$ and $MinVar(f)$ are both functions of Slope, $(\bar{f}_1 - \bar{f}_0)$ and Variance of outcome index, $(\bar{d}(1-\bar{d})$, we can establish a relationship between $Cov(f,d)$ and $MinVar(f)$ as follows. Equation 5.19 can be rearranged to represent the Slope as follows:

(5.21) $$(\bar{f}_1 - \bar{f}_0) = \sqrt{\frac{MinVar(f)}{Var(d)}}$$

Substituting 5.21 into 5.11 and after simplification we arrive at the following relationship that combines Covariance of forecast probabilities, Minimum Variance and Variance of outcome index as follows:

(5.22) $Cov(f,d)=\sqrt{MinVar(f)*Var(d)}$

According to equation 5.22, variance of outcome index and Minimum Variance are positively related to the covariance of forecast probabilities and outcome index. It is an obvious fact that variance of the outcome index, $Var(d)$ is beyond the control of the forecasting model and only determined externally by the actual observations. Therefore, the only model generated variable that affect the $Cov(f,d)$ is $MinVar(f)$. We can conclude that higher the Slope, the higher the $MinVar(f)$, the higher the $Cov(f,d)$. In other words, high $MinVar(f)$ is associated with high $Cov(f,d)$. This result has a leverage in explaining the forecasting model's sorting power (resolution) and $Cov(f,d)$. We also can conclude that, high resolution is associated with high $Cov(f,d)$.

<u>Multiple Event Covariance Decomposition of the Brier Score</u>

The Brier score and the Yates partition of the Brier score can be formulated for a multiple event case. Let $A_1,......,A_K$ represent a *K*-event outcome space partition with $K \geq 2$. Let d_k represent the outcome index for each event $k=1,....,K$. Let f_k represent the probability forecast for each event $k=1,....,K$. The outcome indexes and probabilities generated can be represented more compactly by vectors $d=(d_1,d_2,....d_k)$ and $f=(f_1,f_2,.......,f_k)$, respectively. The multiple event probability score *(PSM)* (Murphy, 1972b) for a single occasion is given as:

(5.23) $PSM(f,d)=(f-d)'(f-d)$

If we introduce the summation notation in lieu of above vector notation, *PSM* can be represented as follows:

(5.24) $$PSM(f,d)=\sum_{k=1}^{K}(f_k-d_k)^2$$

and

(5.25) $$PSM(f,d)=\sum_{k=1}^{K}PS(f_k,d_k)$$

It is important to note that $0 \le PSM \le 2$. If i, with $i=(1,......,N)$ is used to index multiple-event probability events f_i and outcome indexes d_i over N different occasions, then the mean of PSM can be defined the following way:

(5.26) $$\overline{PSM}(f,d)=\frac{1}{N}\sum_{i=1}^{N}PSM(f_i,d_i)$$

Furthermore:

(5.27) $$\overline{PSM}(f,d)=\sum_{k=1}^{K}\overline{PS}(f_k,d_k)$$

and

(5.28) $$\overline{PSM}(f,d)=\sum_{k=1}^{K}\overline{PS}_k$$

where $\overline{PS}_k$ represents the mean probability score for the *k*th event in the partition. Therefore, the sum of the mean probability scores for the individual events constitutes an overall measure of accuracy for the multiple-event judgments. Yates (1988) further states that, the single event situation is equivalent to the multiple-event situation in which the partition of the sample space consists of two events *(K=2)*, the target event and its complement. In that case, $PS=(1/2)PSM$. The covariance decomposition of the Brier score for a multiple-event forecast is as follows:

(5.29) $$\overline{PSM}(f,d) = \sum_{k=1}^{K} Var(d_k) + \sum_{k=1}^{K} MinVar(f_k) + \sum_{k=1}^{K} Scat(f_k) + \sum_{k=1}^{K} Bias_k^2 - 2\sum_{ki=1}^{K} Cov(f_k, d_k)$$

It should be noted that each term in the multiple-event case has an interpretation similar to that given in the single event case discussed above.

It is important to note that, although the Brier score gives an overall indication of the model's ability to forecast (the lower the Brier score, the better the forecast), the components of the covariance decomposition of the Brier score provides a clearer indication of the model's ability to forecast.

Data Analysis and Discussion

In this section we offer an explanation to the evaluation of forecast probabilities generated through probit and logit models using the Brier score and the Yates partition of the Brier score (alternatively named covariance decomposition of the mean probability score). The Brier score (the mean probability score) basically maps the deviation between the forecast probabilities and the outcome index, hence the lower the Brier score, the better the forecast offered. Our analysis focused on a single event, namely *"purchase"* or *"did not purchase"* a given non-alcoholic beverage, hence the use of single event decomposition of the mean probability score.

Tables 5.81 through 5.84 show the Brier score and covariance decomposition of the Brier score for forecast probabilities generated using probit and logit models for the decision to purchase a given non-alcoholic beverage. We have generated both within-sample and out-of-sample forecasts and evaluated them using the Brier score and the Yates partition of the Brier score. Below, we explain part-by-part, the Brier score and the Yates partition of the Brier score.

Table 5.81: The Brier Score and the Yates Partition of the Brier Score: Probit Within-Sample

	Isotonics	Regular Soft Drinks	Diet Soft Drinks	High Fat Milk	Low Fat Milk	Fruit Drinks	Fruit Juices	Bottled Water	Coffee	Tea
Brier Score	0.1579	0.0826	0.2107	0.1408	0.2235	0.1701	0.0614	0.1939	0.1630	0.1910
Dvar[25]	0.1724	0.0887	0.2266	0.1495	0.2378	0.1874	0.0646	0.2080	0.1942	0.2013
Min Var	0.0012	0.0004	0.0011	0.0005	0.0009	0.0017	0.0001	0.0010	0.0051	0.0005
Scatter	0.0132	0.0053	0.0146	0.0079	0.0134	0.0163	0.0029	0.0131	0.0267	0.0100
Bias	1.2E-10	5.2E-09	3.1E-08	6.7E-09	3.7E-09	2.3E-08	7.7E-10	7.9E-11	8.9E-07	1.4E-08
2Cov[26]	0.0289	0.0118	0.0316	0.0171	0.0286	0.0352	0.0061	0.0282	0.0630	0.0209

Table 5.82: The Brier Score and the Yates Partition of the Brier Score: Probit Out-of-Sample

	Isotonics	Regular Soft Drinks	Diet Soft Drinks	High Fat Milk	Low Fat Milk	Fruit Drinks	Fruit Juices	Bottled Water	Coffee	Tea
Brier Score	0.1542	0.0785	0.2170	0.1377	0.2164	0.1684	0.0559	0.1983	0.1778	0.1904
Dvar	0.1599	0.0815	0.2262	0.1426	0.2307	0.1796	0.0577	0.2092	0.2020	0.1974
Min Var	0.0007	0.0001	0.0006	0.0003	0.0009	0.0007	0.0001	0.0006	0.0040	0.0003
Scatter	0.0140	0.0035	0.0139	0.0073	0.0129	0.0103	0.0027	0.0099	0.0283	0.0087
Bias	4.8E-04	6.2E-05	2.9E-05	1.4E-04	8.6E-04	1.4E-04	4.2E-05	3.2E-05	1.6E-04	3.1E-05
2Cov	0.0208	0.0068	0.0237	0.0127	0.0290	0.0223	0.0047	0.0215	0.0566	0.0161

[25] DVAR is the variance of the 0-1 dummy variable
[26] COV is the covariance measure

Table 5.83: The Brier Score and the Yates Partition of the Brier Score: Logit Within-Sample

	Isotonics	Regular Soft Drinks	Diet Soft Drinks	High Fat Milk	Low Fat Milk	Fruit Drinks	Fruit Juices	Bottled Water	Coffee	Tea
Brier Score	0.1578	0.0824	0.2102	0.1407	0.2235	0.1701	0.0613	0.1938	0.1631	0.1910
Dvar	0.1724	0.0887	0.2266	0.1495	0.2378	0.1874	0.0646	0.2080	0.1942	0.2013
Min Var	0.0012	0.0004	0.0012	0.0005	0.0009	0.0017	0.0002	0.0010	0.0052	0.0005
Scatter	0.0133	0.0055	0.0148	0.0081	0.0134	0.0162	0.0033	0.0132	0.0270	0.0100
Bias	9.0E-16	0.0E+00	1.0E-16	0.0E+00	0.0E+00	1.0E-16	4.0E-16	4.0E-16	1.0E-16	0.0E+00
2Cov	0.0291	0.0123	0.0324	0.0174	0.0286	0.0351	0.0067	0.0283	0.0633	0.0208

Table 5.84: The Brier Score and the Yates Partition of the Brier Score: Logit Out-of-Sample

	Isotonics	Regular Soft Drinks	Diet Soft Drinks	High Fat Milk	Low Fat Milk	Fruit Drinks	Fruit Juices	Bottled Water	Coffee	Tea
Brier Score	0.1542	0.0785	0.2164	0.1377	0.2164	0.1684	0.0558	0.1982	0.1778	0.1905
Dvar	0.1599	0.0815	0.2262	0.1426	0.2307	0.1796	0.0577	0.2092	0.2020	0.1974
Min Var	0.0007	0.0001	0.0007	0.0003	0.0009	0.0007	0.0001	0.0006	0.0040	0.0003
Scatter	0.0141	0.0037	0.0140	0.0075	0.0129	0.0103	0.0030	0.0101	0.0286	0.0087
Bias	4.8E-04	6.2E-05	2.5E-05	1.4E-04	8.6E-04	1.4E-04	3.8E-05	3.4E-05	1.3E-04	3.1E-05
2Cov	0.0209	0.0069	0.0245	0.0129	0.0290	0.0223	0.0051	0.0217	0.0570	0.0161

The Brier Score

According to the calculated Brier score, fruit juices show the lowest Brier score followed by the second lowest, regular soft drinks (for both probit and logit models). In numbers, the Brier score value for fruit juices is 0.06 for within-sample estimates and it is 0.05 for out-of-sample estimates. One may sometimes erroneously conclude that out-of-sample forecasts are better, because they are associated with a low Brier score value. However, one must remember that the Brier score value can be decomposed into it covariance parts, which would provide a better explanation to the realized Brier score. This will be dealt in the next section.

The Brier score is associated with low-fat milk is 0.22 and 0.21 for within-sample and out-of-sample forecasts respectively. Notice that again the out-of-sample Brier score value for low-fat milk is lower than the within-sample value. However, the Brier score values calculated for diet soft drinks is 0.21 for within-sample forecasts and 0.22 for out-of-sample forecasts and it shows the opposite of the observation with respect to the Brier score we had with low-fat-milk. Other non-alcoholic beverages have varying values of the Brier score depending on the forecast probabilities and outcome index values observed for each observation. We did not observe for the most part a large discrepancy between the Brier score values generated for forecast probabilities using probit and logit models.

Even though the Brier score provides a simple yet rigorous number to compare forecast probabilities generated through alternative models, it does not tell anything about the calibration or resolution property of forecast probabilities. However, it is a good measure independent of cut-off probability values in sorting probabilities which were used in expectation-prediction success tables.

The Yates Partition of the Brier Score

Although the Brier score gives an overall indication of the ability of a model to forecast accurately, the components of the covariance decomposition provides a clearer and broader indication of the model's ability to forecast. In the following section we offer a discussion from the results obtained for the covariance decomposition of the Brier score applied to forecast probabilities generated through logit and probit models (both within-sample and out-of-sample). We compare and contrast values pertaining to different non-alcoholic beverages. Covariance decomposition includes the variance of the outcome index (DVar), minimum variance (Min Var), Scatter, Bias; covariance of forecast probabilities and outcome indexes (2cov).

Variance of the Outcome Index (DVar)

Variance of the outcome index is a measure that cannot be controlled through the model under consideration. It is determined through the behavior of the agent (purchasing behavior in our study). Market penetration value for a given non-alcoholic beverage or the number of individuals that actually purchased a non-alcoholic beverage has a direct leverage on the variance of the outcome index.

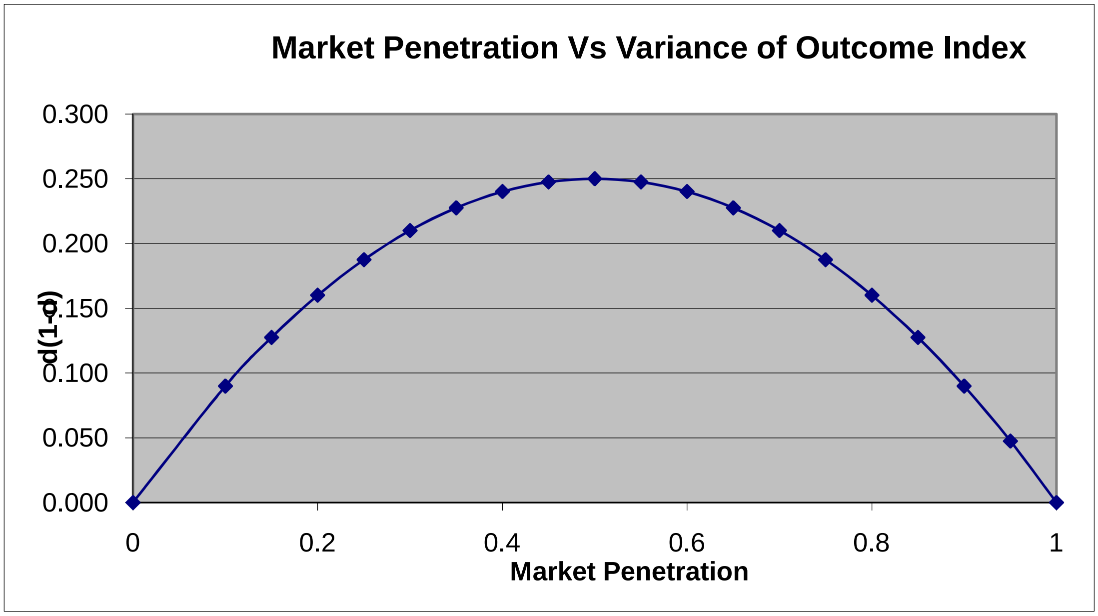

Figure 5.81: Market Penetration Versus Variance of Outcome Index

Figure 5.81 shows the plot of market penetration value against the variance of the outcome index. According that, highest variance value of the outcome index (0.25) could be observed for the market penetration value 0.50. Any other market penetration value is associated with the variance value less than 0.25. In our study, fruit juices have the highest market penetration value, which is 0.93. It is associated with the variance of outcome index 0.0651, which is the lowest variance of the outcome index reported. Highest variance of the outcome index is 0.23 which is reported for low-fat-milk and it is associated with a market penetration value 0.63 (close to 0.50). Therefore, the market penetration value which is outside the control of the forecasting model has a direct impact on the value of the calculated variance of the outcome index (*DVar*). Since variance of the outcome index is a component of the covariance decomposition of the Brier score, it has a direct influence on the calculated Brier score. Therefore, a highly inflated Brier score value may be a result of a contribution coming from a large variance of the outcome index. In our study, the highest Brier score value is reported for low-fat milk and it also has the highest variance value of the outcome index exhibiting the large contribution of the variance of the outcome index toward the Brier score.

Minimum Variance and Scatter

Unlike the variance of the outcome index *(DVar)*, variance of the forecast probabilities, i.e. $Var(f)$ is something that the forecasting model has control of. Variance of forecast probabilities is comprised two other variance components, namely the Minimum Variance and Scatter (Scatter is an indicator of overall noise of model generated probabilities). We would like to have small $Var(f)$ to be associated with a good probability forecast, hence lower scatter. It was made clear earlier that the Minimum Variance is the variability that is tolerated to have a positive slope of the covariance graph while minimizing scatter, then in tern minimizing $Var(f)$.

The highest Scatter is associated with coffee within-sample forecasts, which is 0.027. This is clear if one looks at the covariance graphs associated with coffee (see Figures 5.73, 5.74, 5.75, and 5.76). Coffee out-of-sample forecasts show slightly high Scatter (0.0283) compared to that of within-sample forecasts, indicating more spread of the forecast probabilities around their mean values.

We observe the lowest Scatter with forecast probabilities associated with fruit juices within-sample estimates, which is recorded at 0.0029. This result is evident in Figures 5.65, 5.66, 5.67, and 5.68, where the spread of forecast probabilities associated with outcome index one and zero are very small compared to that of for coffee.

Minimum Variance has a direct relationship with the Slope (defined as $\bar{f}_1 - \bar{f}_0$) where higher slope is associated with high Minimum Variance. The highest Slope is observed with respect to forecast probabilities associated with coffee, which is 0.16, hence largest Minimum Variance 0.0051 for within-sample forecasts. For out-of-sample forecasts we observe a low Minimum Variance, 0.0040, hence lower Slope (0.14) compared to within-sample forecasts. All other non-alcoholic beverages showed very small Minimum Variance values, hence very small slope indicating more flat covariance graphs.

Bias

The overall mis-calibration of the forecast is captured through Bias component of the covariance decomposition of the mean probability score. Put it differently, it the ability of the model to match mean forecasts to relative frequencies. Bias contributes positively to the probability score similar to what we observed for the variance of outcome index, Scatter and Minimum Variance. Therefore, the model has to minimize the Bias in evaluating forecast probabilities. It is clear from Tables 5.81 through 5.84 that the Bias associated with the covariance decomposition if very small (almost negligible) compared to other part of the covariance decomposition. It must be emphasized that for all non-alcoholic beverages considered, the Bias associated with out-of-sample forecasts are relatively larger than those of within-sample forecasts. This is indicative of presence of more mis-calibration with respect to out-of-sample generated probability forecasts compared to those generated within-sample. We did not observe a large difference associated with Bias values generated in probit models compared to logit model. Overall, we should emphasize that the contribution of the Bias toward the Brier score is very minimal in our analysis.

Covariance of Forecast Probabilities and Outcome Index (2cov)

Covariance of forecast probabilities and outcome index is the most important part of the forecasting property of a model. Covariance enters negatively to the Yates partition of the probability score; hence in order to get a low Brier score, we need to maximize the value associated with covariance.

Highest covariance value is associated with coffee within-sample forecasts obtained from logit model. Covariance value obtained from out-of-sample forecast probabilities is slightly lower than that of within-sample counterpart, indicating better forecasts obtained from within-sample forecasts compared to out-of-sample forecasts. Also, we observed that the logit model did beat the probit model in both scenarios. Notice that if one considered the covariance of forecast probabilities and outcome index to comment on the forecasting ability of a model, probability forecasts associated with coffee outperforms forecasts for other beverages. However, coffee has a higher Brier score compared to other beverages. On the other hand, fruit juices not only have the lowest Brier score but also the lowest covariance of forecast probabilities and outcome index. Even though the low Brier score is in favor of better forecasting ability, low covariance of forecast probabilities and outcome index is an indication of poor forecasting performance.

We also find relatively higher covariance values associated with fruit drinks, diet soft drinks and bottled water for both within-sample and out-of-sample forecasts for both probit and logit models even though they were not necessarily associated with low Brier score s. In terms of calculated covariance of forecast probabilities and outcome index, we can order the non-alcoholic beverages considered in the study from the best to the worst probability forecasts as follows: coffee; fruit drinks; diet soft drinks; isotonics; low-fat milk; bottled water; tea; regular soft drinks; high-fat milk; and fruit juices (this ordering is consistent with probit and logit models for within and out-of-sample forecasts).

However, use of the Brier score gives us a different result. According to the Brier score, we can order the goodness of probability evaluations for different non-alcoholic beverages in the following order: fruit juices; regular soft drinks; high-fat milk; isotonics; coffee; fruit drinks; tea; bottled water; diet soft drinks; and low-fat milk (this ordering is consistent with probit and logit models for within and out-of-sample forecasts).

Therefore, use of just the Brier score to comment on the goodness of the probability forecasts can be misleading because the results may be different if one had partitioned the Brier score into its covariance components. Such decomposition will introduce more accuracy to forecast evaluation and therefore correct decision making.

According to equation 5.22, we can observe the relationship with $Cov(f,d)$ and $MinVar(f)$ for forecast probabilities generated for decision to purchase non-alcoholic beverages. Coffee has the highest $Cov(f,d)$ and highest $MinVar(f)$ for probit and logit models (for both within-sample and out-of-sample forecasts). It also has the highest calculated Slope (0.16). On the other hand, fruit juices has the lowest $Cov(f,d)$ and lowest $MinVar(f)$ hence the lowest Slope (0.04) for both probit and logit models (both within-sample and out-of-sample forecasts).

Therefore we can conclude that, in terms of the Yate's partition of the Brier score, probit and logit models do an excellent job in generating probability forecasts with respect to coffee and do a very poor job in generating probability forecasts for fruit juices. Probability forecasts generated for other non-alcoholic beverages lie somewhere in-between the probability forecasts generated for coffee and fruit juices.

Despite the fact that Yate's partition of the Brier score does an exceptional job in evaluating probability forecasts, we are not in a position to test the numbers statistically, because sampling distributions of these decompositions are yet to be derived.

CHAPTER VI

DEMAND FOR NON-ALCOHOLIC BEVERAGES IN THE UNITED STATES: INTERRELATIONSHIPS, DYNAMICS AND HABITS

In this chapter, we discuss the methodology, data analysis and discussion with respect to the *demand systems study*. We focus our attention on three major pieces. They are, demand interrelationships, dynamics and habits in the consumption of non-alcoholic beverages by U.S. consumers. A modified version (linear approximation) of the Quadratic Almost Ideal Demand System (LA/QUAIDS) (Banks, Blundell, and Lewbel, 1997, and Matsuda, 2006), Barten's Synthetic Model (BSM) (Barten 1993 and Matsuda, 2005) and State Adjustment Model (SAM) (Houthakker and Taylor, 1970 and Capps and Nayga, 1990) are used to capture interrelationships and dynamics of demand for non-alcoholic beverages. Dominance of habit formation or inventory behavior in consumption of non-alcoholic beverages is captured through the State Adjustment Model. We offer some commentary on nutrition policy (such as tax on sugar-sweetened beverages) and its effect on non-alcoholic beverage choices. Also, we offer a section on comparing own-price, cross-price and expenditure sensitivity values recovered from each model. Finally, we offer a brief comparison of our results with previous studies in the literature.

Demand for Non-alcoholic Beverages: Linear Approximated Quadratic Almost Ideal Demand System (LA/QUAIDS) Model

In the following section we first discuss the theoretical (model) development with respect to the QUAIDS and its linearized version (LA/QUAIDS) model. We explain the desirable properties of QUAIDS and LA/QUAIDS over AIDS and LA/AIDS models of Deaton and Muellbauer (1980). Next we offer a narrative on data analysis related to our work on estimating demand for non-alcoholic beverages in a systemwide framework. Our analysis concentrates on estimating the LA/QUAIDS model imposing theoretical restrictions from the demand theory, such as adding-up, homogeneity and symmetry. We also discuss the auxiliary regression run to handle the endogeneity issue with respect to the total expenditure variable. Methods to appropriately deal with the autocorrelation issue also are discussed.

Theoretical Development

We use the QUAIDS model developed by Banks, Blundell and Lewbel (1997) applying a linearized version suggested by Matsuda (2006) to capture interrelationships among non-alcoholic beverage categories. The QUAIDS model not only nests the popular almost ideal demand system of Deaton and Muellbauer (1980), but also retains all of the desirable properties of the AIDS model.

In addition, the QUAIDS model is more versatile in modeling consumer expenditure patterns (Matsuda, 2006). In particular, QUAIDS model gives rise to Engel curves that are quadratic (nonlinear) in the logarithm of total expenditure in contrast the popular AIDS model which gives rise to Engel curves that are linear in the logarithm of total expenditure. This feature of the QUAIDS model introduces more flexibility to the demand system. Furthermore, the expenditure elasticity depends on the level of expenditure for QUAIDS model. However, in the AIDS model, the elasticity is independent of expenditure level.

After the development of QUAIDS model by Banks, Blundell and Lewbel (1997), it has been used widely in various demand system estimation studies due to its useful properties over AIDS model. Some of the past studies that used QUAIDS model are

Blundell and Robin (1999 and 2000), Michelini (1999 and 2001), Deaton et al. (1999), Fisher et al. (2001), Moro and Sckokai (2000), Luo (2002), Lyssiotou et al. (2002), Tiezzi (2002), Cranfield et al. (2003), Lyssiotou (2003), Nicol (2003), Abdulai and Aubert (2004), Unayama (2004), Karagiannis and Velentzas (2004), Dhar and Foltz (2005) and Matsuda (2006). According to Matsuda (2006) in most of above studies the quadratic terms of the system were found to be important in explaining consumer behavior.

Some of the past work has been done using the full version of QUAIDS (not a linearized version) and owing to the capacity of computers we have at the current time it was not a problem to estimate a highly non-linear model like QUAIDS. However, just as with the linearized version of the AIDS model, at the estimation stage, some studies have used a linearized version of the QUAIDS model. In our work, we use a linearized version of QUAIDS model because we have a limited number of observations with which to deal (we have only 72 monthly observations of total expenditure and quantity of each non-alcoholic beverage considered). With that many observations, if we had used the full non-linear version of QUAIDS model, we would have run into a degrees-of-freedom problem. That is to say, number of parameters to estimate outnumbers the number of observations. Therefore, we used a linearized version of the QUAIDS model. It should be noted that there are different ways to linearize the QUAIDS model. We have used a version suggested by Matsuda (2006) (to be explained below).

Quadratic Almost Ideal Demand System (QUAIDS)

The following discussion on the QUAIDS model and its linear approximations is borrowed heavily from Banks, Blundell and Lewbel (1997), Diewert (1987) and Matsuda (2006).

The indirect utility function of the QUAIDS model can be specified as follows:

(6.1) $$\ln V(\mathbf{p}, y) = \left\{ \left[\frac{\ln m - \ln f(\mathbf{p})}{g(\mathbf{p})} \right]^{-1} + \lambda(\mathbf{p}) \right\}^{-1}$$

where $\mathbf{p} = (p_1, p_2 ..., p_n)$ is the price vector of n goods and m denotes the total expenditure of the goods. Distinct price aggregator functions $f(\mathbf{p})$, $g(\mathbf{p})$ and $\lambda(\mathbf{p})$ are defined as follows. In particular, $f(\mathbf{p})$ has the translog form:

(6.2) $$\ln f(\mathbf{p}) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1} \gamma_{ij} \ln p_i \ln p_j$$

and $g(\mathbf{p})$ is the simple Cobb-Douglas price aggregator term defined below:

(6.3) $$g(\mathbf{p}) = \prod_{i=1}^{n} p_i^{\beta_i}$$

or alternatively above Cobb-Douglas price aggregator term can be defined in *log-log* form as follows (Matsuda, (2006):

(6.4) $$\ln g(\mathbf{p}) = \beta_0 + \sum_{i=1}^{n} \beta_i \ln p_i$$

and $\lambda(\mathbf{p})$ is defined as follows:

(6.5) $$\lambda(\mathbf{p}) = \lambda_0 + \sum_{i=1}^{n} \lambda_i \ln p_i$$

It must be noted that $f(\mathbf{p})$ is homogeneous of degree one in $\mathbf{p}$ and $g(\mathbf{p})$ and $\lambda(\mathbf{p})$ are homogeneous of degree zero in $\mathbf{p}$, satisfying that $V(\mathbf{p}, m)$ is homogeneous of degree zero in $\mathbf{p}$ and m, as required.

According to Banks, Blundell and Lewbel (1997), $\left[\frac{\ln m - \ln f(\mathbf{p})}{g(\mathbf{p})} \right]$ is the indirect utility function of a demand system with budget shares which are linear in log of total expenditure (such demand systems are called price independent generalized logarithmic (PIGLOG) demand systems). The popular AIDS model of Deaton and Muellbauer (1980) falls into the PIGLOG category. However, the QUAIDS model has an extra term $\lambda(\mathbf{p})$ which is differentiable, and homogeneous of degree zero in prices $\mathbf{p}$. Notice when $\lambda(\mathbf{p})$ is independent of prices, the indirect utility function associated with QUAIDS model reduces to an indirect utility function of a PIGLOG system like AIDS model. The presence of $\lambda(\mathbf{p})$ introduces non-linearity into the QUAIDS system compared to the AIDS system where $\lambda(\mathbf{p})$ is not present. Using Roy's identity from equation (6.1):

$$(6.6) \qquad w_i = -\left(\frac{\partial \ln V / \partial \ln p_i}{\partial \ln V / \partial \ln m} \right)$$

from equation (6.6) we can derive the following:

$$(6.7) \qquad w_i = \frac{\partial \ln f(\mathbf{p})}{\partial \ln p_i} + \frac{\partial \ln g(\mathbf{p})}{\partial \ln p_i}\left(\ln m - \ln f(\mathbf{p})\right) + \frac{\partial \lambda}{\partial \ln p_i}\frac{1}{g(\mathbf{p})}\left(\ln m - \ln f(\mathbf{p})\right)^2$$

where w_i is the budget share (expenditure share) of the *i*th good. Further simplification of equation (6.7) results in the familiar form of the QUAIDS model:

$$(6.8) \qquad w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{m}{f(\mathbf{p})}\right] + \frac{\lambda_i}{g(\mathbf{p})}\left\{\ln\left[\frac{m}{f(\mathbf{p})}\right]\right\}^2$$

where $i = 1,2,3,......., n$.

To satisfy the theoretical properties associated with demand theory, restrictions on parameters of QUAIDS model are necessary. Restrictions imposed are, adding-up:

$$(6.9) \qquad \sum_{i=1}^{n} \alpha_i = 1$$

(6.10) $\sum_{i=1}^{n} \beta_i = 0$

(6.11) $\sum_{i=1}^{n} \lambda_i = 0$

(6.12) $\sum_{i=1}^{n} \gamma_{ij} = 0,$

where $j = 1,2,.....,n$

and homogeneity:

(6.13) $\sum_{j=1}^{n} \gamma_{ij} = 0,$ where $i = 1,2,.....,n$

Slutsky symmetry conditions are satisfied via the restriction:

(6.14) $\gamma_{ij} = \gamma_{ji}$ for $i, j = 1,2,......,n$

Due to the additional terms in the equation (6.8) compared to the AIDS model (above QUAIDS model represented in equation (6.8) turns into AIDS model if λ_i is statistically not different from zero), expressions to calculate elasticity (own-price, cross-price and expenditure both uncompensated and compensated) differs from what is suggested by Green and Alston (1990). Differentiating equation (6.8) with respect to both $\ln m$ and $\ln p_j$ respectively we obtain following expressions μ_i and μ_{ij} :

(6.15) $$\frac{\partial w_i}{\partial \ln m} \equiv \mu_i = \beta_i + \frac{2\lambda_i}{g(\mathbf{p})}\left\{\ln\left[\frac{m}{f(\mathbf{p})}\right]\right\}$$

(6.16) $$\frac{\partial w_i}{\partial \ln p_j} \equiv \mu_{ij} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum_{k=1}^{n} \gamma_{jk} \ln p_k\right) - \frac{\lambda_i \beta_j}{g(\mathbf{p})}\left\{\ln\left[\frac{m}{f(\mathbf{p})}\right]\right\}^2$$

Next, aforementioned expressions (6.15) and (6.16) are used to calculate expressions for elasticities. Expenditure elasticity e_i is calculated as:

(6.17) $e_i = \dfrac{\mu_i}{w_i} + 1$

The specific feature of expenditure elasticity formula of QUAIDS model over regular AIDS model suggested by Deaton and Muellbauer (1980) is that the expenditure elasticity calculated from the latter model does not depend on the expenditure. However, expenditure elasticity calculated from QUAIDS model depends on the expenditure due to the presence of λ_i (see equation 6.15). Therefore, the QUAIDS model allows more flexibility in the calculation of expenditure elasticities. Uncompensated price elasticities e_{ij}^{u} are calculated as:

(6.18) $e_{ij}^{u} = \dfrac{\mu_{ij}}{w_i} - \delta_{ij}$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1 \ if i = j$ and $\delta_{ij} = 0 \ if i \neq j$). We recover the compensated price elasticities e_{ij}^{c} using the Slutsky derivative expressed in elasticity form as follows:

(6.19) $e_{ij}^{c} = e_{ij}^{u} + e_i w_j$

Next, following expression in equation (6.20) was used to recover symmetric values of compensated cross-price elasticity estimates:

(6.20) $e_{ij}^{c} = \left(\dfrac{w_j}{w_i} \right) e_{ji}^{c} + w_j (e_j - e_i)$

where w 's are budget shares of *i*th and *j*th good and, e_j and e_i are expenditure elasticities of *j*th and *i*th good respectively. We show the detailed steps of above derivations in the Appendix 5.

Linear Approximated Quadratic Almost Ideal Demand System (LA/QUAIDS)

The following discussion on linear approximations to the QUAIDS model is primarily borrowed from Diewert (1987), Moschini (1995) and Matsuda (2006).

To make the QUAIDS model linear at the estimation stage, we need to replace both the translog price aggregator term, i.e. $f(\mathbf{p})$ and the Cobb-Douglas price aggregator term, i.e. $g(\mathbf{p})$ of equation 6.8 with composite variables which do not depend on unknown parameters. The most common composite variable for the approximation of $f(\mathbf{p})$ used was the Stone's (geometric) price index $\ln h(\mathbf{p}^*)$ (Deaton and Muellbauer, 1980):

(6.21) $$\ln h(\mathbf{p}^*) = \sum_{i=1}^{n} w_i \ln p_i$$

In our analysis we used a one-period lag value for the budget shares in equation (6.21) to avoid any contemporaneous correlation between the budget share in the Stone's price index and the dependent variable, w_i. Hence the modified Stone's price index that was used in our work is as follows:

(6.22) $$\ln h(\mathbf{p}^*) = \sum_{i=1}^{n} w_{it-1} \ln p_{it}$$

We used the Stone's price index in our work to approximate the translog price aggregator term. However, Matsuda (2006) has suggested alternative price indexes such as Tornqvist[27], Paasche and Laspeyres to be used in lieu of Stone's price index, because

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[27] Tornqvist price index P^T is specified as $\ln P^T = 0.5\sum_i (\overline{w}_i - \overline{w}_i^0)\ln(p_i - p_i^0)$. The log-linear analog of Paasche index is specified as $\ln P^S = \sum_i \overline{w}_i \ln(p_i - p_i^0)$ and the log-linear analog of Laspeyres index is specified as $\ln P^C = \sum_i \overline{w}_i^0 \ln p_i$. All of these price indexes are exact for a linearly homogeneous Cobb-Douglas aggregator function (Diewert, 1981 and Matsuda, 2006). Equation (6.23) uses a zero degree homogeneous version of P^T (Matsuda, 2006).

Stone's price index is influenced by changes in units of measurements. Moshini (1995) made a similar argument. Nevertheless, we used the Stone's price index since units of measurements were consistent in our analysis across ten non-alcoholic beverage categories (all quantities are measured in gallons and price is measured through dollars per gallon).

The Cobb-Douglas price aggregator term of QUAIDS model (equation (6.8)) was linearized through price index suggested by Diewert (1987) and Matsuda (2006). It is as follows:

$$(6.23) \quad \ln P^Z = \sum_{i=1}^{n} (\overline{w}_{it} - \overline{w}_{it}^0)(\ln p_{it} - \ln p_{it}^0)$$

The superscript zero associated with budget shares and prices represent the base budget share and base price value respectively. One can use any specific observation period for the base (say the first observation or midpoint observation, etc). However, Diewert (1987) suggested the use of values at time $(t-1)$ as the base for time t, which he called the "chained principle". We used one-period lag value of expenditure shares as the observation and two-period lag value of expenditure shares as the base value. Therefore, the workable form of equation (6.23) is written below:

$$(6.24) \quad \ln P^Z = \sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^0)(\ln p_{it-1} - \ln p_{it-2}^0)$$

We used the price index suggested by equation (6.24) along with Diewert's (1987) chained principle to linearize the Cobb-Douglas price aggregator term in the QUAIDS model.

Equation 6.25 shows the linear approximated version of the QUAIDS model, i.e. LA/QUAIDS. We used LA/QUAIDS model in our analysis in estimating the demand for non-alcoholic beverages in the United States:

$$(6.25)\quad \begin{aligned} w_{it} &= \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_{it}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{ti}\right] + \\ &\frac{\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right]^2 \end{aligned}$$

Differentiating equation (6.23) with respect to income and price results in the following:

$$(6.26)\quad \frac{\partial w_i}{\partial \ln m} \equiv \mu_i = \beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right)$$

$$(6.27)\quad \begin{aligned} \frac{\partial w_i}{\partial \ln p_j} &\equiv \mu_{ij} = \gamma_{ij} - \mu_i w_{jt-1} - \\ &\frac{\lambda_i (\overline{w}_{jt-1} - \overline{w}_{jt-2}^{0})}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right)^2 \end{aligned}$$

Plugging in equations (6.26) and (6.27) in equation (6.17) and equation (6.18) results in the formula for expenditure and compensated price elasticities. Detailed derivations of expenditure and uncompensated price elasticity formula are given in the Appendix 5. Next we used the Slutsky symmetry condition to recover compensated price elasticities. We used compensated cross price elasticities to assess the symmetry conditions using equation (6.20).

It should be noted that above linear approximation is used at the estimation stage for practical convenience. Linearized forms are not integrable to recover the underlying utility function unless restrictive constraints are imposed to remove the flexibility arising from linearization.

Serial Correlation of Disturbance Terms in a System of Equations

Serial correlation of disturbance terms (or when one uses time-series data sets it is more popularly known as autocorrelation of disturbance terms) is a diagnostic test a system of equation must pass to give rise to efficient parameter estimates (similar to single-equation regression models). However, in a system of equations, in addition to serially correlated disturbances, we also observe contemporaneous cross correlation in disturbance terms.

The problem of efficient estimation of system of regression equations in the case where disturbances are contemporaneously correlated was first considered by Zellner (1962). In Zellner (1962) and in other subsequent papers such as Zellner (1963), Zellner and Huang (1962), Zellner and Theil (1962), and Telser (1964) the presence of serial correlation among disturbance terms had not been addressed (Parks, 1967). Subsequently, Parks (1967) introduced a more general covariance specification to the disturbance structure which included both serial correlation and contemporaneous correlation in disturbances. Berndt and Savin (1975) formalized the fix for serial correlation in a system of equations introducing autoregressive disturbances of order one (or $AR(1)$ process). Historically, most of the studies have used an $AR(1)$ process in modeling autoregressive disturbances in correcting for serial correlation in demand systems.

Let $\mathbf{W}_t$ is a vector of expenditure shares, $\mathbf{X}_t$ is a vector of explanatory variables such as prices for different goods, $\mathbf{\Pi}$ is a matrix of parameters that we estimate through the demand system, $\mathbf{V}_t$ is a vector of contemporaneous disturbance terms, $\mathbf{V}_{t-1}$ is a vector of disturbance terms lagged period one, $\mathbf{R}$ is a matrix of autocorrelation coefficients($\rho' s$) and $\boldsymbol{\varepsilon}_t$ is a vector of white noise disturbance terms (non-autocorrelated vector of disturbance terms with a constant variance matrix). We can write the demand systems model and autoregressive disturbances of order one in matrix form as follows:

(6.28) $\mathbf{W}_t = \mathbf{\Pi X}_t + \mathbf{V}_t$

(6.29) $\mathbf{V}_t = \mathbf{R V}_{t-1} + \boldsymbol{\varepsilon}_t$

Modifying equation (6.28) to represent a one-period lag and pre-multiplying by through matrix $\mathbf{R}$ give rise to the following equation:

(6.30) $\mathbf{R W}_{t-1} = \mathbf{R \Pi} X_{t-1} + \mathbf{R V}_{t-1}$

Subtracting equation (6.30) from equation (6.28) and adjusting for budget shares results in the following equation (this is in fact our estimating equation taking care of the serial correlation problem):

(6.31) $\mathbf{W}_t = \mathbf{R W}_{t-1} + \mathbf{\Pi X}_t - \mathbf{R}(\mathbf{\Pi X}_{t-1}) + \boldsymbol{\varepsilon}_t$

The matrix $\mathbf{R}$ can be expressed the following way, where ρ_{ij} s are autocorrelation coefficients:

(6.32) $R = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1} & \rho_{n2} & \cdots & \rho_{nn} \end{bmatrix}$

and adding-up of the expenditure shares implies the following restrictions on ρ :

(6.33) $\rho_{1i} + \rho_{2i} + \rho_{3i} + \cdots + \rho_{ni} = k$

where k is a constant and $i = 1,2,3,\cdots,n$

Berndt and Savin (1975) showed that if one assumes no cross-equation autocorrelation, (i.e., $\mathbf{R}$ is diagonal), the autocorrelation coefficient for each equation must be identical. That is to say:

(6.34) $\rho_{11} = \rho_{22} = \rho_{33} = \cdots = \rho_{nn} = \rho$

Now, let us assume that our budget share equation is given as follows:

(6.35) $w_{it} = f(x_{it}, \beta) + v_{it}$

where $i = 1,2,....,n$ and $t = 1,2,......,T$,

w_{it} is the budget share, x_{it} is the list of explanatory variables, β is unknown parameters, and v_{it} is the serially and contemporaneously correlated disturbance term. If error terms follow an *AR(1)* process, it can be shown as follows:

(6.36) $v_{it} = \rho v_{it-1} + \varepsilon_{it}$

where v_{it-1} is the serially and contemporaneously correlated disturbance term lag period one, ε_{it} is the white noise disturbance term, and ρ is the autocorrelation coefficient. Combining above equation (6.35) and equation (6.36), the estimating equation can be written as follows:

(6.37) $w_{it} = \rho w_{it-1} + f(x_{it}, \beta) - \rho f(x_{it-1}, \beta) + \varepsilon_{it}$

Equation (6.37) also can be written for more general *n*th order autoregressive disturbance terms:

(6.38) $w_{it} = \sum_{k} \rho_k w_{it-k} + f(x_{it}, \beta) - \sum_{k} \rho_k f(x_{it-k}, \beta) + \varepsilon_{it}$

Data Analysis and Discussion

We employed a linear approximation to the QUAIDS model developed by Banks, Blundell and Lewbel (1997) and Matsuda (2006) to capture interrelationships among ten non-alcoholic beverage categories. Expenditure, own-price and cross-price demand elasticities (both uncompensated and compensated) were estimated for the ten non-alcoholic beverage categories over the 72-month period. We posited the following LA/QUAIDS model with an additive disturbance term and a seasonal adjustment using quarterly seasonal dummies:

$$
\begin{aligned}
w_{it} &= \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_{it}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{ti}\right] + \\
&\quad \frac{\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^0_{it-2})(\ln p_{it-1} - \ln p^0_{it-2})}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right]^2 + \\
&\quad \sum_{j=1}^{3} d_j Q_{ijt} + e_{it}
\end{aligned}
\tag{6.39}
$$

where $i = (1,2,.....,10)$ indexes ten non-alcoholic beverages categories in the system, t indexes the time in months, i.e. $t = (1,2,3,.......,72)$ p_{jt} is monthly real prices for each non-alcoholic beverage considered in study, m is the real per capita total expenditure calculated using real price, p_{jt} and per capita quantity consumed in each non-alcoholic beverage, q_{it} . Q_{ijt} is the quarterly dummy used to capture the seasonality pertaining to four quarters of the year. Monthly budget shares of each non-alcoholic beverage consumed is denoted by w_{it} where $w_{it} = \frac{p_{it} q_{it}}{m}$. The additive disturbance term is denoted by e_{it} .

In estimating the LA/QUAIDS model, we imposed theoretical restrictions on parameters explained in equation (6.9) through equation (6.14) (adding-up, homogeneity and Slutsky symmetry). Given the fact that all expenditure shares add up to one, i.e. $\sum_{i=1}^{10} w_{it} = 1$, and above adding up conditions, we estimated the LA/QUAIDS model with only 9 equations (dropping the budget share equation pertaining to tea consumption) to avoid the singularity of the error variance-covariance matrix. The parameters of the tea budget share equation were recovered using adding-up restrictions.

The model was estimated using SAS 9.2 statistical software. We used the Proc Model procedure to estimate model parameters and subsequently to calculate expenditure, own-price and cross-price elasticities. A possible endogeneity issue with the real per capita total expenditure was removed through predictions of real per capita total expenditure (*m_hat*) obtained through an auxiliary regression. In the auxiliary regression, natural log of per capita real total expenditure was regressed on two instruments; natural log of real price, $\ln p_{jt}$ and natural log of real per capita income, $\ln inc_{it}$ using Proc Autoreg procedure in SAS 9.2 (Proc Autoreg procedure in SAS takes care of possible serial correlation problem in the auxiliary regression). Random disturbance term in the auxiliary regression is denoted by k_{it}. Thus predicted values were used as real per capita total expenditure in the LA/QUAIDS model (variable *m* in equation (6.28)). The auxiliary regression used is as follows:

(6.40) $$\ln m_{it} = c_0 + \sum_{j=1}^{n} c_{ij} \ln p_{jt} + c_{11} \ln inc_{it} + k_{it}$$

Furthermore, we corrected above auxiliary regression for autocorrelation with an *AR(1)* process of the disturbance term.

Presence of possible autocorrelation (serial correlation) was examined through the autocorrelation and partial autocorrelation function. It must be emphasized that the Durbin-Watson statistic could not be used to test for serial correlation due the presence of lag of dependent variable (expenditure share in our work) amongst the explanatory variables in the LA/QUAIDS model. Alternatively, the test statistic suggested for such situations, i.e. Durbin-*h* statistic could not be used due to the fact that Durbin-*h* statistic broke down for situations where the product of the number of observations and variance of the estimated coefficient associated with the lagged dependent variable exceeded unity[28].

Calculated autocorrelation and partial autocorrelation functions of the residuals of all non-alcoholic beverages indicated the presence of possible serial correlation. A close study of these functions indicated the presence of second-order or third-order autoregressive process of disturbance terms in the system. Therefore, each system was fitted with first- second- and third-order autoregressive process of disturbance terms and the significance of autocorrelation coefficients was examined. Through this exercise, we found that disturbance terms behave as an *AR(2)* process. Thus LA/QUAIDS model was fitted assuming the disturbance process was:

(6.41) $e_{it} = \rho_{i1} e_{i,t-1} + \rho_{i2} e_{i,t-2} + u_{it}$

where ρ_{i1} and ρ_{i2} are fist and second order autoregressive parameters respectively. The white-noise disturbance term is denoted by u_{it} which is independently and identically

[28] Durbin-*h* statistic is calculated as follows:
$h = \left(1 - \frac{1}{2} d\right)\sqrt{\frac{T}{1 - T * Var(\hat{\beta}_i)}}$ where d is the Durbin-Watson statistic, T is the total number of observations, $Var(\hat{\beta}_i)$ is the variance of the estimated coefficient. Note that, if $T * Var(\hat{\beta}_i) > 1$ the test breaks down.

distributed with zero mean and constant variance. Ultimately the estimating form of the LA/QUAIDS model taking into account *AR(2)* disturbances can be written as follows:

$$
\begin{aligned}
w_{it} &= \rho_1 w_{it-1} + \rho_2 w_{it-2} + \\
&\left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt} + \beta_{it} \left[\ln m - PS_t \right] + \frac{\lambda_i}{PZ_t} \left[\ln m - PS_t \right]^2 \right\} - \\
&\rho_1 \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt-1} + \beta_{it} \left[\ln m - PS_{t-1} \right] + \frac{\lambda_i}{PZ_{t-1}} \left[\ln m - PS_{t-1} \right]^2 \right\} - \\
&\rho_2 \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jt-2} + \beta_{it} \left[\ln m - PS_{t-2} \right] + \frac{\lambda_i}{PZ_{t-2}} \left[\ln m - PS_{t-2} \right]^2 \right\} + \\
&\sum_{j=1}^{3} d_j Q_{ijt} + e_{it}
\end{aligned}
\tag{6.42}
$$

$$PS = \sum_{i=1}^{n} w_{it-1} \ln p_{it} \tag{6.43}$$

and

$$PZ = \sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^{0}_{it-2})(\ln p_{it-1} - \ln p^{0}_{it-2}) \tag{6.44}$$

The magnitude of calculated cross-price elasticities does not tell the entire story about the strength of substitutability or complementarity of non-alcoholic beverages under consideration, because the elasticity formulae depend on the budget share of the good. A better measure of the strength of substitutability or complementarity can be obtained through a measure called the Diversion Ratio (DR). Diversion ratios pertain to the change of the volume of one good to a change in the volume of another good. Mathematically, DR is expressed as follows (see the Appendix 5 for a complete derivation of DR):

$$DR_{ji} = \frac{e_{ji}}{e_{ii}} \frac{\overline{q}_j}{\overline{q}_i} \tag{6.45}$$

where e_{ji} is the cross-price elasticity of demand between goods j and i; e_{ii} is the own-price elasticity of demand of good i; $\overline{q}_j$ is the average volume consumed in good j; and $\overline{q}_i$ is the average volume consumed in good i. Negative signs associated with DR would tell us the decrease in volume of one good due to an increase in the volume of another good (and vice versa), hence substitutability between goods. On the other hand, a positive sign associated with DR tells us about the decrease in the volume of one good due to a decrease in the volume of another good (and vice versa), hence the complementarity between goods.

Summary Statistics

Table 6.1 shows the summary statistics for quantity (per capita gallons/month), real price (dollars/gallon) and budget shares for the data used in this study. The most heavily consumed non-alcoholic beverage per month at home was coffee on per-capita basis (0.93 gallons per person per month). Coffee was followed by regular soft drinks (non-diet type) where 0.91 gallons per person per month was consumed. At-home per capita high-fat and low-fat milk consumption per month on average was 0.53 gallons and 0.38 gallons respectively. On average, per capita bottled water consumption at home was 0.35 gallons per month. Isotonics (for example Gatorade) was the least consumed non-alcoholic beverage at home, were only about 0.03 gallons per person per month.

Table 6.1: Quantity (per capita gallons/month), Real Price ($/gallon) and Budget Share Summary Statistics: January 1998 through December 2003

		Mean	Std Dev[29]	Minimum	Maximum
Per Capita Quantity gallons/month	Isotonics	0.03	0.013	0.01	0.06
	Regular soft drinks	0.91	0.126	0.66	1.24
	Diet soft drinks	0.56	0.060	0.45	0.72
	High fat milk	0.53	0.061	0.39	0.67
	Low fat milk	0.38	0.069	0.26	0.53
	Fruit drinks	0.23	0.037	0.15	0.29
	Fruit juice h	0.45	0.053	0.34	0.55
	Bottled water	0.35	0.072	0.19	0.52
	Coffee	0.93	0.128	0.67	1.15
	Tea	0.34	0.034	0.28	0.42
Real Price $/gallon	Isotonics	2.55	0.177	2.24	3.01
	Regular soft drinks	1.38	0.046	1.28	1.48
	Diet soft drinks	1.38	0.045	1.30	1.49
	High fat milk	1.60	0.061	1.49	1.76
	Low fat milk	1.59	0.057	1.47	1.74
	Fruit drinks	1.91	0.083	1.75	2.06
	Fruit juice	2.45	0.068	2.29	2.59
	Bottled water	0.78	0.049	0.66	0.86
	Coffee	0.61	0.064	0.52	0.75
	Tea	0.78	0.045	0.68	0.91
Budget Share[30]	Isotonics	0.01	0.004	0.01	0.02
	Regular soft drinks	0.20	0.013	0.17	0.23
	Diet soft drinks	0.13	0.006	0.11	0.14
	High fat milk	0.14	0.007	0.12	0.15
	Low fat milk	0.10	0.009	0.08	0.12
	Fruit drinks	0.07	0.009	0.05	0.09
	Fruit juice	0.18	0.013	0.15	0.20
	Bottled water	0.05	0.015	0.02	0.08
	Coffee	0.09	0.011	0.07	0.11
	Tea	0.04	0.005	0.03	0.05
	Per capita real total expenditure, $/month	1.82	0.122	1.49	2.06

[29] Std Dev is Standard Deviation
[30] Budget shares may not add up to one due to rounding.

Isotonics and fruit juices were the most expensive non-alcoholic beverages consumed during the period considered. They were, on average, $2.55 per gallon and $2.45 per gallon respectively. Coffee was the least expensive non-alcoholic beverage at $0.61 per gallon on average.

The highest budget share is associated with consumption of regular soft drinks at home (20%), and the lowest budget share is associated with isotonics (1%). The average budget share for fruit juice stands at second highest. Per capita real total expenditure for all of the ten non-alcoholic beverages consumed at home was on average $1.82 per month.

Trends in Budget Shares and Seasonality

Figures 6.1 through 6.10 shows the trends in budget shares of non-alcoholic beverages considered in our study from January 1998 through December 2003 (on a monthly basis). Budget shares pertaining to isotonics, regular soft drinks, low-fat milk and coffee trend down over the period. Fruit drinks, bottled water and tea exbit upward trends in budget shares. Diet soft drinks show a downward trend to start with, but then turn upward from February 2001. The budget share associated with high-fat milk does not trend upward or downward from January 1998 to June 2002; thereafter it shows a slight downward trend. Fruit juices budget shares show a slight upward trend from the beginning up to January 2000, dropping thereafter over the remainder of the sample period.

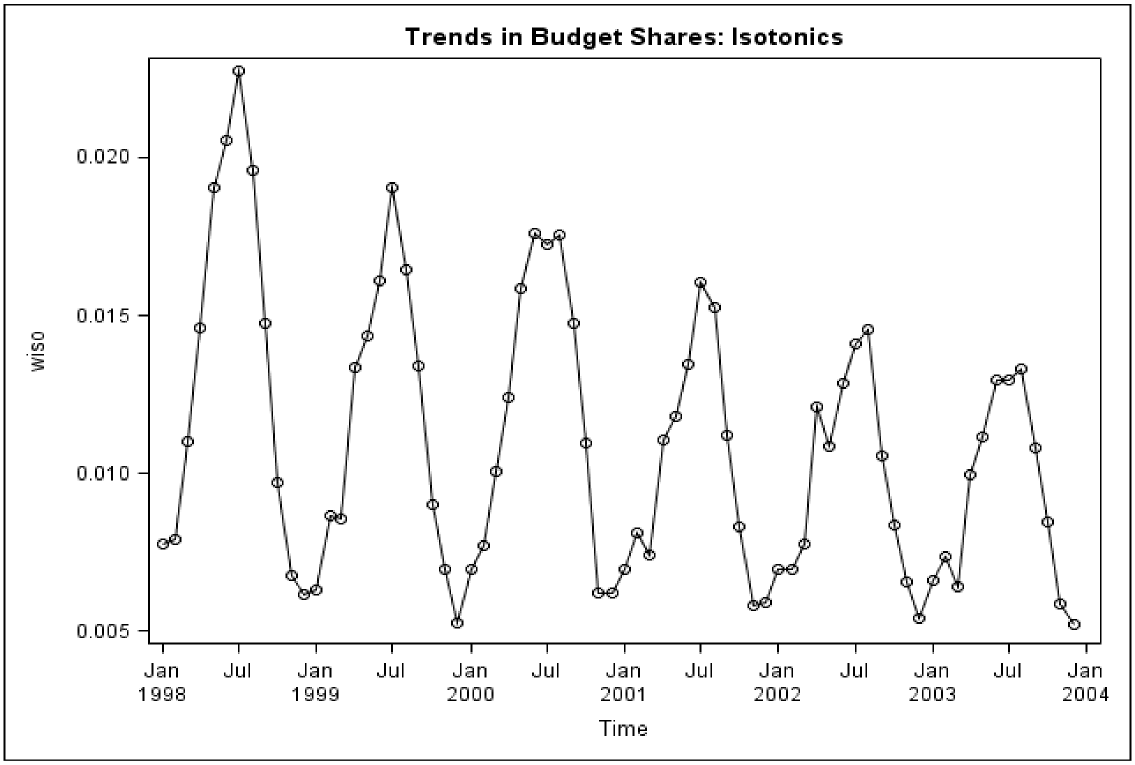

Figure 6.1: Trends in budget shares: isotonics

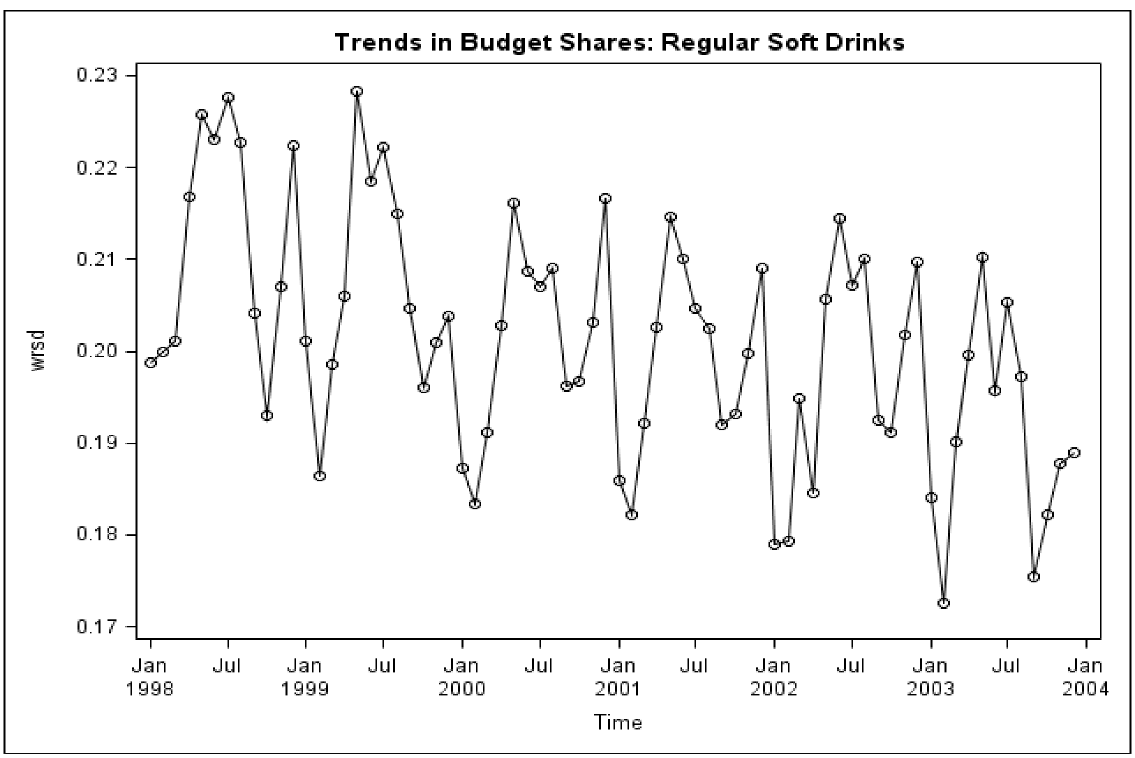

Figure 6.2: Trends in budget shares: regular soft drinks

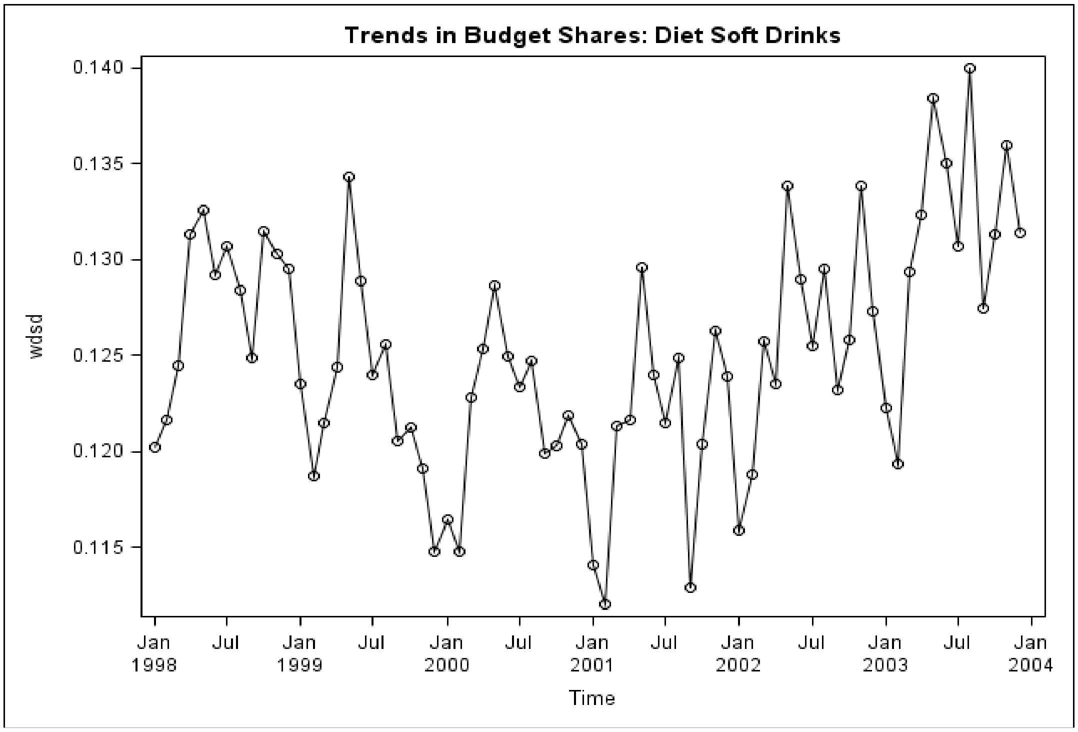

Figure 6.3: Trends in budget shares: diet soft drinks

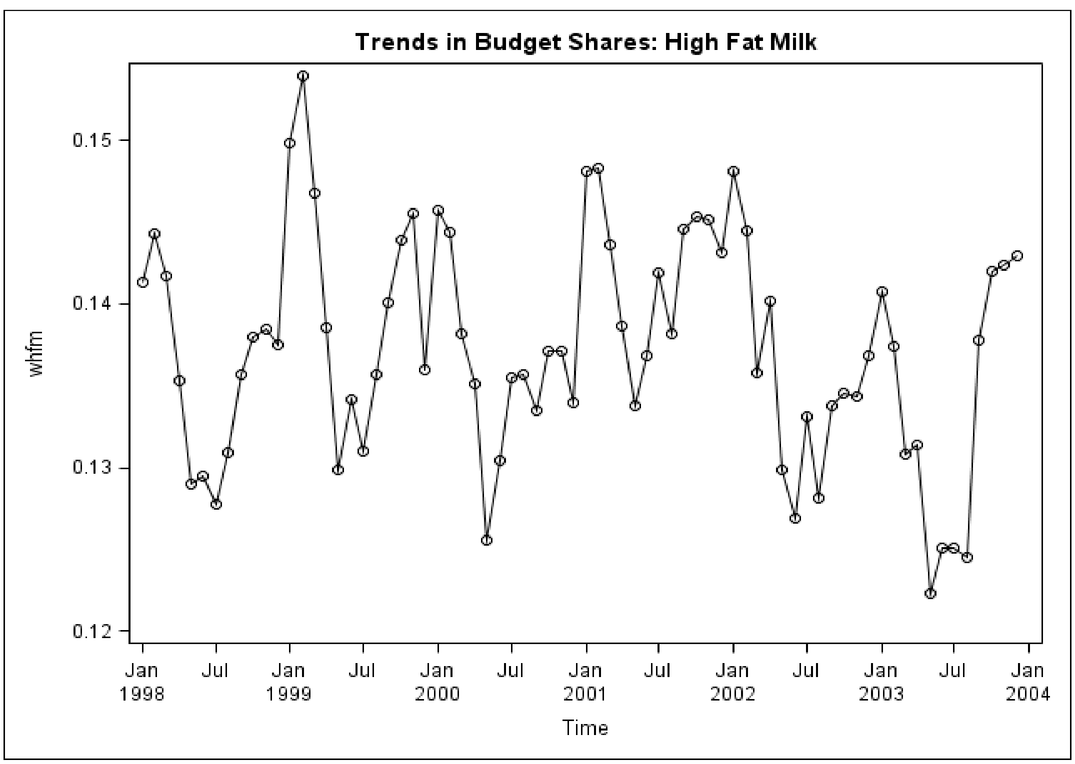

Figure 6.4: Trends in budget shares: high-fat milk

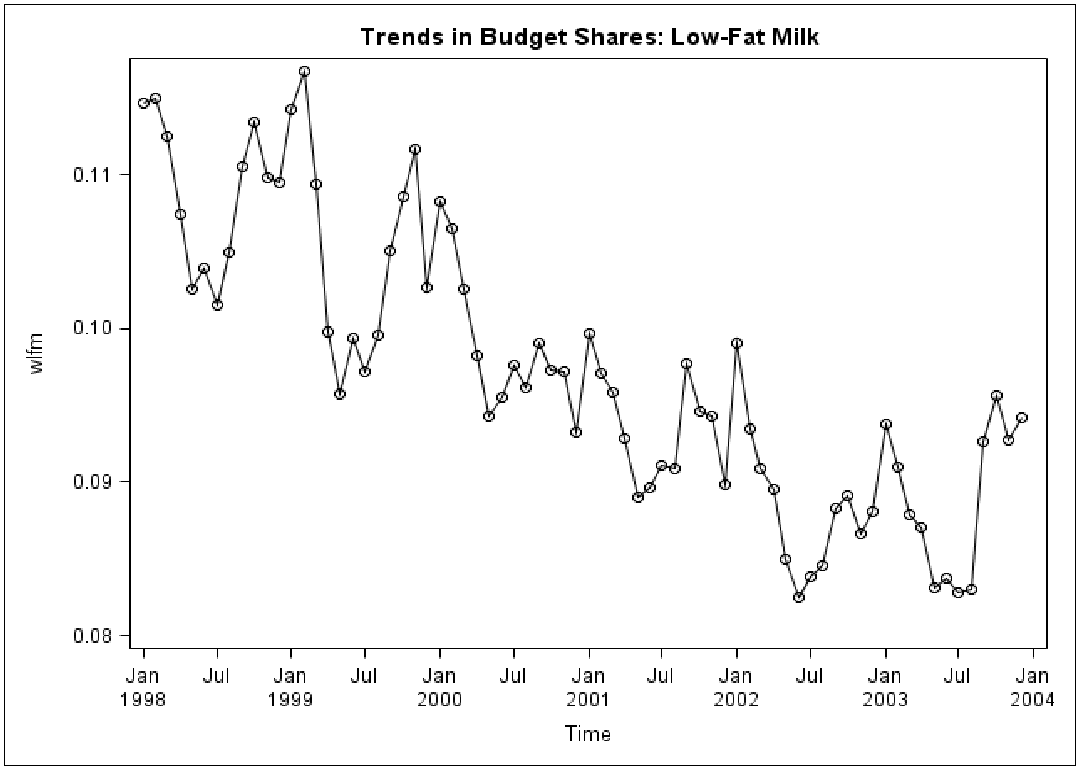

Figure 6.5: Trends in budget shares: low-fat milk

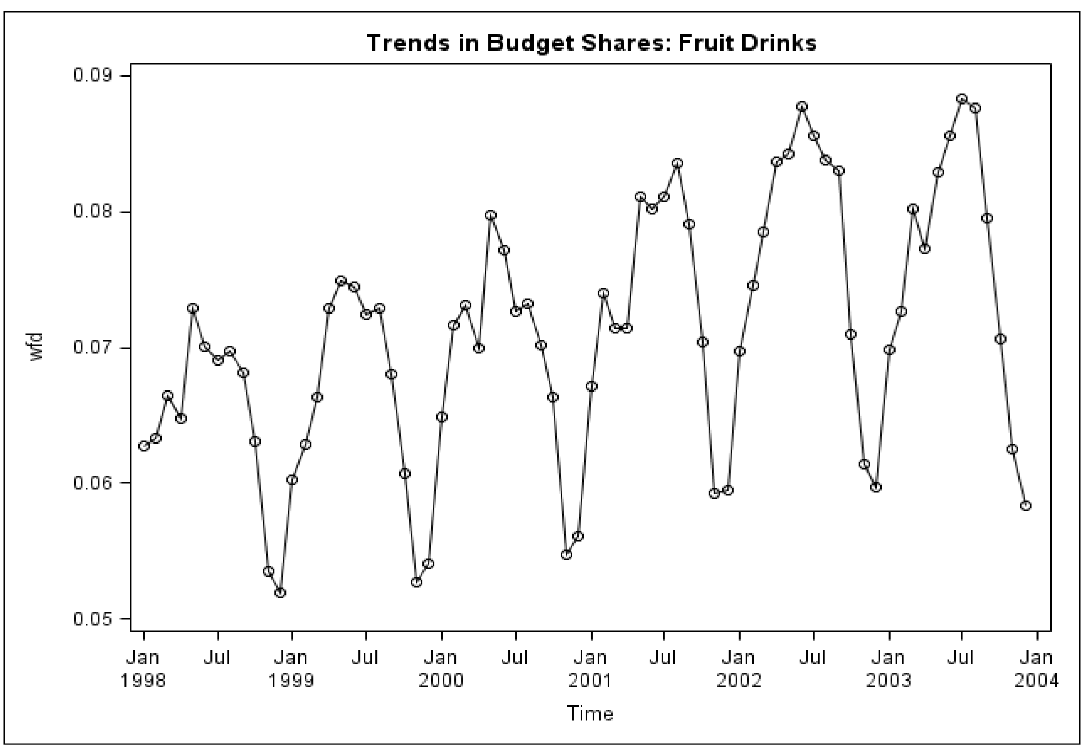

Figure 6.6: Trends in budget shares: fruit drinks

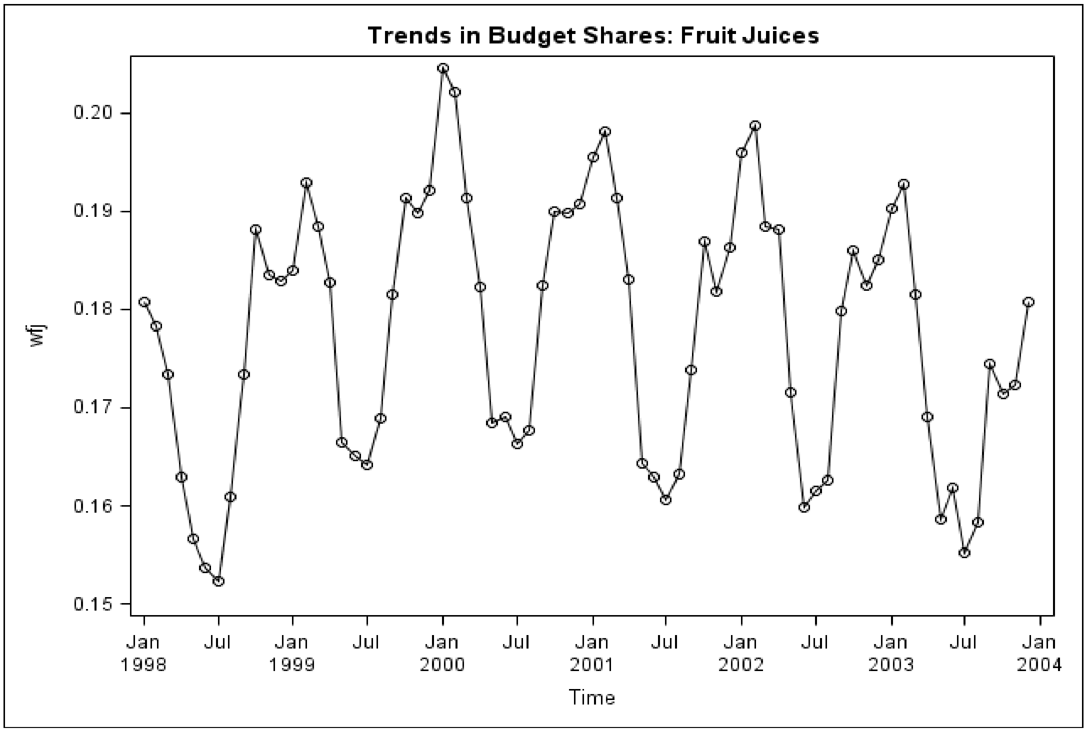

Figure 6.7: Trends in budget shares: fruit juices

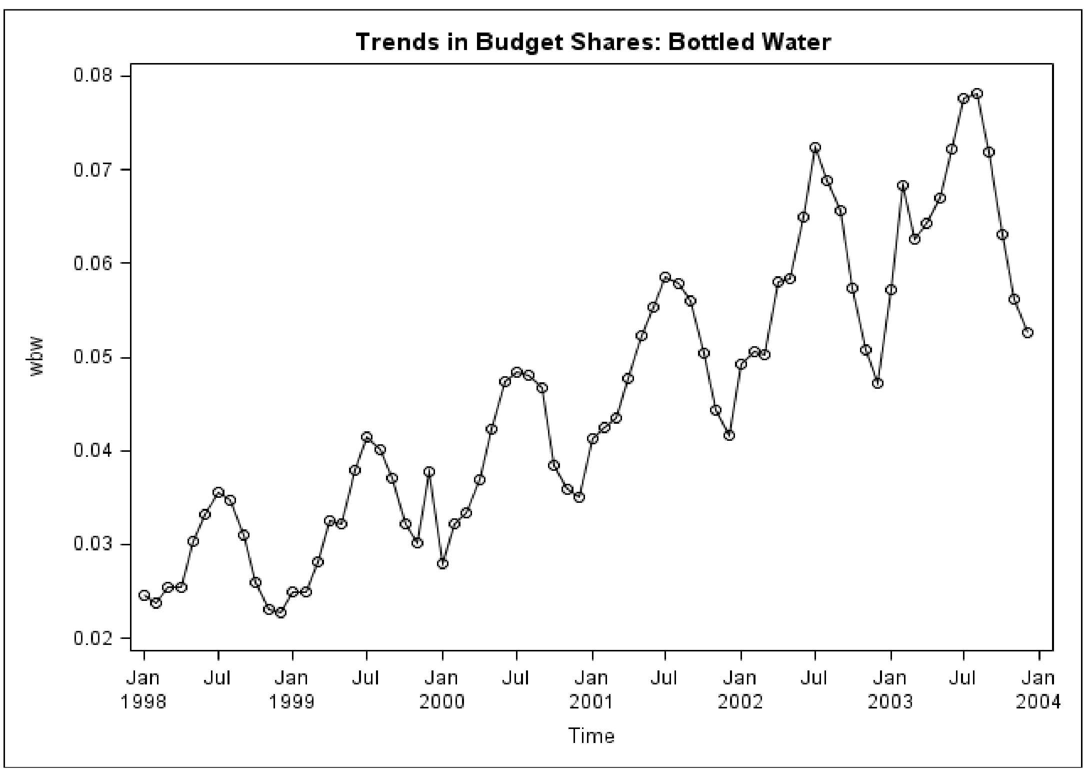

Figure 6.8: Trends in budget shares: bottled water

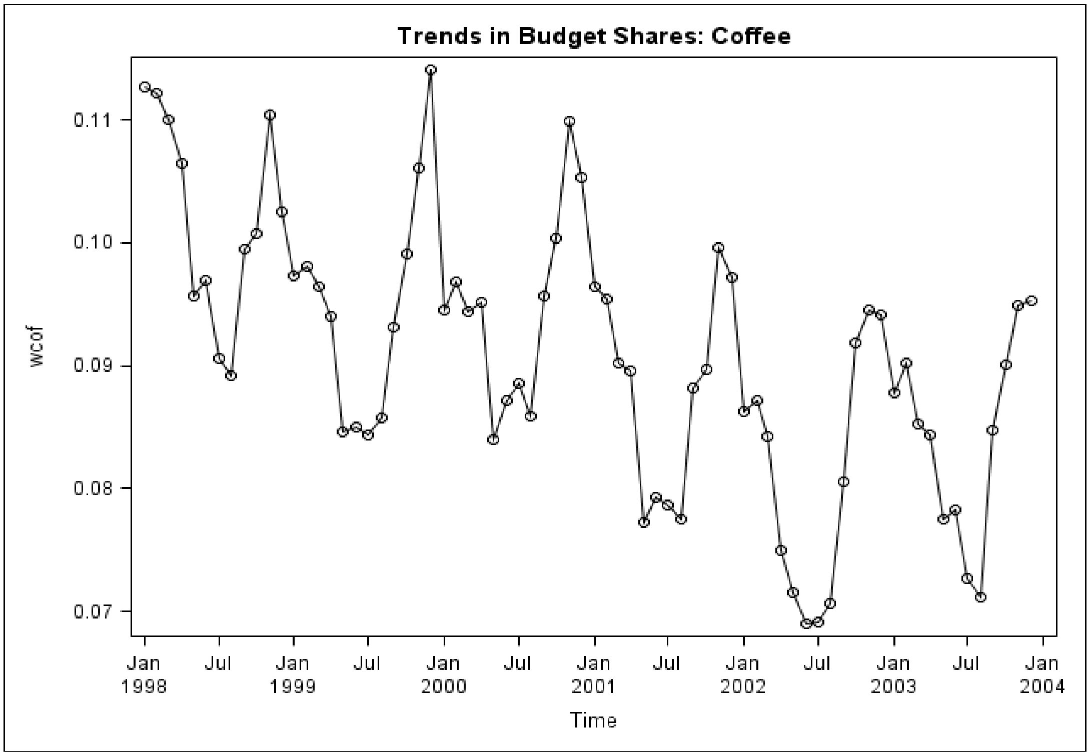

Figure 6.9: Trends in budget shares: coffee

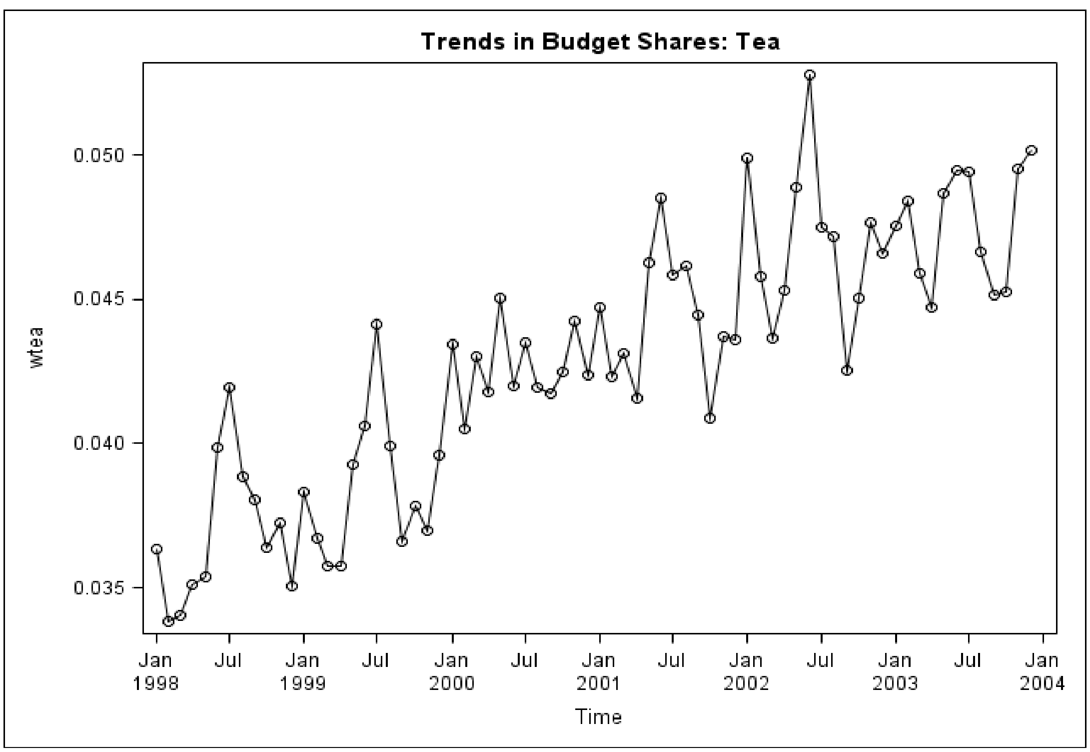

Figure 6.10: Trends in budget shares: tea

Visual observation reveals that all non-alcoholic beverages show seasonality in the movement of budget shares over the sample period. More specifically, consumption of isotonics, regular soft drinks, diet soft drinks, fruit drinks, bottled water and tea is high in the second and third quarters and low in fourth and first quarters. High-fat milk, low-fat milk, fruit juices and coffee are consumed heavily during the fourth and first quarters (associated more with winter and holiday season), and relatively low consumption is observed during second and third quarters.

LA/QUAIDS Model Parameter Estimates

Parameter estimates of the LA/QUAIDS model are reported in the Appendix 5. Fifty four out of 114 parameters estimated were significant at a level of significance of 0.10. The model was corrected for serial correlation using an *AR(2)* process in the disturbance terms. Calculated autocorrelation coefficients were statistically significant at the 0.10 level.

Joint hypotheses tests for seasonal dummies and lambda (we used letter L in lieu of lambda) are shown in the Appendix 5. Significance of seasonal dummies for all non-alcoholic beverages but diet soft drinks confirms the presence of seasonality in the data set.

Examination of individual seasonal dummies associated with each non-alcoholic beverage revealed the following. More isotonics are consumed in quarters 1, 2, and 3 compared to the fourth quarter. The most is consumed in the second quarter. This result is in accordance with Figure 6.1. Most of regular soft drinks are consumed in the second quarter compared to the fourth quarter and the least is consumed in the first quarter. Again, this result reinforced the budget share trends graphed in Figure 6.2. Even though more diet soft drinks are consumed in the first and second quarter compared to the fourth quarter, it is not significant at the 0.10 level. This result is further confirmed through the joint hypothesis test we performed for the quarterly dummies of diet soft drinks. We fail to reject that the effect of all quarterly dummies associated with diet soft drinks is significantly different from zero. Less high-fat milk is consumed in the second quarter compared to the fourth. Budget share trends shown in the Figure 6.4 reinforced this result for high-fat milk. More low-fat milk is consumed in the third quarter compared to the fourth quarter. Again, budget share trends shown in the Figure 6.5 provide evidence to support this result.

We observe that more fruit drinks are consumed in the first, second and third quarter compared to the fourth quarter. The highest level of fruit drinks is consumed in the first quarter. Budget share trends showed in Figure 6.6 confirms this result for fruit drinks. All seasonal dummy coefficients associated with fruit juice consumption are significant. Less amounts of fruit juices are consumed in the first, second and third quarter compared to fourth quarter. On the other hand, according to the significance of seasonal dummies, more bottled water is consumed in the first, second and third quarter compared to fourth quarter. These results with respect to fruit juices and bottled water are backed by the budget share trend representation shown in Figures 6.7 and 6.8. Coffee consumption is low in first, second and third quarters compared to the fourth quarter.

Moreover, the joint hypothesis for lambdas equal to zero is rejected; hence QUAIDS model superseded the AIDS model in fitting the data. Preference of the QUAIDS model over the AIDS model is reinforced through the Engel curves associated with consumption of each non-alcoholic beverage. In Figures 6.11 through 6.20, we show the Engel curves (a plot of expenditure share versus the logarithm of total expenditure) drawn for each non-alcoholic beverage. All non-alcoholic beverages showed a quadratic Engel curve, supporting the use of QUAIDS model.

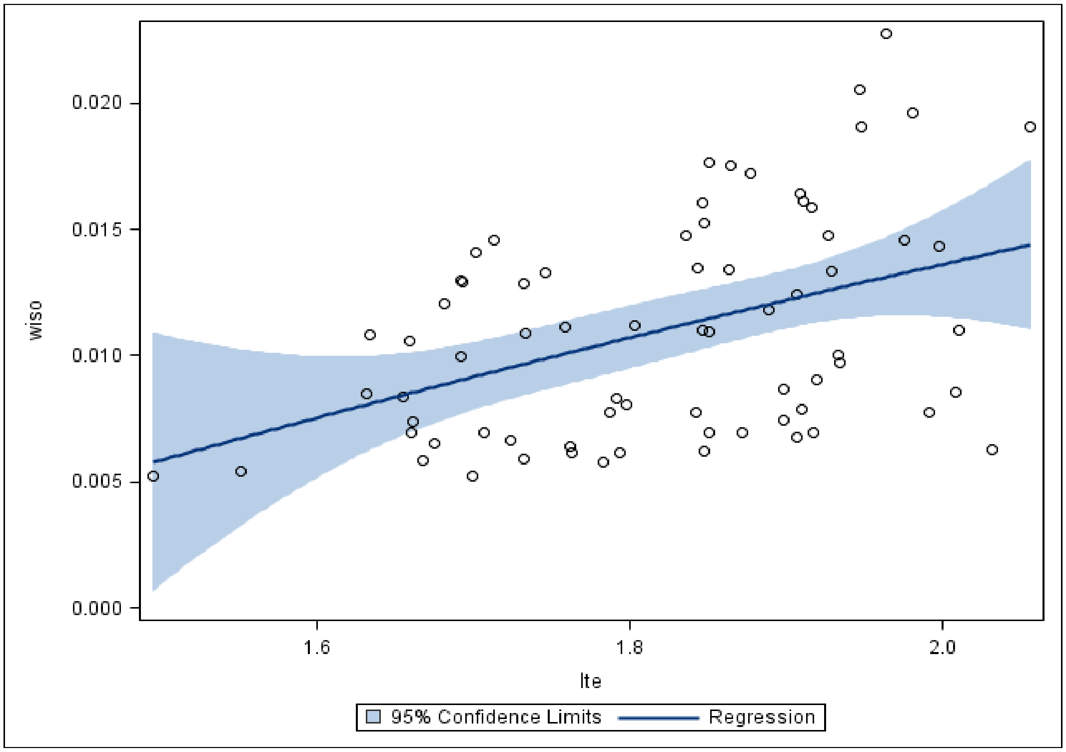

Figure 6.11: Engle curve for isotonics

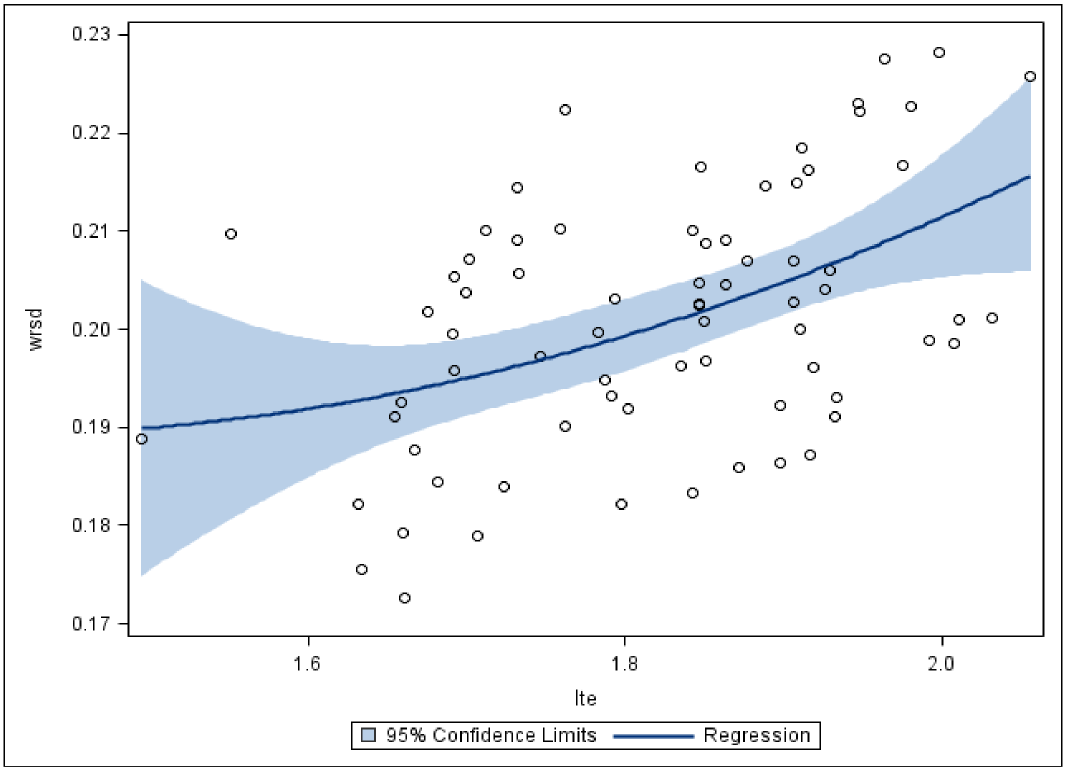

Figure 6.12: Engle curve regular soft drinks

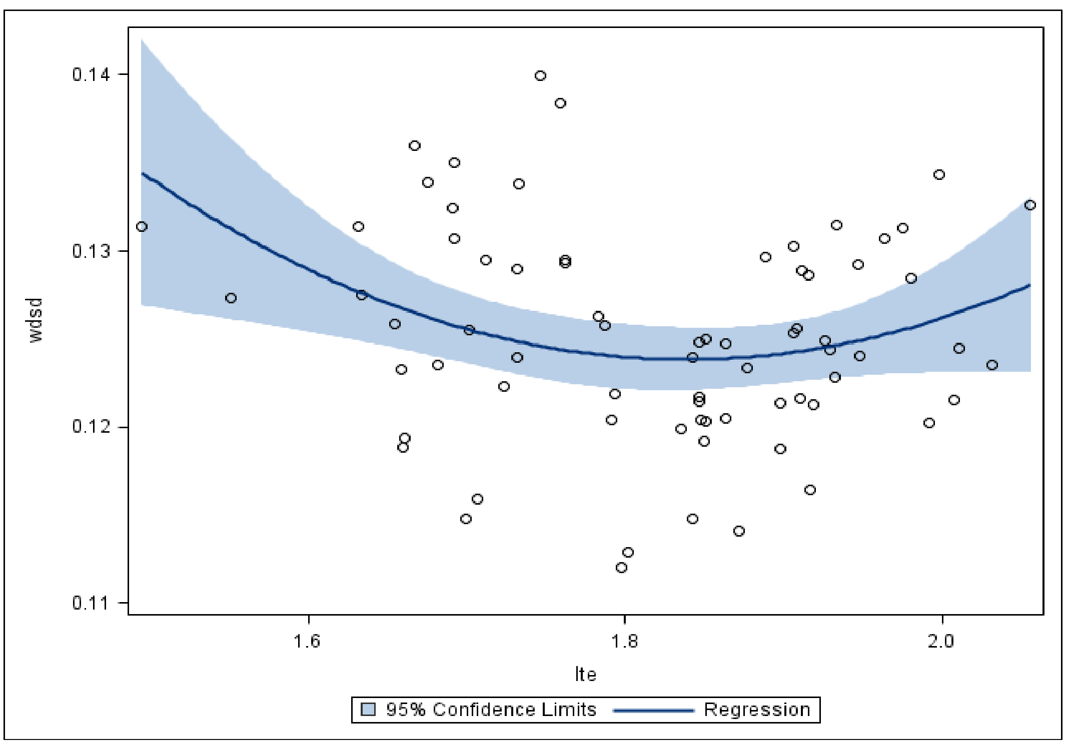

Figure 6.13: Engle curve for diet soft drinks

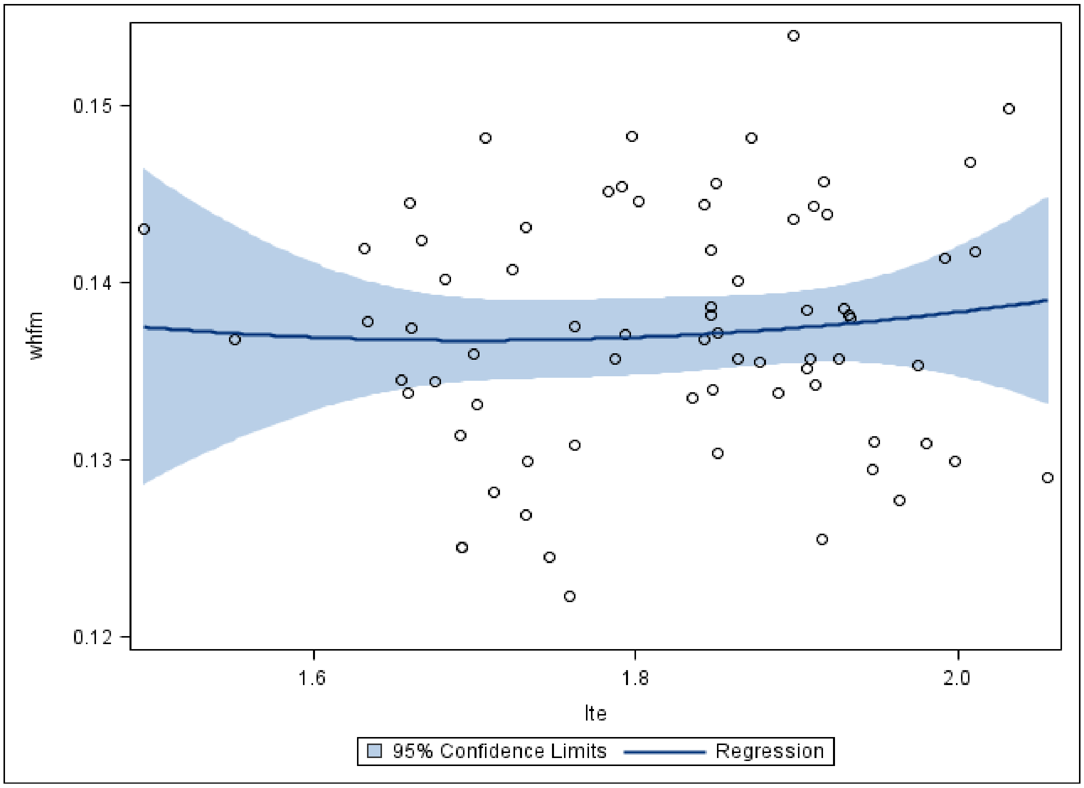

Figure 6.14: Engle curve for high fat milk

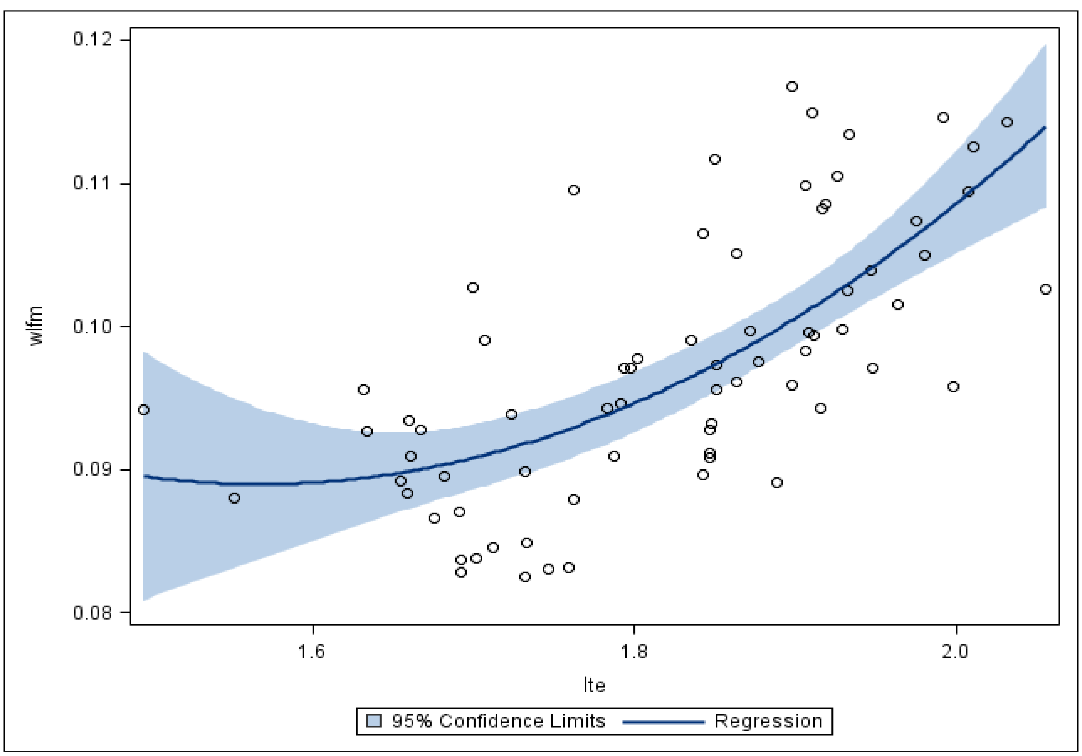

Figure 6.15: Engle curve for low fat milk

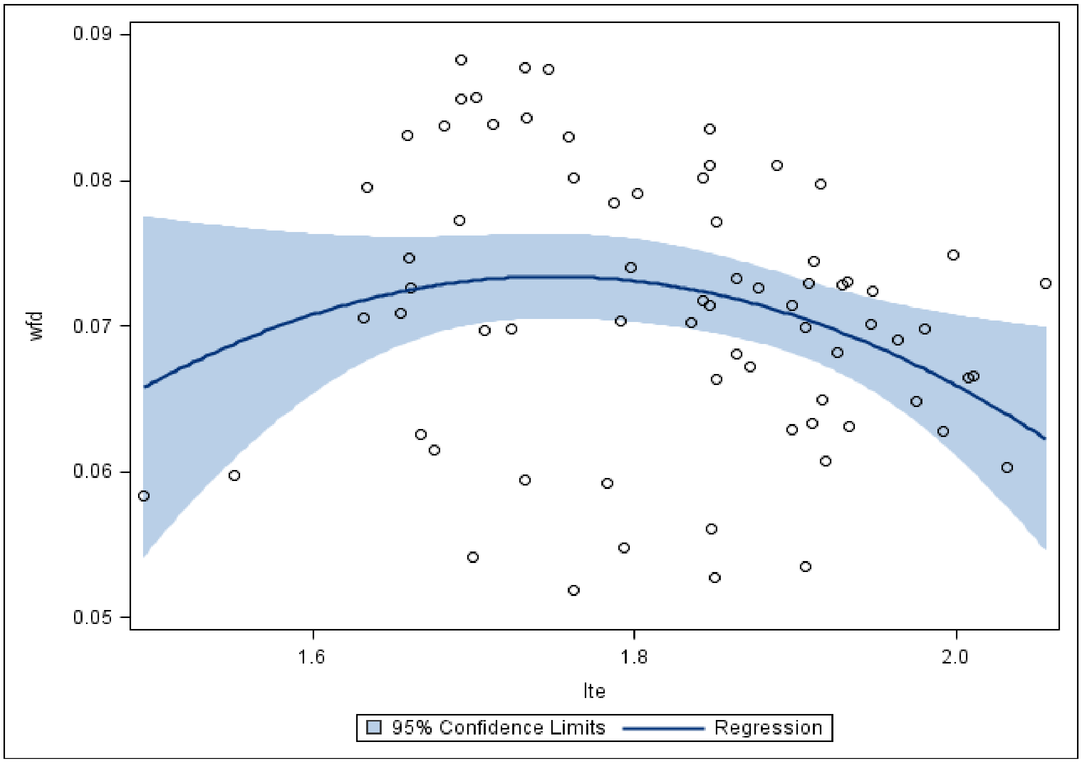

Figure 6.16: Engle curve for fruit drinks

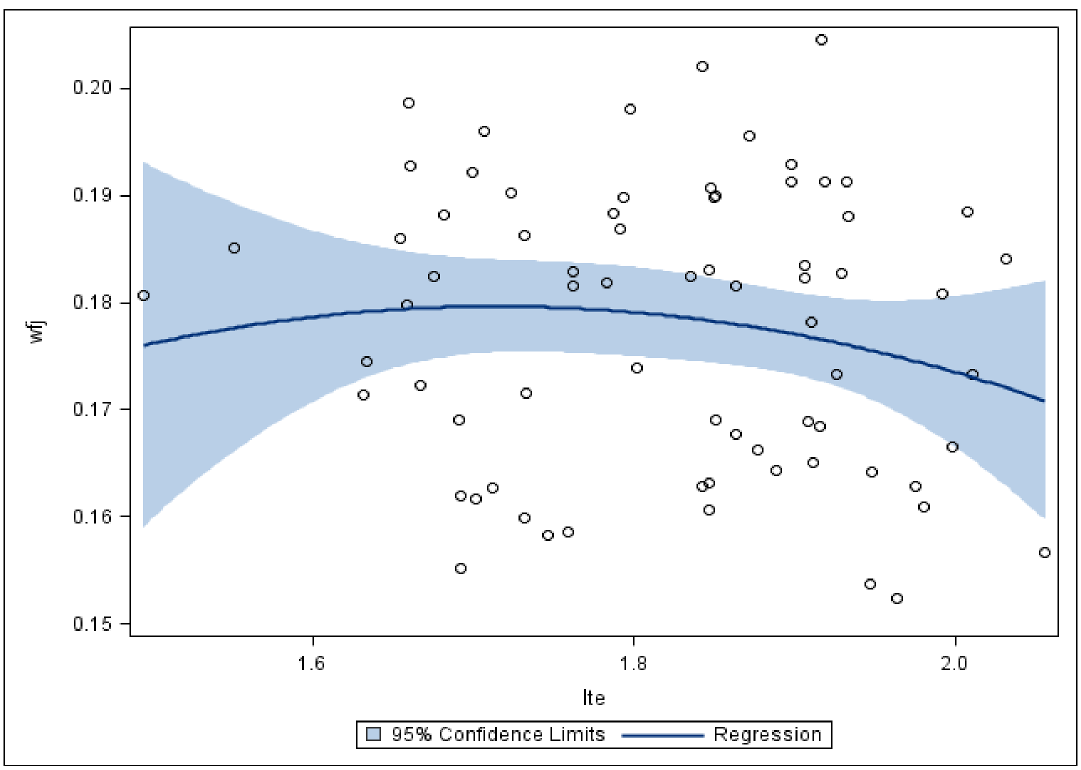

Figure 6.17: Engle curve for fruit juices

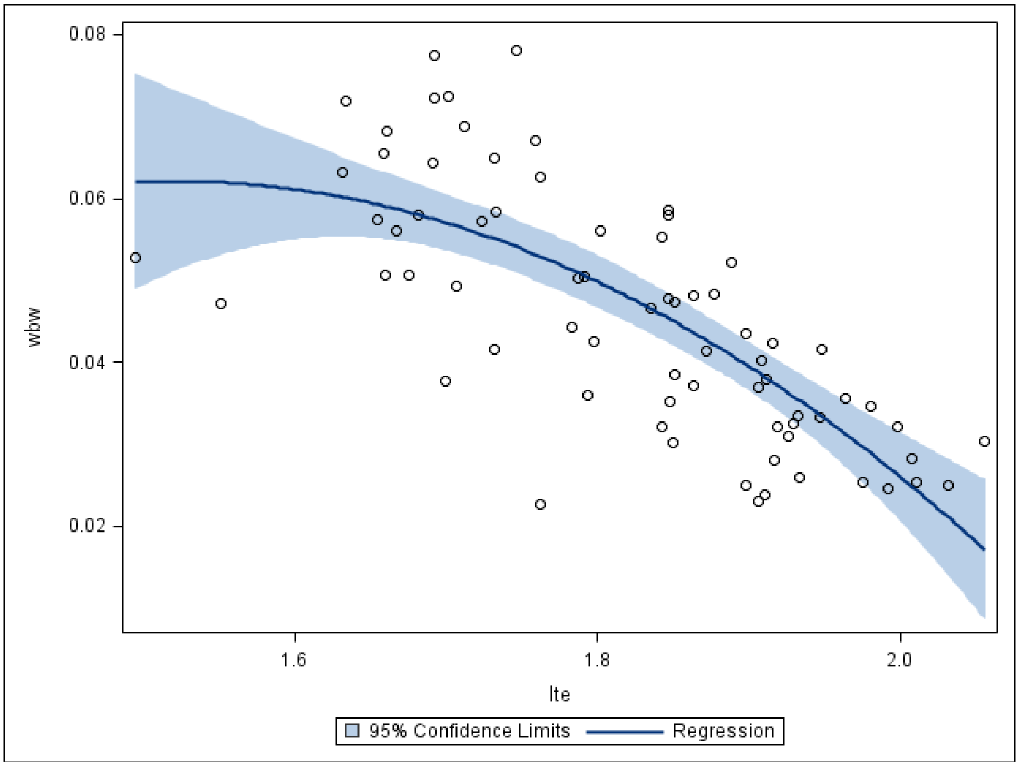

Figure 6.18: Engle curve for bottled water

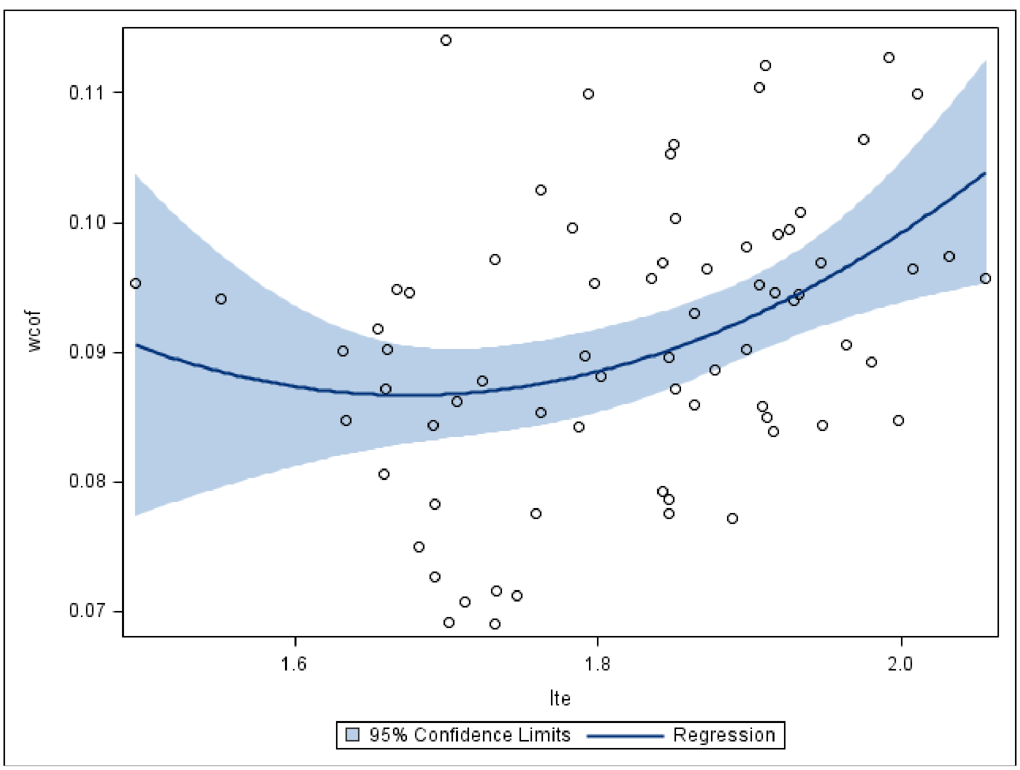

Figure 6.19: Engle curve for coffee

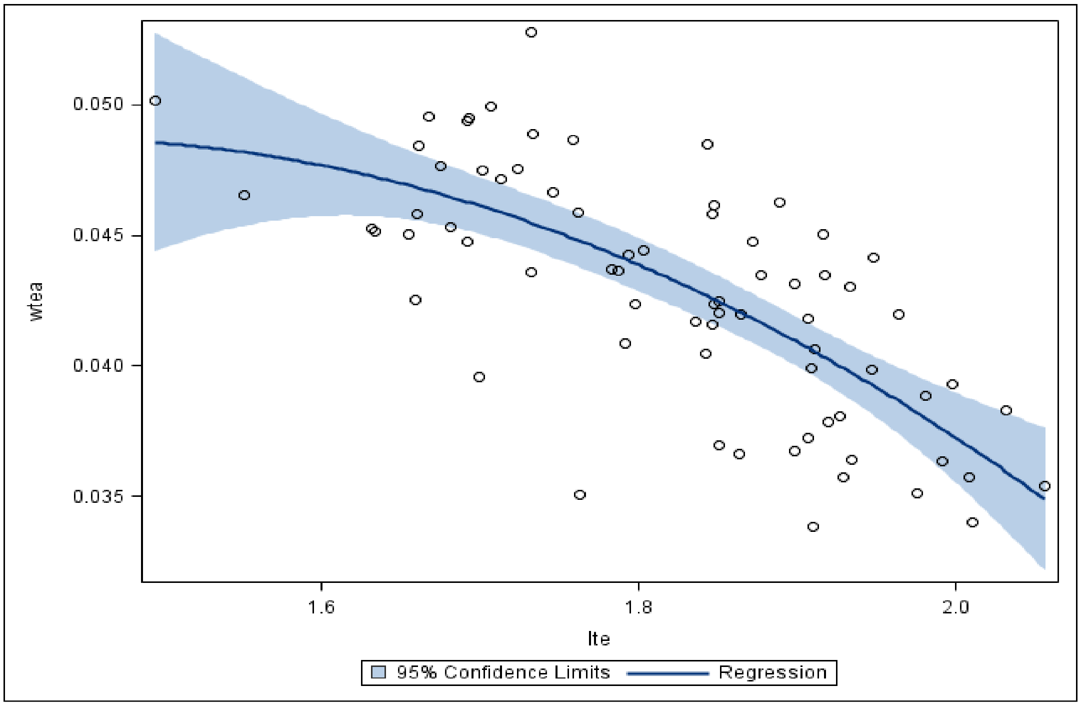

Figure 6.20: Engle curve for tea

LA/QUAIDS Elasticity Estimates

Based on the parameter estimates (shown in the Appendix 5), we calculated expenditure, and uncompensated and compensated own-price and cross-price elasticities for ten non-alcoholic beverages considered in this study. The average of the final twelve observations of each expenditure share data series was used as the local set of coordinates in calculating elasticities (they were as follows: isotonics 0.009; regular soft drinks 0.191; diet soft drinks 0.131; high fat milk 0.134; low fat milk 0.089; fruit drinks 0.076; fruit juices 0.172; bottled water 0.066; coffee 0.084; tea 0.048). Most budget share series were non-stationary; therefore, the sample mean over 72 observations was not the best local coordinate in which to evaluate elasticities. We used elasticity formulae depicted in equations 6.17 and 6.18 to generate expenditure and uncompensated own- and cross-price elasticities respectively. Uncompensated cross-price elasticities show gross substitution and gross complementary effects while its compensated counterpart distinguishes between net substitutes and net complements. Expenditure elasticity reveals the percentage change in the consumption of a given non-alcoholic beverage given a once percent change in expenditure on the set of ten non-alcoholic beverages.

Tables 6.2 and 6.3 show the calculated uncompensated and compensated own-price, cross-price and expenditure elasticities for each non-alcoholic beverage category. Calculated expenditure elasticities revealed that isotonics, regular soft drinks, diet soft drinks and fruit drinks were expenditure elastic. Regular soft drinks were the most expenditure elastic non-alcoholic beverage where one percent increment in expenditure on non-alcoholic beverages would increase the demand for regular soft drinks by 1.5 percent. It is important to understand that our results do not imply that isotonics, regular soft drinks, diet soft drinks and fruit drinks are luxury goods since expenditure elasticities are different from unconditional income elasticities. Coffee having an expenditure elasticity of 0.46, on the other hand, was the most expenditure inelastic beverage category. High-fat milk, low-fat milk, fruit juices, bottled water and tea are expenditure inelastic as well. It should be noted that all expenditure elasticities are significant at the 0.10 level.

All uncompensated and compensated own-price elasticities of demand are negative consistent with demand theory, and they are statistically significant. Isotonics is the most price sensitive beverage category, having a compensated own-price elasticity of demand of -3.85.

Table 6.2: Expenditure Elasticities and Uncompensated Own-Price and Cross-Price Demand Elasticities Estimated through LA/QUAIDS[31]

	iso	Rsd	dsd	Hfm	lfm	fd	fj	Bw	cof	tea	exp
Iso	**-3.8650**	-0.1216	2.2073	-0.8598	0.5235	**-2.4720**	**1.9803**	0.3722	1.0631	-0.0021	**1.1741**
	0.0000	0.9268	0.1168	0.3375	0.5092	0.0016	0.0740	0.6279	0.1749	0.9960	0.0621
Rsd	-0.0088	**-2.2552**	**-0.6208**	0.0424	**0.2373**	**-0.1663**	**1.0338**	-0.0543	**0.2181**	0.0555	**1.5184**
	0.8852	0.0000	0.0020	0.7146	0.0218	0.0847	0.0000	0.6143	0.0632	0.4083	0.0000
Dsd	0.1509	**-0.8550**	**-1.2721**	**0.3856**	-0.1722	**0.3726**	-0.0963	**0.2475**	-0.0051	-0.0121	**1.2562**
	0.1205	0.0037	0.0002	0.0171	0.2117	0.0063	0.6101	0.0661	0.9707	0.8727	0.0000
Hfm	-0.0544	0.1964	**0.4359**	**-0.7591**	0.2989	**-0.2219**	**-0.5556**	0.0173	-0.0185	**-0.1452**	**0.8064**
	0.3641	0.2549	0.0065	0.0009	0.1350	0.0077	0.0000	0.8388	0.8378	0.0056	0.0000
Lfm	0.0558	**0.6358**	-0.2009	0.4435	**-0.9237**	-0.1448	**-0.4669**	-0.1537	-0.0209	-0.0793	**0.8552**
	0.4916	0.0068	0.3279	0.1444	0.0027	0.1549	0.0039	0.1441	0.8501	0.1894	0.0000
Fd	**-0.2934**	-0.3659	**0.6436**	**-0.4501**	**-0.2044**	**-0.6892**	0.0786	**-0.3446**	**0.4709**	-0.0912	**1.2456**
	0.0017	0.1368	0.0063	0.0023	0.0821	0.0005	0.6925	0.0358	0.0119	0.3270	0.0000
Fj	**0.1069**	**1.2844**	-0.0141	**-0.4326**	**-0.2370**	0.0683	**-1.1731**	-0.0769	**-0.2526**	-0.0775	**0.8041**
	0.0730	0.0000	0.9250	0.0000	0.0049	0.4559	0.0000	0.4681	0.0258	0.2437	0.0000
Bw	0.0566	0.0318	**0.5864**	0.0721	-0.1784	**-0.3424**	-0.1532	**-0.7540**	-0.0455	0.1965	**0.5301**
	0.5842	0.9199	0.0282	0.6687	0.1876	0.0680	0.5589	0.0119	0.8329	0.1310	0.0215
Cof	0.1203	**0.6977**	0.0962	0.0166	0.0128	**0.4856**	**-0.4584**	-0.0312	**-1.6459**	**0.2442**	**0.4620**
	0.1571	0.0138	0.6620	0.9091	0.9120	0.0055	0.0431	0.8580	0.0000	0.0274	0.0297
Tea	0.0019	0.3359	0.0117	**-0.4200**	-0.1524	-0.1192	-0.2967	0.2448	**0.3893**	**-0.9104**	**0.9150**
	0.9804	0.2207	0.9552	0.0037	0.1607	0.4184	0.1915	0.1724	0.0395	0.0000	0.0000

[31] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Table 6.3: Compensated Own-Price and Cross-Price Demand Elasticities Estimated through LA/QUAIDS[32]

	Iso	**rsd**	**dsd**	**hfm**	**lfm**	**fd**	**fj**	**bw**	**Cof**	**tea**
iso	**-3.8544**	0.1027	**2.3611**	-0.7024	0.6280	**-2.3827**	**2.1822**	0.4497	1.1617	0.0543
	0.0000	0.9368	0.0950	0.4302	0.4331	0.0024	0.0553	0.5517	0.1421	0.8969
rsd	0.0048	**-1.9652**	**-0.4219**	**0.2459**	**0.3724**	-0.0509	**1.2950**	0.0460	**0.3457**	**0.1283**
	0.9368	0.0000	0.0295	0.0388	0.0006	0.5887	0.0000	0.6645	0.0043	0.0568
dsd	**0.1622**	**-0.6151**	**-1.1075**	**0.5539**	-0.0604	**0.4681**	0.1198	**0.3304**	0.1005	0.0482
	0.0950	0.0295	0.0009	0.0008	0.6625	0.0007	0.5361	0.0140	0.4699	0.5196
hfm	-0.0472	**0.3504**	**0.5415**	**-0.6510**	**0.3707**	**-0.1607**	**-0.4169**	0.0705	0.0492	**-0.1065**
	0.4302	0.0388	0.0008	0.0039	0.0667	0.0489	0.0020	0.3996	0.5902	0.0369
lfm	0.0635	**0.7992**	-0.0889	**0.5581**	**-0.8476**	-0.0798	**-0.3198**	-0.0973	0.0509	-0.0383
	0.4331	0.0006	0.6625	0.0667	0.0059	0.4277	0.0497	0.3423	0.6486	0.5186
fd	**-0.2822**	-0.1280	**0.8068**	**-0.2833**	-0.0935	**-0.5945**	0.2928	-0.2624	**0.5755**	-0.0314
	0.0024	0.5887	0.0007	0.0489	0.4277	0.0022	0.1553	0.1012	0.0027	0.7316
fj	**0.1142**	**1.4380**	0.0912	**-0.3248**	**-0.1655**	0.1294	**-1.0348**	-0.0238	-0.1850	-0.0389
	0.0553	0.0000	0.5361	0.0020	0.0497	0.1553	0.0000	0.8183	0.1015	0.5503
bw	0.0613	0.1330	**0.6558**	0.1432	-0.1312	-0.3021	-0.0621	**-0.7190**	-0.0009	**0.2220**
	0.5517	0.6645	0.0140	0.3996	0.3423	0.1012	0.8183	0.0148	0.9966	0.0852
cof	0.1245	**0.7860**	0.1567	0.0785	0.0540	**0.5207**	-0.3789	-0.0007	**-1.6071**	**0.2664**
	0.1421	0.0043	0.4699	0.5902	0.6486	0.0027	0.1015	0.9966	0.0000	0.0153
tea	0.0102	**0.5107**	0.1315	**-0.2974**	-0.0710	-0.0497	-0.1393	0.3052	**0.4662**	**-0.8665**
	0.8969	0.0568	0.5196	0.0369	0.5186	0.7316	0.5503	0.0852	0.0153	0.0000

[32] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea

Even though there is a small budget share associated with isotonics (approximately one percent) compared to other non-alcoholic beverages, they are the most expensive out of the ten non-alcoholic beverages considered in this study. Given this high price of isotonics, consumers may be more sensitive to changes in its price. The compensated own-price elasticity of demand for regular soft drinks, diet soft drinks, fruit juices, and coffee are -1.97, -1.10, -1.03, and -1.61 respectively, indicating elastic demands. Fruit drinks have the most inelastic compensated own-price elasticity of demand, which is -0.59. In terms of compensated own-price elasticity of demand, high-fat milk is more inelastic than low-fat milk (-0.65 and -0.85 respectively). Bottled water and tea also are inelastic according to calculated compensated own-price elasticity of demand.

Thirty six out of ninety (forty percent) compensated cross-price elasticities have negative signs indicating net complements and sixty percent of compensated cross-price elasticities are indicative of net substitutes. Diet soft drinks and fruit juices are net substitutes for isotonics. Fruit drinks are a net complement for isotonics. High-fat milk, low-fat milk, fruit juices, coffee and tea are net substitutes for regular soft drinks. Diet soft drinks are a net complement for regular soft drinks.

Isotonics, high-fat milk, fruit drinks and bottled water are found to be net substitutes for diet soft drinks. Again, we find that regular soft drinks are a net complement for diet soft drinks.

Regular soft drinks, diet soft drinks, and low-fat milk are net substitutes for high-fat milk. On the other hand, fruit drinks, fruit juices and tea are net complements for high-fat milk. This result is probably justifiable looking at breakfast choices of consumers. Most consumers may consume fruit juices, fruit drinks and tea along with milk at breakfast. Regular soft drinks and high-fat milk are net substitutes for low-fat milk. Fruit juice is a net complement for low-fat milk.

Diet soft drinks and coffee act as net substitutes for fruit drinks. On the other hand, isotonics and high-fat milk are net complements for fruit drinks. Consumers substitute isotonics and regular soft drinks for fruit juices. High-fat and low-fat milk are net complements for fruit juice.

Diet soft drinks and tea are found to be net substitutes for bottled water. There are no significant net complements for bottled water. We find that regular soft drinks, fruit drinks and tea are net substitutes for coffee. There are no significant net complements for coffee. Regular soft drinks, bottled water and coffee are net substitutes for tea. On the other hand we find that high-fat milk is a net complement for tea.

LA/QUAIDS Diversion Ratios (DR) for Non-acoholic Beverages

Table 6.4 shows the calculated Diversion Ratios for significant uncompensated cross-price elasticities. Looking at the magnitude of the DRs, we can talk about the strongest substitute or complement for each non-alcoholic beverage category concerned. According to Table 6.4, the strongest substitute for isotonics is coffee, whereas the strongest complement is fruit drinks. More specifically, the consumer diverts consumption of one gallon of isotonics to 1.18 gallons of coffee (the strongest substitute), 0.97 gallons of diet soft drinks and 0.50 gallons of fruit juices. On the other hand, for every gallon of reduced consumption of isotonics, fruit drink consumption also is going to be reduced by 0.80 gallons (fruit drinks are a net complement for isotonics).

Table 6.4: Diversion Ratios calculated using Cross Price Elasticities[33] of LA/QUAIDS Model Estimates

	Iso	Rsd	dsd	hfm	lfm	fd	fj	Bw	Cof	tea
iso	**1.0000**	0.0015	-0.0699	0.0523	-0.0390	**0.3379**	**-0.0926**	-0.0246	**-0.0170**	0.0002
rsd	0.0829	**1.0000**	**0.7136**	-0.0935	**-0.6417**	**0.8252**	**-1.7537**	0.1302	**-0.1269**	-0.1509
dsd	**-0.9690**	**0.2593**	**1.0000**	**-0.5816**	0.3185	**-1.2641**	0.1117	**-0.4062**	0.0020	0.0225
hfm	0.3053	-0.0520	**-0.2993**	**1.0000**	**-0.4829**	**0.6576**	**0.5630**	-0.0248	0.0064	**0.2361**
lfm	-0.2097	**-0.1128**	0.0924	**-0.3915**	**1.0000**	**0.2876**	**0.3170**	**0.1477**	0.0049	0.0864
fd	**0.8057**	**0.0475**	**-0.2164**	**0.2904**	**0.1617**	**1.0000**	-0.0390	**0.2419**	**-0.0801**	0.0726
fj	**-0.5046**	**-0.2862**	0.0082	**0.4794**	**0.3222**	-0.1702	**1.0000**	0.0927	**0.0738**	0.1059
bw	-0.2935	-0.0078	**-0.3725**	-0.0879	**0.2666**	**0.9387**	0.1437	**1.0000**	0.0146	**-0.2956**
cof	**-1.1797**	**-0.3231**	-0.1154	-0.0382	-0.0363	**-2.5160**	**0.8120**	0.0782	**1.0000**	**-0.6941**
tea	-0.0073	-0.0601	-0.0054	**0.3739**	**0.1664**	0.2387	**0.2031**	**-0.2371**	**-0.0914**	**1.0000**

strongest substitute	
strongest complement	

[33] Bold numbers are significant at the 0.10 level
Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea

The strongest substitute for regular soft drinks is coffee, where reduction in every gallon of regular soft drinks is substituted by an intake in 0.32 gallons of coffee. The strongest complement for regular soft drinks is diet soft drinks. In particular, for reduction in every gallon of regular soft drinks, diet soft drink consumption is going to be reduced by 0.26 gallons.

The strongest substitute for diet soft drinks is bottled water, where increase of one gallon of diet soft drinks would decrease the consumption of bottled water by 0.37 gallons. Regular soft drinks is found to be the strongest complement to diet soft drinks, where one gallon increase in diet soft drinks would increase the intake of regular soft drinks by 0.71 gallons.

Diet soft drinks and regular soft drinks were found to be the strongest substitutes for high-fat milk and low-fat milk respectively. On the other hand, fruit juices were the strongest complement for both regular and diet soft drinks. More specifically, taking one gallon of high-fat milk and/or low-fat milk away from the consumer would also take away respectively, 0.48 and 0.32 gallons of fruit juices. Every one gallon of high-fat milk that is taken away, diet-soft drinks consumption us increased by 0.58 gallons.

The strongest substitute for fruit drinks was found to be coffee, where reduction in every gallon of fruit drinks is substituted by 2.5 gallons of coffee. Every gallon of fruit drinks taken away from the consumer is substituted by 0.94 gallons of bottled water. Bottled water was found to be the strongest complement for fruit drinks. Regular soft drinks are the strongest substitute for fruit juices. In particular, 1.76 gallons of regular soft drinks would be taken in for each gallon of fruit juices taken away. The strongest the complement for fruit juices is coffee. With every gallon of fruit juice which is taken away would also take 0.81 gallon of coffee away.

Diet soft drinks are the strongest substitute for bottled water, where 0.40 gallons of diet soft drinks is taken in for every gallon of bottled water that is taken away. On the other hand, fruit drinks are the strongest complement for bottled water. Every gallon of bottled water that is taken away would lead to the reduction of 0.24 gallons of fruit drinks.

The strongest substitute for coffee is regular soft drinks, where every gallon of coffee that is taken away would increase the intake of regular soft drinks by 0.13 gallons. In contrast to that, the strongest complement for coffee is found to be fruit juice. For every gallon of more coffee consumed would increase the consumption of fruit juice by 0.07 gallons. Coffee is found to be the strongest substitute for tea, where every gallon of more tea consumed would reduce the coffee consumption by 0.69 gallons. On the other hand, the strongest complement for tea is high-fat milk, where every gallon of reduced consumption of tea also would decrease the high-fat milk consumption by 0.24 gallons.

Nutrition Policy and Non-alcoholic Beverage Choices

Looking at the nutrition labels of non-alcoholic beverages in the market, it is clear that they do contribute a substantial amount of daily required nutrients and calories to the diet of the consumer (our next chapter, i.e., Chapter VII, is completely devoted to evaluate the nutritional contributions of non-alcoholic beverages to the diet of the consumer). Let us take a situation where nutrition policy on sugar intake derived from consumption of non-alcoholic beverages have to be implemented. First we identify the non-alcoholic beverages where, once consumed the intake of sugar is a concern. Isotonics (sports drinks like Gatorade), regular soft drinks (like classic Coke), and fruit drinks (like KoolAid) do qualify as high in sugar content. Let us assume the government imposes a "sugar tax" on these beverages in order to reduce the intake of sugar through reduced consumption of so-called sugary beverages. The aforementioned diversion ratios with respect to each non-alcoholic beverage type that we calculated would come in handy in answering where consumption would be diverted as a result of this tax policy.

If as a result of the tax, consumers reduce the intake of isotonics by a gallon per month, they would also reduce the intake of fruit drinks (according to calculated DR values, fruit drinks intake ought to reduce by 0.81 gallons with every one gallon of decreased intake of isotonics). This result is promising. However, they would increase the consumption of coffee by a greater volume (by 1.18 gallons of more coffee intake for every one gallon of less isotonics intake). Consequently, this policy designed to affect sugar intake my result in more caffeine intake. Also, they would increase the consumption of fruit juices and diet soft drinks by a large proportion. This latter result is supportive of objectives of the "sugar tax".

Let us assume now that consumer is responding positively to "sugar tax" and consuming less regular soft drinks instead. According to the DR calculations, they would also decrease the consumption of diet soft drinks by 0.26 gallons for every one gallon less regular soft drinks consumed.

This is not supportive of beverage companies that are promoting diet soft drinks in lieu of regular soft drinks and defeating the purpose of diet soft drinks in the market. However, decrease in diet soft drinks as a result of decrease in regular soft drinks would increase the intake of bottled water, which is a healthy alternative (because according to our DR calculations, bottled water is the strongest substitute for diet soft drinks).

On the other hand, a decrease in fruit drinks as a result of the “sugar tax” may decrease the intake of bottled water (because, according to our DR calculations, bottled water is the strongest complement for fruit drinks), which is not a desired result from a nutritional perspective. Over all we see that a sugar tax on isotonics, regular soft drinks and fruit drinks would increase the consumption of coffee (coffee is the strongest substitute for all of above three types of beverages), which may interfere with another nutrition policy trying to deal with caffeine intake.

Above we demonstrated the way we could use our DR calculations in designing nutrition policy. The bottom line, we have to consider interrelationships between beverages in designing policy and concentrate more may be on indirect effects than direct effects.

Dynamics in Demand for Non-alcoholic Beverages: Barten's Synthetic Model

In the following section we first offer a narrative on the theoretical development of the differential demand systems and a popular nested version, the Barten synthetic model. Second, we discuss data analysis related to our work on estimating demand for non-alcoholic beverages in a dynamic systemwide framework. Our analysis will concentrate on estimating the Barten synthetic model imposing theoretical restrictions from the demand theory, such as adding-up, homogeneity and symmetry.

Theoretical Development

In this section, first we discuss in general the class of differential demand systems and four such systems that are quite popular in demand system estimation, such as Rotterdam system (Theil 1965), differential version of AIDS system of Deaton and Muellbauer (1980), the (Dutch) Central Bureau of Statistics (CBS) model of Keller and van Driel (1985) and NBR model of Neves (1987). Next, we offer a description on Barten synthetic model that nests all of above four differential demand models. We also discuss correction methods for possible autocorrelation problem inherent in the system.

Class of Differential Demand Systems

Following discussion on general class of differential demand systems is largely borrowed from Matsuda (2005). Let the Marshallian demand function for good i be $q_i(\mathbf{p}, m)$ where, $\mathbf{p} = (p_1, p_2, ..., p_n)$ denote the price vector of n goods and m represents the total expenditure on the goods. Totally differentiating the $q_i(\mathbf{p}, m)$ gives us the following relationship:

(6.46) $$dq_i(\mathbf{p}, m) = \frac{\partial q_i(\mathbf{p}, m)}{\partial m} dm + \sum_{j=1}^{n} \frac{\partial q_i(\mathbf{p}, m)}{\partial p_j} dp_j$$

where $i = 1,2,....,n$.

The Slutsky equation relating Marshallian and Hicksian demands can be written as follows:

(6.47) $$\frac{\partial q_i(\mathbf{p},m)}{\partial p_j} = \frac{\partial h_i(\mathbf{p},u)}{\partial p_j} - \frac{\partial q_i(p,m)}{\partial m} q_j(\mathbf{p},m)$$

where $h_i(\mathbf{p},u)$ is the Hicksian compensated demand function of good i, and u is the reference utility level. $i, j = 1,2,3,......,n$.

The adding-up condition can be totally differentiated as follows:

(6.48) $$\sum_{i=1}^{n} p_i dq_i = dm - \sum_{i=1}^{n} q_i dp_i$$

Now, substituting equation (6.47) in equation (6.46) and using the relation equation (6.48) and multiplying both sides of equation by p_i/m we obtain:

(6.49) $$w_i d \ln q_i = p_i \frac{\partial q_i(\mathbf{p},m)}{\partial m} d \ln Q + \sum_{j=1}^{n} \frac{p_i p_j}{m} \frac{\partial h_i(\mathbf{p},u)}{\partial p_j} d \ln p_j$$

where $w_i = \dfrac{p_i q_i}{m}$ denotes the expenditure share of *i*th good, $d \ln Q = \sum_{i=1}^{n} w_i d \ln q_i$ is the Divisia volume index, $p_i \partial q_i / \partial m$ is the marginal budget share of good i, $\dfrac{p_i p_j}{m} \dfrac{\partial h_i(\mathbf{p},u)}{\partial p_j}$ is the *ij*th element of the Slutsky matrix which involves the substitution effect of the price changes. Equation 6.49 behaves as a general equation for the differential demand system, where different approximations to the marginal budget share and Slutsky terms would generate different classes of differential demand systems (such as Rotterdam, CBS, first differenced form of AIDS and NBR models).

If we approximate the marginal budget share and Slutsky terms to be constant, we could generate the well-known and widely used Rotterdam model. Equation (6.50) shows the Rotterdam model:

(6.50) $$w_i d\ln q_i = b_i d\ln Q + \sum_{j-1}^{n} s_{ij} d\ln p_j$$

where, $i = 1,2,....,n$.

Next, by subtracting $w_i d\ln Q$ from both sides of equation (6.50) and defining a new parameter $c_i \equiv b_i - w_i$ another specification of differential demand system can be formulated as follows:

(6.51) $$w_i(d\ln q_i - d\ln Q) = c_i \ln Q + \sum_{j=1}^{n} s_{ij} d\ln p_j$$

Equation 6.51 above shows the CBS model. CBS model consists of Rotterdam price coefficient and LA/AIDS expenditure coefficient (shown below).

Let $d\ln P \equiv \sum_i w_i d\ln p_i = d\ln m - d\ln Q$ denote the Divisia price index, and δ_{ij} is the Kronecker delta (δ_{ij} =1 if $i = j$ and δ_{ij} =0 otherwise). Now, adding $w_i(d\ln p_i - d\ln P)$ to both sides of equation 6.51 would give us the following:

(6.52) $$w_i(d\ln p_i + d\ln q_i - d\ln m) = dw_i$$

and using new parameter $r_{ij} \equiv s_{ij} + w_i(\delta_{ij} - w_j)$ we obtain the following relationship, which is the linear approximation of the AIDS model in differential form:

(6.53) $$dw_i = c_i d\ln Q + \sum_{j=1}^{n} r_{ij} d\ln p_j$$

where $i = 1,2,....,n$.

Another alternative form of differential demand system can be represented in the equation 6.43, where following expression is added to the both sides of equation 6.52; $w_i d \ln Q$:

(6.54) $$dw_i + w_i d \ln Q = b_i d \ln Q + \sum_{j=1}^{n} r_{ij} d \ln p_j$$

where $i = 1,2,....,n$. Expression in equation (6.53) is referred to as the NBR model. It has the expenditure coefficient coming form Rotterdam model and price coefficient from LA/AIDS model (in differential form).

Notice that all right-hand side expressions of equations (6.50), (6.51), (6.53), and (6.54) are same, even though the left-hand sides are different from each other. Now, let us transform equations (6.51), (6.53) and (6.54) into equations (6.55), (6.56), and (6.57) respectively below, where all left-hand side expressions are the same as equation (6.50) (Rotterdam model):

(6.55) $$w_i d \ln q_i = (c_i + w_i) d \ln Q + \sum_{j=1}^{n} s_{ij} d \ln p_j$$

(6.56) $$w_i d \ln q_i = (c_i + w_i) d \ln Q + \sum_{j=1}^{n} [r_{ij} - w_i(\delta_{ij} - w_j)] d \ln p_j$$

(5.67) $$w_i d \ln q_i = b_i d \ln Q + \sum_{j=1}^{n} [r_{ij} - w_i(\delta_{ij} - w_j)] d \ln p_j$$

According to equations 6.50, 6.55, 6.56, and 6.57, marginal budget shares of the Rotterdam and NBR model are constant and those with CBS and LA/AIDS model vary with expenditure shares. On the other hand, the Slutsky terms are constant in the Rotterdam and CBS models, while they vary with expenditure shares in the NBR and the LA/AIDS model.

Barten Synthetic Model

Equations (6.50), (6.55), (6.56), and (6.57) can be nested into a single system, which is called the Barten synthetic system (Barten, 1993). The nested system can be represented as follows:

(6.58) $$w_i d\ln q_i = (\beta_i + \lambda w_i) d\ln Q + \sum_{j=1}^{n} \left[\gamma_{ij} - \mu w_i (\delta_{ij} - w_j)\right] d\ln p_j$$

where $i = 1,2,....,n$ and $\beta_i \equiv (1-\lambda)b_i + \lambda c_i$, and $\gamma_{ij} \equiv (1-\mu)s_{ij} + \mu r_{ij}$.

Depending on the restrictions we impose on coefficients μ and λ in equation (6.58), we could recover the Rotterdam, the LA/AIDS, the CBS and the NBR models. $(\lambda, \mu) = (0,0)$ would yield the Rotterdam model; $(\lambda, \mu) = (1,0)$ would yield the CBS model; $(\lambda, \mu) = (0,1)$ would give rise to the NBR model; $(\lambda, \mu) = (1,1)$ would yield the AIDS model.

To satisfy the theoretical properties associated with the demand theory, we assume following restrictions on parameters of Barten synthetic model. Restrictions imposed are, adding-up:

(6.59) $$\sum_{i=1}^{n} \beta_i + \lambda = 1$$

(6.60) $$\sum_{i=1}^{n} \gamma_{ij} = 0,$$

and homogeneity:

(6.61) $$\sum_{j=1}^{n} \gamma_{ij} = 0, \text{ where } i = 1,2,.....,n.$$

Slutsky symmetry condition is satisfied via the restriction:

(6.62) $$\gamma_{ij} = \gamma_{ji} \text{ for } i, j = 1,2,......,n \text{ and } i \neq j$$

Expenditure and price elasticity (compensated own- and cross-price elasticities) formulae derived from Barten synthetic model are as follows (see the Appendix 5 for derivation of expenditure and own- and cross-price elasticity formulae for Barten synthetic model). Compensated price elasticity formula is expressed as follows:

(6.63) $e_{ij}^{C} = \frac{\gamma_{ij}}{w_i} - \mu(\delta_{ij} - w_j)$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1 \; if \, i = j$ and $\delta_{ij} = 0 \; if \, i \neq j$). We recover the uncompensated price elasticities e_{ij}^{U} using the Slutsky derivative expressed in elasticity form as follows:

(6.64) $e_{ij}^{U} = e_{ij}^{C} - e_i w_j$

Next, compensated cross price elasticities were used to assess the symmetry conditions using following expression:

(6.65) $e_{ij}^{c} = \left(\frac{w_j}{w_i}\right) e_{ji}^{c} + w_j (e_j - e_i)$

where w 's are budget shares of *i*th and *j*th good and, e_j and e_i are expenditure elasticities of *j*th and *i*th good respectively. Expenditure elasticity formula for Barten synthetic system is given as follows:

(6.66) $e_i = \frac{\beta_i}{w_i} + \lambda$

Serial correlation problem of disturbance term associated with the Barten synthetic model is dealt using the same technique discussed in the LA/QUAIDS section above.

Data Analysis and Discussion

We used Barten synthetic model developed by Barten (1993) to capture dynamic interrelationships among ten non-alcoholic beverage categories. Expenditure, own-price and cross-price demand elasticities (both uncompensated and compensated) were estimated for the ten non-alcoholic beverage categories over the 72-month period. We employed the following version of Barten synthetic model with an additive disturbance term and a seasonal adjustment done using quarterly seasonal dummies:

$$(6.67) \quad w_{it} d \ln q_{it} = (\beta_i + \lambda w_{it}) d \ln Q + \sum_{j=1}^{n} [\gamma_{ij} - \mu w_{it}(\delta_{ij} - w_{jt})] d \ln p_{jt} + \sum_{j=1}^{3} d_j Q_{ijt} + e_{it}$$

where $i = (1,2,.....,10)$ indexes ten non-alcoholic beverages categories in the system, t indexes the time in months, i.e. $t = (1,2,3,.......,72)$ p_{jt} is monthly real prices for each non-alcoholic beverage considered in study, q_{it} is per capita quantity consumed in each non-alcoholic beverage, Q_{ijt} is the quarterly dummy used to capture the seasonality pertaining to four quarters of the year. Monthly budget share of each non-alcoholic beverage consumed is denoted by w_{it} where $w_{it} = \frac{p_{it} q_{it}}{m}$. Additive disturbance term is denoted by e_{it}.

In estimating the Barten synthetic model, we imposed theoretical restrictions on parameters explained in equation (6.59) through equation (6.62) above (adding-up, homogeneity and Slutsky symmetry). Given the fact that all expenditure shares add up to one, i.e. $\sum_{i=1}^{10} w_{it} = 1$, and above adding up conditions, we estimated the Barten synthetic model with only 9 equations (dropping the budget share equation pertaining to tea consumption) to avoid the singularity of the error variance-covariance matrix. The parameters of the tea budget share equation were recovered using adding-up restrictions.

It should be noted that for the purpose of empirical analysis, differential demand systems have to be converted into finite changes (difference form). Logarithmic differences are computed for price and expenditure share (budget share) terms in the Barten synthetic model depicted in equation (6.67). For example, $d\ln q_{it}$ is approximated by $(\ln q_{it} - \ln q_{it-1})$; $d \ln p_{jt}$ is approximated by $(\ln p_{jt} - \ln p_{jt-1})$; w_{it} is calculated taking the average of two consecutive budgets shares (Matsuda, 2005) i.e., $w_i = 0.5(w_{it} + w_{it-1})$; and $d\ln Q = \sum_i 0.5(w_{it} + w_{it-1})(\ln q_{it} - \ln q_{it-1})$.

Again, just like we did for LA/QUAIDS model estimation, presence of possible autocorrelation (serial correlation) was examined through the autocorrelation and partial autocorrelation function generated for each series. It must be emphasized that the popular Durbin-Watson statistic could not be used to test for autocorrelation due the presence of lag of dependent variable (expenditure share and quantity in our work) in calculating the Divisia quantity index and average of budget shares in our Barten model. Alternatively, the test statistic suggested for such situations, i.e. Durbin-*h* statistic could not be used due to the fact that Durbin-*h* statistic broke down for situations where the product of the number of observations and variance of the estimated coefficient exceeded unity.

Calculated autocorrelation and partial autocorrelation functions of the residuals of all non-alcoholic beverages indicated the presence of possible serial correlation (this was expected to be the case given the time-series nature of the data set). A close study of above functions indicated the presence of second-order or third-order autoregressive process of disturbance terms in the system. Therefore, each system was fitted with first- second- and third-order autoregressive process of disturbance terms and significance of autocorrelation coefficient was looked at. Through such exercise, we found that disturbance terms behave as an *AR(3)* process. Thus Barten synthetic model was fitted assuming the disturbance process was:

(6.68) $e_{it} = \rho_{i1}e_{i,t-1} + \rho_{i2}e_{i,t-2} + \rho_{i3}e_{i,t-3} + u_{it}$

where ρ_{i1}, ρ_{i2}, and ρ_{i3} are fist, second, and third order autoregressive parameters respectively. The white-noise disturbance term is denoted by u_{it} which is independently and identically distributed with zero mean and constant variance. Finally, the estimating form of the Barten synthetic model taking into account *AR(3)* disturbances can be written as follows:

$$
\begin{aligned}
w_{it} d\ln q_{it} = {} & \rho_1 (w_{it} d\ln q_{it})_{t-1} + \rho_2 (w_{it} d\ln q_{it})_{t-2} + \rho_3 (w_{it} d\ln q_{it})_{t-3} + \\
& (\beta_i + \lambda w_{it}) d\ln Q_t + \sum_{j=1}^{n} \left[\gamma_{ij} - \mu w_{it}(\delta_{ij} - w_{jt})\right] d\ln p_{jt} - \\
& \rho_1 \left\{ (\beta_i + \lambda w_{it-1}) d\ln Q_{t-1} + \sum_{j=1}^{n} \left[\gamma_{ij} - \mu w_{it-1}(\delta_{ij} - w_{jt-1})\right] d\ln p_{jt-1} \right\} - \\
& \rho_2 \left\{ (\beta_i + \lambda w_{it-1}) d\ln Q_{t-2} + \sum_{j=1}^{n} \left[\gamma_{ij} - \mu w_{it-2}(\delta_{ij} - w_{jt-2})\right] d\ln p_{jt-2} \right\} - \\
& \rho_3 \left\{ (\beta_i + \lambda w_{it-3}) d\ln Q_{t-3} + \sum_{j=1}^{n} \left[\gamma_{ij} - \mu w_{it-3}(\delta_{ij} - w_{jt-3})\right] d\ln p_{jt-3} \right\} + \\
& \sum_{j=1}^{3} d_j Q_{ijt} + e_{it}
\end{aligned}
\tag{6.69}
$$

The model was estimated using SAS 9.2 statistical software. We used the Proc Model procedure to estimate model parameters and subsequently to calculate expenditure, own-price and cross-price elasticities.

Barten Synthetic Model Parameter Estimates

We present the parameter estimates of the Barten synthetic model in the Appendix 5. Fifty nine out of 97 parameters estimated were significant at the 0.01 level of significance. Estimated Barten synthetic model was corrected for serial correlation using an *AR(3)* process of disturbance terms. Calculated autocorrelation coefficients were statistically significant at 90% level indicating the presence of *AR(3)* disturbance terms.

The joint hypotheses tests for seasonal dummies, λ (lambda) and μ (mu) also are shown in the Appendix 5. Significance (at 0.10 level) of seasonal (quarterly) dummy variables for all non-alcoholic beverages confirms the presence of quarterly seasonality in the data set. However, examination of individual seasonal dummy variables associated with each non-alcoholic beverage revealed some mixed results.

Isotonics consumption is significant for the second quarter. More isotonics are consumed in the second quarter compared to the fourth quarter. This result somewhat supports the Figure 6.1 budget share trends associated with isotonics. Most of regular soft drinks are consumed in the second quarter compared to the fourth quarter and the least is consumed in the first quarter. Again, this result reinforced the budget share trends graphed in Figure 6.2. This result is similar to the LA/QUAIDS model. More diet soft drinks are consumed in the second quarter compared to the fourth quarter. Less high-fat milk is consumed in the second quarter compared to the fourth quarter. On the other hand, more high-fat milk is consumed in the first quarter compared to the fourth quarter. Budget share trends shown in the Figure 6.4 reinforced this result for high-fat milk. More low-fat milk is consumed in the third quarter compared to the fourth quarter and less is consumed in the second quarter in comparison to fourth quarter. Budget share trends shown in the Figure 6.5 provide evidence for above result.

According to the seasonal dummies associated with fruit drinks, notice more fruit drinks are consumed in the first and second quarters compared to the fourth quarter. The highest level of fruit drinks is consumed in the second quarter. Budget share trends showed in Figure 6.6 confirms this result for fruit drinks. We observe that more fruit juice is consumed in the first quarter compared to the fourth quarter. On the other hand, fruit juice intake is less in the second quarter compared to the fourth quarter.

According to the significance of seasonal dummies, more bottled water is consumed in the second and third quarters compared to the fourth quarter. These results with respect to fruit juices and bottled water are strengthened by the budget share trend graphs depicted in Figures 6.8 and 6.9. Coffee consumption is low in first and second quarters compared to the fourth quarter.

Moreover, the joint hypothesis for *lambda* and *mu* is rejected for possibility of data support for Rotterdam, AIDS and NBR versions of differential demand systems. According to the significance of the chi-square statistic for the joint hypothesis of *lambda* and *mu*, the data support the Central Bureau of Statistics (CBS) version of differential demand system.

<u>Barten Synthetic Model Elasticity Estimates</u>

Parameter estimates (as shown in the Appendix 5) were used in calculating expenditure, and uncompensated and compensated own-price and cross-price elasticities for ten non-alcoholic beverages considered in this study. Again, we used the average of the final twelve observations of each expenditure share data series as the local set of coordinates in calculating elasticities. We used elasticity formulae showed in equations (6.51) through (6.54) above to generate compensated and uncompensated own- and cross-price and expenditure elasticities respectively. Uncompensated own- and cross-price elasticities were generated using the Slutsky derivative expressed in elasticity form. Tables 6.5 and 6.6 show the calculated uncompensated and compensated own-price, cross-price and expenditure elasticities for each non-alcoholic beverage category.

According to Table 6.5, all the calculated expenditure elasticity estimates are significant at the 0.10 level. Isotonics are found to be the most expenditure elastic non-alcoholic beverage. In other words, isotonics is the most responsive non-alcoholic beverage category for varying total expenditure values. Other expenditure elastic non-alcoholic beverages are regular soft drinks (expenditure elasticity 1.21), diet soft drinks (1.29), fruit drinks (1.44), bottled water (1.12), and tea (1.11). Responsiveness of high-fat milk, low-fat milk, fruit juices and coffee are inelastic for changes in total expenditure. They are, 0.83, 0.86, 0.67, and 0.54 respectively.

All uncompensated and compensated own-price elasticity estimates have negative sign. This result is indicative of theoretically consistent own-price elasticity estimates with demand theory. Compensated own-price elasticity of demand for Isotonics is -4.70, which is the highest amongst all own-price elasticities of demand for non-alcoholic beverages. Very small budget share and high prices associated with Isotonics may have contributed to yield higher own-price elasticity of demand for isotonics. In other words, marginal consumers are more sensitive to a price change in isotonics compared to that of other non-alcoholic beverages.

Table 6.5: Expenditure Elasticities and Uncompensated Own-Price and Cross-Price Demand Elasticities Estimated through Barten Synthetic Model[34]

	iso	Rsd	Dsd	hfm	lfm	Fd	fj	bw	cof	tea	exp
iso	**-4.7177**	1.9784	1.4701	**-1.5973**	0.4351	**-3.4580**	1.5706	0.5814	**1.8347**	0.1677	**1.7351**
	0.0000	0.1468	0.2592	0.0675	0.5802	0.0002	0.2194	0.5017	0.0282	0.7124	0.0000
rsd	0.0979	**-1.7485**	**-0.4944**	0.0803	0.0977	-0.0015	**0.5640**	0.1346	0.0148	0.0442	**1.2110**
	0.1243	0.0000	0.0109	0.5127	0.3668	0.9895	0.0029	0.2595	0.9004	0.5009	0.0000
dsd	0.1050	**-0.7358**	**-0.9834**	0.1486	-0.1033	**0.4130**	-0.2937	0.1553	0.0100	-0.0051	**1.2892**
	0.2418	0.0101	0.0026	0.3725	0.4948	0.0028	0.1066	0.2306	0.9354	0.9403	0.0000
hfm	**-0.0991**	0.1874	0.2056	**-0.6441**	0.2211	**-0.3051**	-0.1658	-0.1352	0.0475	**-0.1411**	**0.8289**
	0.0891	0.2896	0.2060	0.0052	0.2804	0.0012	0.2111	0.1217	0.5879	0.0040	0.0000
lfm	0.0519	0.2763	-0.0961	0.3285	**-0.9185**	**-0.2131**	-0.2142	-0.1286	0.1365	-0.0843	**0.8617**
	0.5143	0.2408	0.6654	0.2886	0.0036	0.0644	0.1987	0.2230	0.2134	0.1617	0.0000
fd	**-0.4069**	-0.0482	**0.6918**	**-0.6202**	**-0.3013**	**-0.7651**	0.0563	**-0.4342**	**0.5498**	-0.1651	**1.4431**
	0.0002	0.8711	0.0037	0.0003	0.0260	0.0039	0.8360	0.0406	0.0160	0.1223	0.0000
fj	0.0918	**0.7302**	-0.1421	-0.1075	-0.0935	0.0839	**-1.0126**	-0.0969	-0.1649	0.0447	**0.6668**
	0.1702	0.0007	0.3030	0.2986	0.2755	0.4870	0.0000	0.4436	0.1883	0.5116	0.0000
bw	0.0849	0.4077	0.3310	**-0.3130**	-0.1960	**-0.4751**	-0.3297	-0.3383	-0.2049	-0.1453	**1.1157**
	0.4711	0.2389	0.1950	0.0780	0.1658	0.0511	0.3170	0.3652	0.3713	0.5233	0.0000
cof	**0.2074**	0.1622	0.1140	0.1147	0.1734	**0.5662**	-0.3153	-0.1228	**-1.5925**	0.1550	**0.5375**
	0.0214	0.5521	0.5559	0.4161	0.1380	0.0067	0.2201	0.4975	0.0000	0.1376	0.0000
tea	0.0371	0.1953	0.0097	**-0.4315**	-0.1784	-0.2361	0.0841	-0.1994	0.2233	**-0.7005**	**1.1100**
	0.6635	0.4565	0.9582	0.0018	0.1077	0.1621	0.7296	0.5248	0.2165	0.0000	0.0000

[34] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Table 6.6: Compensated Own-Price and Cross-Price Demand Elasticities Estimated through Barten Synthetic Model[35]

	iso	Rsd	dsd	hfm	lfm	fd	fj	bw	cof	tea
iso	**-4.7021**	**2.3098**	1.6974	-1.3648	0.5896	**-3.3262**	1.8690	0.6959	**1.9805**	0.2509
	0.0000	0.0885	0.1944	0.1153	0.4540	0.0003	0.1444	0.4205	0.0187	0.5810
rsd	**0.1088**	**-1.5172**	**-0.3357**	**0.2425**	**0.2054**	0.0905	**0.7722**	**0.2145**	0.1165	0.1024
	0.0885	0.0000	0.0792	0.0509	0.0613	0.4414	0.0000	0.0733	0.3276	0.1214
dsd	0.1166	**-0.4895**	**-0.8145**	**0.3214**	0.0114	**0.5110**	-0.0719	**0.2404**	0.1183	0.0568
	0.1944	0.0792	0.0118	0.0559	0.9398	0.0003	0.6892	0.0649	0.3401	0.4013
hfm	-0.0917	**0.3457**	**0.3142**	**-0.5331**	0.2949	**-0.2421**	-0.0232	-0.0805	0.1171	**-0.1013**
	0.1153	0.0509	0.0559	0.0193	0.1516	0.0090	0.8600	0.3509	0.1854	0.0355
lfm	0.0596	**0.4409**	0.0168	0.4440	**-0.8418**	-0.1476	-0.0660	-0.0717	**0.2089**	-0.0430
	0.4540	0.0613	0.9398	0.1516	0.0074	0.1959	0.6889	0.4923	0.0606	0.4706
fd	**-0.3939**	0.2274	**0.8808**	**-0.4268**	-0.1728	**-0.6555**	0.3045	-0.3389	**0.6710**	-0.0958
	0.0003	0.4414	0.0003	0.0090	0.1959	0.0125	0.2653	0.1061	0.0037	0.3648
fj	0.0978	**0.8576**	-0.0548	-0.0181	-0.0342	0.1346	**-0.8979**	-0.0529	-0.1088	0.0767
	0.1444	0.0000	0.6892	0.8600	0.6889	0.2653	0.0003	0.6741	0.3842	0.2612
bw	0.0949	**0.6208**	**0.4772**	-0.1635	-0.0967	-0.3903	-0.1378	-0.2646	-0.1112	-0.0918
	0.4205	0.0733	0.0649	0.3509	0.4923	0.1061	0.6741	0.4764	0.6275	0.6870
cof	**0.2122**	0.2649	0.1844	0.1868	**0.2213**	**0.6071**	-0.2229	-0.0873	**-1.5473**	**0.1809**
	0.0187	0.3276	0.3401	0.1854	0.0606	0.0037	0.3842	0.6275	0.0000	0.0828
tea	0.0471	0.4073	0.1551	**-0.2827**	-0.0796	-0.1517	0.2750	-0.1262	**0.3165**	**-0.6472**
	0.5810	0.1214	0.4013	0.0355	0.4706	0.3648	0.2612	0.6870	0.0828	0.0000

[35] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea

Regular soft drinks and coffee too show elastic own-price elasticity estimates; they are -1.52 and -1.55 respectively. All other non-alcoholic beverages under consideration showed inelastic demands. The most price inelastic non-alcoholic beverage was high-fat milk where the estimated own-price elasticity of demand was -0.53. Compensated own-price elasticity of demand for diet soft drinks, low-fat milk, fruit drinks, fruit juices, and tea was respectively -0.81, -0.84, -0.66, -0.89, and -0.65. It should be noted that the compensated own-price elasticity of demand for bottled water was not significant at the 0.10 level.

Thirty six out of ninety (forty percent) compensated cross-price elasticities have negative sign indicating net complements. Sixty percent of compensated cross-price elasticities are indicative of net substitutes (positive sign). Regular soft drinks and coffee are found to be net substitutes for isotonics, while fruit drink is a net complement. Isotonics, high-fat milk, low-fat milk, fruit juices, and bottled water are net substitutes for regular soft drinks. Diet soft drinks were found to be a net complement to regular soft drinks.

Net substitutes for diet soft drinks were high-fat milk, fruit drinks, and bottled water, while regular soft drinks were a net complement. Regular soft drinks and diet soft drinks were found to be strong net substitutes for high-fat milk, while low-fat milk was a weak net substitute[36]. Fruit drinks and tea were strong net complements for high-fat milk, whereas coffee was a weak net complement. This result can be supported by breakfast choices consumers make, where they often consume milk and coffee/and or tea at the same time. Regular soft drinks and coffee were found to be strong net substitutes for low-

[36] Strong net substitutes or net complements were cross price elasticities that were significant at 0.10 level, where weak net substitute may allow for significance level up to 20%.

fat milk, while, high-fat milk was is weak net substitute. There were no strong net complements for low fat milk, however fruit drinks were found to be a weak net complement.

Diet soft drinks and coffee were net substitutes for fruit drinks, whereas, isotonics and high-fat milk were found to be strong net complements. On the other hand, low-fat milk and bottled water were weak net complements for fruit drinks. Results show that regular soft drinks were a strong net substitute for fruit juices, while isotonics was a weak net substitute. We did not observe any strong or weak net complements for fruit juices.

Regular soft drinks and diet soft drinks were found to be strong net substitutes. We did not find any strong net complements associated with bottled water, however, fruit drinks were found to be a weak net complement. Strong net substitutes for coffee were found to be isotonics, low-fat milk, fruit drinks and tea. High-fat milk was a weak net substitute for coffee. We did not observe any net complements associated with coffee. Coffee was the only strong net substitute for tea, while regular soft drinks were a weak net substitute. High-fat milk was found to be a strong net complement for tea.

Habit Persistence and Inventory Behavior: The State Adjustment Model

In the following section we discuss in detail the theoretical development and data analysis and discussion with respect to the State Adjustment Model of Houthakker and Taylor (1970) (SAM for short). In the first section we offer a detailed narrative on Houthakker and Taylor (1970) model along with some estimation issues one has to deal with such as autocorrelation (serial correlation), over-identification, and the adding-up condition. We also will offer an alternative derivation to the SAM compared to the Houthakker and Taylor (1970) derivation of SAM developed by Winder (1971).

In the section on analysis and discussion, first we state the estimating equation of the Houthakker and Taylor model taking into account autocorrelation and over-identification issues. We also develop and discuss compensated and uncompensated own-price and cross-price elasticity matrices. We also discuss the inventory behavior and habit formation issues in demand estimation. Finally we offer a narrative on short-run and long-run effects derived from SAM.

Theoretical Development

Most of the following discussion on theoretical development is borrowed from Houthakker and Taylor (1970), Sexauer (1977), Wohlgenant and Hahn (1982), and Capps and Nayga (1990). The model used in this study is the Houthakker and Taylor (1970) state adjustment model which takes into account the past behavior of the consumer in current decision making. This past behavior is embodied in a *stock* or *state* variable that encompasses past physical stocks held by the consumer as well as past habits formed in consumption. This is the dynamic component of this model (in short, effect of past behavior on current consumption expenditure). Hence the model is defined through two equations: *a short-run demand function* and a *stock depreciation equation*. Short run demand function relates the rate of quantity demanded to the state variable (rate of stock variable), rate of income (or expenditure) and rate of price of goods considered (all variables considered are a function of time, hence the *"rate"*). The stock depreciation equation (a first order differential equation) relates the rate at which a sock depreciates, given the quantity available and depreciation rate. Mathematically, we can state the model as follows:

(6.70) $$q_i(t) = \alpha_i + \beta_i S_i(t) + \gamma_i m_i(t) + \sum_{j=1}^{n} k_{ij} p_{ij}(t)$$

(6.71) $$\frac{dS_{it}(t)}{dt} = \dot{S}_i(t) = q_i(t) - \delta_i S_i(t)$$

where, $i,\ j = 1,2,3,....,n$; $\dot{S}_{it}$ is the rate of change of stock and, δ_i is the constant stock depreciation rate. According to equation (6.71), stock depreciates at a declining geometric rate over time.

Short-run demand function and stock depreciation equation together is called the *primal form*. In equations (6.70) and (6.71), all but the state variable can be observed. Therefore, combining equations (6.70) and (6.71), a reduced form equation is defined where the state variable is no longer in the estimating equation. The *reduced form* equation is comprised of quantity demanded on the left-hand side, and price, income (expenditure) and lag of the quantity variable on the right-hand side (it is a finite approximation to the dynamic model shown in equations (6.70) and (6.71)). See the Appendix 5 for a complete derivation of the equation (6.72) using a finite approximation of the dynamic model developed using equations (6.70) and (6.71). Furthermore, The Appendix 5 also contains the derivation of short-run and long-run effects on quantity consumed. Dynamic models give extra pieces of information such as the ability to measure short-run and long-run behavior of a policy instrument. Short-run and long-run effects respectively can be defined as follows:

Short-term derivative of consumption with respect to income/expenditure is given by:

(6.72) $$\frac{dq_i(t)}{dm_i(t)} = \gamma_i$$

Short-term derivative of consumption with respect to price is given by:

(6.73) $$\frac{dq_i(t)}{dp_j(t)} = k_j$$

Short-term derivative tells us the instantaneous adjustment of consumption before state variables have a chance to adjust.

Long-term derivative is obtained by setting each equation (6.71) into zero and substituting the result in equation (6.70) to get the following:

(6.74) $$\frac{dq_{it}}{dm_{it}} = \frac{\delta_i \gamma_i}{(\delta_i - \beta_i)}$$

(6.75) $$\frac{dq_{it}}{dp_j} = \frac{\delta_i k_j}{(\delta_i - \beta_i)}$$

(6.76) $$q_{it} = A_{i0} + A_{i1} q_{it-1} + A_{i2} \Delta m_{it} + A_{i3} m_{it-1} + \sum_{j=1}^{n} A_{ij} \Delta p_{ijt} + \sum_{k}^{k} A_{ik} p_{ikt-1}$$

In equation 6.72, $i = 1,2,.....,n$; and $t = 1,2,3,.....,T$, $j = 4,6,8,....,even$; and $k = 5,7,9,.....,odd$. Structural parameters of primal equation (6.70) can be recovered through the reduced form equation parameters (the A's) as follows:

(6.77) $$A_{i0} = \frac{\alpha_i \delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.78) $$A_{i1} = \frac{1+\frac{1}{2}(\beta_i - \delta_i)}{1-\frac{1}{2}(\beta_i - \delta_i)}$$

(6.79) $$A_{i2} = \frac{\gamma_i\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i - \delta_i)}$$

(6.80) $$A_{i3} = \frac{\gamma_i \delta_i}{1-\frac{1}{2}(\beta_i - \delta_i)}$$

(6.81) $$A_{ij} = \frac{k_{ij}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i - \delta_i)}$$

(6.82) $$A_{ik} = \frac{k_{ik} \delta_i}{1-\frac{1}{2}(\beta_i - \delta_i)}$$

Data Analysis and Discussion

In this section we first discuss the empirical model (Houthakker and Taylor, 1970) used with the ten non-alcoholic beverages categories, seasonal adjustment, and a correction for over-identification of constant depreciation parameter and autocorrelation issues. Second, we calculate uncompensated and compensated own-price and cross-price elasticities for the ten non-alcoholic beverage categories. Third, we offer an explanation to short-run and long-run effects as derived through the dynamic model. Finally, we discuss the inventory behavior or habit persistence in the demand for non-alcoholic beverages.

Following is the structural form equation (equation (6.83)), (quantity of each non-alcoholic beverage is on the left-hand side; state variable *(S)*, expenditure *(m)* and prices of non-alcoholic beverages[37] are on the right-hand side). It is also called the short-run demand equation. The specification of the Houthakker and Taylor (1970) model for the *i*th non-alcoholic beverage is:

(6.83) $$q_{it} = \alpha_i + \beta_i S_{it} + \gamma_i m_t + k_{i1} piso_t + k_{i2} prsd_t + k_{i3} pdsd_t + k_{i4} phfm + k_{i5} plfm_t + k_{i6} pfd_t + k_{i7} pfj_t + k_{i8} pbw_t + k_{i9} pcof_t + k_{i10} ptea_t$$

(6.84) $$\dot{S}_{it} = q_{it} - \delta_i S_{it}$$

Equation (6.84) depicts the geometric stock depreciation equation. $i =$ the *i*th non-alcoholic beverage (see the footnote below for definitions of non-alcoholic beverage acronyms used in equation (6.83)).

The sign of the coefficient associated with the state variable, i.e., β, indicates the presence of an inventory-adjustment or habit-formation. If β is positive, we say that habit-formation effect dominates and on the other hand, if β is negative, we say that inventory-effect dominates. Consequently, consumer demand at time *t* increases with decrease in inventory (physical stock) and increase with stock of habits (psychological stocks). It is expected that inventory effects dominate habit formation for durable goods. However, for non-durable goods, habit effects may dominate inventory effects. According to Sexauer (1977), this distinction between durables and non-durables depends on the time dimension. When the time dimension in the question is short, any good that provide a stream of services over a period of time can be classified into the durable goods category. As well, consumers may purchase more non-alcoholic beverages of some particular kind (such as carbonated soft drinks, tea or coffee) when price decreases.

[37] *piso*=price of isotonics, *prsd*=price of regular soft drinks, *pdsd*=price of diet soft drinks, *phfm*=price of high fat milk, *plfm*=price of low fat milk, *pfd*=price of fruit drinks, *pfj*=price of fruit juices, *pbw*=price of bottled water, *pcof*=price of coffee, *ptea*=price of tea

Following Houthakker and Taylor (1970), the reduced-form equation for each of the non-alcoholic beverage products is as follows. Equation (6.85) is estimated using iterated seemingly unrelated regression *(itsur)* technique in SAS statistical software proc model procedure:

$$(6.85)\quad \begin{aligned} q_{it} = {} & A_{i0} + A_{i1}q_{it-1} + A_{i2}\Delta m_t + A_{i3}m_{t-1} + A_{i4}\Delta piso_t + A_{i5}\, piso_{t-1} + \\ & A_{i6}\Delta prsd_t + A_{i7}\, prsd_{t-1} + A_{i8}\Delta pdsd_t + A_{i9}\, pdsd_{t-1} + A_{i10}\Delta phfm_t + \\ & A_{i11}\, phfm_{t-1} + A_{i12}\Delta plfm_t + A_{i13}\, plfm_{t-1} + A_{i14}\Delta pfd_t + A_{i15}\, pfd_{t-1} + \\ & A_{i16}\Delta pfj_t + A_{i17}\, pfj_{t-1} + A_{i18}\Delta pbw_t + A_{i19}\, pbw_{t-1} + A_{i20}\Delta pcof_t + \\ & A_{i21}\, pcof_{t-1} + A_{i22}\Delta ptea_t + A_{i23}\, ptea_{t-1} + \\ & d_{i1}Q_{i1} + d_{i2}Q_{i2} + d_{i3}Q_{i3} + u_{it} \end{aligned}$$

where, A_{i0}, A_{i1}, A_{i2} and A_{i3} specified similar to equations (6.77), (6.78), (6.79) and (6.80) above and A_{i4} through A_{i23} specified as below:

$$(6.86)\quad A_{i4} = \frac{k_{i1}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

$$(6.87)\quad A_{i5} = \frac{k_{i1}\delta_i}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

$$(6.88)\quad A_{i6} = \frac{k_{i2}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

$$(6.89)\quad A_{i7} = \frac{k_{i2}\delta_i}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

$$(6.90)\quad A_{i8} = \frac{k_{i3}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.91) $$A_{i9} = \frac{k_{i3}\delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.92) $$A_{i10} = \frac{k_{i4}\left(1 + \frac{\delta_i}{2}\right)}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.93) $$A_{i11} = \frac{k_{i4}\delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.94) $$A_{i12} = \frac{k_{i5}\left(1 + \frac{\delta_i}{2}\right)}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.95) $$A_{i13} = \frac{k_{i5}\delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.96) $$A_{i14} = \frac{k_{i6}\left(1 + \frac{\delta_i}{2}\right)}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.97) $$A_{i15} = \frac{k_{i6}\delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.98) $$A_{i16} = \frac{k_{i7}\left(1 + \frac{\delta_i}{2}\right)}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.99) $$A_{i17} = \frac{k_{i7}\delta_i}{1 - \frac{1}{2}(\beta_i - \delta_i)}$$

(6.100) $$A_{i18} = \frac{k_{i8}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.101) $$A_{i19} = \frac{k_{i8}\delta_i}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.102) $$A_{i20} = \frac{k_{i9}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.103) $$A_{i21} = \frac{k_{i9}\delta_i}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.104) $$A_{i22} = \frac{k_{i10}\left(1+\frac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

(6.105) $$A_{i23} = \frac{k_{i10}\delta_i}{1-\frac{1}{2}(\beta_i-\delta_i)}$$

Problem of Over-identification of Constant Depreciation Parameter

It should be noted that the structural parameter, δ_i (the constant depreciation rate) is over-identified (meaning parameter value can be estimated using more than one equation and it is not guaranteed that it would give the same value). For example, let us see the following two methods of calculating δ_i . Consider the following relationship where equation (6.80) is divided by equation (6.79) to recover the parameter δ_i :

(6.106) $$\frac{A_{i3}}{A_{i2}} = \frac{\dfrac{\gamma_i \delta_i}{1-\frac{1}{2}(\beta_i - \delta_i)}}{\dfrac{\gamma_i\left(1+\dfrac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i - \delta_i)}} = \frac{\delta_i}{\left(1+\dfrac{\delta_i}{2}\right)}$$

Now let us divide equation (6.87) by equation (6.86) to recover structural parameter δ_i :

(6.107) $$\frac{A_{i5}}{A_{i4}} = \frac{\dfrac{k_{i1} \delta_i}{1-\frac{1}{2}(\beta_i - \delta_i)}}{\dfrac{k_{i1}\left(1+\dfrac{\delta_i}{2}\right)}{1-\frac{1}{2}(\beta_i - \delta_i)}} = \frac{\delta_i}{\left(1+\dfrac{\delta_i}{2}\right)}$$

It is clear that δ_i can be derived at least through two ways as shown in equations (6.106) and (6.107), hence δ_i is over-identified. Therefore, we need to impose additional restrictions on reduced-form equation parameters to obtain a unique estimate for δ_i .

Following are the additional parameter restrictions imposed to deal with the over-identification problem of δ_i :

(6.108) $$A_{i4} = A_{i5}\frac{A_{i2}}{A_{i3}}$$

(6.109) $$A_{i6} = A_{i7}\frac{A_{i2}}{A_{i3}}$$

(6.110) $$A_{i8} = A_{i9}\frac{A_{i2}}{A_{i3}}$$

(6.111) $$A_{i10} = A_{i11}\frac{A_{i2}}{A_{i3}}$$

(6.112) $$A_{i12} = A_{i13} \frac{A_{i2}}{A_{i3}}$$

(6.113) $$A_{i14} = A_{i15} \frac{A_{i2}}{A_{i3}}$$

(6.114) $$A_{i16} = A_{i17} \frac{A_{i2}}{A_{i3}}$$

(6.115) $$A_{i18} = A_{i19} \frac{A_{i2}}{A_{i3}}$$

(6.116) $$A_{i20} = A_{i21} \frac{A_{i2}}{A_{i3}}$$

(6.117) $$A_{i22} = A_{i23} \frac{A_{i2}}{A_{i3}}$$

Problem of Autocorrelation

Calculated autocorrelation and partial autocorrelation functions of the residuals of all non-alcoholic beverages indicated the presence of possible serial correlation. A close study of above functions indicated the presence of second-order or third-order autoregressive process of disturbance terms in the system.

Since we do not impose any theoretical restrictions from the demand theory on the Houthakker and Taylor state adjustment model, we do not want to assume that residuals from each equation in the system add-up to zero. Hence there is no restriction on the autocorrelation coefficient matrix. Therefore, we can entertain fixes for autocorrelation equation-by-equation for each equation in the system. In that light, each equation in the system was fitted with first- second- and third-order autoregressive process of disturbance terms and significance of autocorrelation coefficient was looked at. We found that disturbance terms behave as an *AR(2)* process for each equation.

Therefore, *each* equation in the Houthakker and Taylor SAM was fitted assuming the following disturbance process:

(6.118) $$e_t = \rho_1 e_{t-1} + \rho_2 e_{t-2} + u_t,$$

where ρ_1, and ρ_2 are fist and second order autoregressive parameters respectively. The white-noise (non-autocorrelated) disturbance term is denoted by u_t which is independently and identically distributed with zero mean and constant variance.

<u>*Recovery of Structural Parameters from Reduced-form Parameters*</u>

Once the reduced-form system of equations is estimated, we can recover structural-form parameters for the system ($\alpha, \beta, \gamma, \delta$ and k s) from the reduced-form parameters (the *A*s). Following relationships would facilitate such recovery:

(6.119) $$\alpha_i = \frac{2A_{i0}\left(A_{i2} - \frac{1}{2}A_{i3}\right)}{A_{i3}\left(A_{i1}+1\right)}$$

(6.120) $$\beta_i = \frac{2(A_{i1}-1)}{A_{i1}+1} + \frac{A_{i3}}{\left(A_{i2} - \frac{1}{2}A_{i3}\right)}$$

(6.121) $$\gamma_i = \frac{2\left(A_{i2} - \frac{1}{2}A_{i3}\right)}{A_{i1}+1}$$

(6.122) $$\delta_i = \frac{A_{i3}}{\left(A_{i2} - \frac{1}{2}A_{i3}\right)}$$

(6.123) $$k_{i1} = \frac{2\left(A_{i4} - \frac{1}{2}A_{i5}\right)}{A_{i1}+1}$$

(6.124) $$k_{i2} = \frac{2\left(A_{i6} - \frac{1}{2}A_{i7}\right)}{A_{i1} + 1}$$

(6.125) $$k_{i3} = \frac{2\left(A_{i8} - \frac{1}{2}A_{i9}\right)}{A_{i1} + 1}$$

(6.126) $$k_{i4} = \frac{2\left(A_{i10} - \frac{1}{2}A_{i11}\right)}{A_{i1} + 1}$$

(6.127) $$k_{i5} = \frac{2\left(A_{i12} - \frac{1}{2}A_{i13}\right)}{A_{i1} + 1}$$

(6.128) $$k_{i6} = \frac{2\left(A_{i14} - \frac{1}{2}A_{i15}\right)}{A_{i1} + 1}$$

(6.129) $$k_{i7} = \frac{2\left(A_{i16} - \frac{1}{2}A_{i17}\right)}{A_{i1} + 1}$$

(6.130) $$k_{i8} = \frac{2\left(A_{i18} - \frac{1}{2}A_{i19}\right)}{A_{i1} + 1}$$

(6.131) $$k_{i9} = \frac{2\left(A_{i20} - \frac{1}{2}A_{i21}\right)}{A_{i1} + 1}$$

(6.132) $$k_{i10} = \frac{2\left(A_{i22} - \frac{1}{2}A_{i23}\right)}{A_{i1} + 1}$$

Short-run Versus Long-run Structural Equations

Short-run structural equation is depicted in equation (6.83). To obtain the long-run structural equation, we need to set equation (6.84) to zero and substitute the result in equation (6.83) and simplify to obtain the following (see the derivation in the Appendix 5):

$$
\begin{aligned}
q_{it} = {} & \frac{\delta_i \alpha_i}{\delta_i - \beta_i} + \frac{\delta_i \gamma_i}{\delta_i - \beta_i} m_t + \frac{\delta_i k_{i1}}{\delta_i - \beta_i} piso_t + \frac{\delta_i k_{i2}}{\delta_i - \beta_i} prsd_t + \frac{\delta_i k_{i3}}{\delta_i - \beta_i} pdsd_t + \\
& \frac{\delta_i k_{i4}}{\delta_i - \beta_i} phfm + \frac{\delta_i k_{i5}}{\delta_i - \beta_i} plfm_t + \frac{\delta_i k_{i6}}{\delta_i - \beta_i} pfd_t + \frac{\delta_i k_{i7}}{\delta_i - \beta_i} pfj_t + \frac{\delta_i k_{i8}}{\delta_i - \beta_i} pbw_t + \\
& \frac{\delta_i k_{i9}}{\delta_i - \beta_i} pcof_t + \frac{\delta_i k_{i10}}{\delta_i - \beta_i} ptea_t
\end{aligned}
\tag{6.133}
$$

It is evident that long-run parameters have derived from short-run expenditure and price parameters, constant depreciation parameter and parameter associated with state variable in the primal equation.

Reduced-form Equation Parameter Estimates

Parameter estimates from the reduced-form system estimation is illustrated in the Appendix 5. Lag of the quantity parameter was significant for isotonics, low-fat milk, fruit juices, bottled water and coffee. Expenditure effect (both lag effect and first-differenced effect) was significant for all non-alcoholic beverage categories. Sixty six out of one hundred price parameters estimated were significant at the 0.20 level.

The joint chi-squared test performed as shown in the Appendix 5 reveals the significance of quarterly dummy variable for all beverages included in the system estimation. In other words, seasonality (quarterly) significantly affects the demand for all categories of non-alcoholic beverages considered in this study. The magnitude of the value of the seasonal dummy variable in each equation shows similar patterns and results that were obtained in previous demand system analyses (LA/QUAIDS and Barten synthetic procedures). In particular, more isotonics are consumed in first, second and third quarter compared to the fourth quarter, in which most are consumed in the second quarter (see Figure 6.1 for similar trends). More regular soft drinks are consumed in the fourth quarter compared to the first and third quarters (results for second quarter is not significant). This result is in accordance with budget share trends shown in Figure 6.2. Less diet soft drinks are consumed in the first and third quarter compared to fourth quarter and Figure 6.3 would testify for above result. Our results show that high-fat milk is consumed more in first and third quarter compared to first quarter. This result does not exactly match with the graphical analysis we did in Figure 6.4.

More low-fat milk is consumed in the first and third quarter (second quarter effect is not significant) in comparison to the fourth quarter. This result is evident in Figure 6.5. Fruit drink consumption is high in first, second and third quarter compared to the fourth quarter. Fruit drinks budget share trend shown in Figure 6.6 supports our result. Fruit drink consumption is highest in the fourth quarter. It is clear in the Figure 6.7 as well as the regression result we have obtained through reduced-form parameter estimation. More bottled water is consumed in the first, second and third quarters compared to the fourth quarter. The highest coffee consumption is observed in the fourth quarter compared to others. The lowest coffee consumption is recorded in the second quarter of the year. Again, Figure 6.9 testifies our regression result. Tea consumption is high in first and second quarters compared to the fourth quarter. This result is evident in the budget share trends shown in Figure 6.10.

Autocorrelation coefficients depicting second order autoregressive process are significant at the 0.10 level for the most part. Few were significant at 20% level. Adjusted R-squared values are high for all non-alcoholic beverage categories. They range from 0.9818 for low-fat milk to 0.9020 for isotonics to 0.8189 for tea.

Short-Run and Long-Run Structural Parameter Estimates

Estimated parameters from reduced form system are used to recover structural equation parameters. The short-run structural parameter estimates are exhibited in the Appendix 5. The sign of the coefficient (i.e., β) associated with the state variable is looked at in categorizing the effect as habit formation (psychological stock) or inventory effect (physical stock). Positive β s are associated with habit forming behavior and negative β s are associated with inventory dominance. According to the calculated β s, we observe a habit forming behavior with respect to the consumption of isotonics, regular soft drinks, high-fat milk, fruit drinks, fruit juices and bottled water. Inventory dominance on demand is observed with diet soft drinks, low-fat milk, coffee and tea.

Value of δ tells about the depreciation rate of the available stock. According to that, all non-alcoholic beverages but fruit juices have a large stock depreciation rate.

Long-run structural parameter estimates are depicted in the Appendix 5. Long-run structural parameters associated with total expenditure and price variables are named *eta* and *theta* respectively in the table. Long-run structural parameter estimates are higher for those non-alcoholic beverages that are identified to show a habit forming effect. This is indicative of purchase of small amounts of such beverages in the short-run and large amounts in the long-run due to habit forming behavior. For example, the own-price coefficient associated with isotonics in the short run is -0.0122 and in the long-run it is -

0.0367 (which is higher in absolute value). Also, recollect that isotonics show a habit forming behavior in consumption. Same is true with respect to the calculated short-run and long-run total expenditure coefficients as well. For example, low-fat milk shows the inventory dominant behavior, hence large short-run total expenditure coefficient (0.0533) followed by a small long-run expenditure coefficient (0.0522). It should be noted that similar effects are reflected in short-run and long-run elasticities (expenditure, own-price and cross-price) as well (discussion on elasticities are below).

We have only used monthly purchase information in our analysis. However, if one wants to investigate behavior of estimated coefficients over time, a finer breakdown of time periods such as weekly, bi-weekly, monthly and quarterly would have to be used. We could find two such studies in the past literature, both done with respect to meet demand. They are, Wohlgenant and Hahn (1982) and Capps and Nayga (1990). The former had conventional aggregated meat products such as beef, pork and chicken. However, Capps and Nayga (1990) used expenditure information from finer disaggregated meat cuts within beef, namely, brisket, chuck, ground, loin, rib and round. Similar analysis with respect to non-alcoholic beverages is saved for future work.

Short-Run and Long-Run Elasticity Formulae

Given the calculated short-run and long-run structural equation parameter estimates, we can calculate the respective short-run and long-run expenditure and uncompensated own-price and cross-price demand elasticities as follows.

Short-run expenditure elasticity e_i^{SR} is calculated as:

(6.134) $$e_i^{SR} = \gamma_i \frac{\overline{m}}{\overline{q}_i}$$

where γ_i is the short-run coefficient associated with total expenditure variable, $\overline{m}$ is the average total expenditure share, and $\overline{q}_i$ is the average of the quantity of the *i*th non-alcoholic beverage[38], and $i = (1,2,....,10)$ non-alcoholic beverage categories. The long-run expenditure elasticity e_i^{LR} is calculated as:

$$(6.135) \qquad e_i^{LR} = \left(\frac{\delta_i \gamma_i}{\delta_i - \beta_i}\right)\frac{\overline{m}}{\overline{q}_i}$$

where, δ_i is the constant depreciation rate with respect to *i*th non-alcoholic beverage considered, β_i is the coefficient associated with the state variable in the short-run structural equation (equations 6.83 and 6.84), and $i = (1,2,....,10)$ non-alcoholic beverage categories.

Short-run uncompensated price elasticity of demand e_{ij}^{SR} is defined as follows:

$$(6.136) \qquad e_{ij}^{SR} = k_{ij}\,\frac{\overline{p}_{ij}}{\overline{q}_{ij}}$$

where, $i, j = (1,2,....,10)$ non-alcoholic beverage categories, $\overline{p}_{ij}$ is he average price of non-alcoholic beverages, $\overline{q}_{ij}$ is the average quantity of non-alcoholic beverages, and k_{ij} is the parameter associated with short-run price variables. Long-run uncompensated price elasticities of demand are calculated using the following formula:

$$(6.137) \qquad e_{ij}^{LR} = \left(\frac{\delta_i k_{ij}}{\delta_i - \beta_i}\right)\frac{\overline{p}_{ij}}{\overline{q}_{ij}}$$

Compensated price elasticities are recovered through the Slutsky equation interpreted in the elasticity form.

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[38] Average of the total expenditure and quantity of the *i*th non-alcoholic beverage is calculated using final 12 observations of each series.

Short-Run Elasticity Estimates

Calculated *short-run* uncompensated and compensated price elasticities and expenditure elasticities are exhibited in Tables 6.7 and 6.8 respectively. All expenditure elasticities were significant at the 0.10 level. Regular soft drinks and diet soft drinks showed elastic expenditure elasticities (1.13 and 1.20 respectively). Bottled water was highly expenditure inelastic; resulting in an expenditure elasticity of 0.17. Other non-alcoholic beverages showed following expenditure elasticities: isotonics 0.86; high-fat milk 0.84; low-fat milk 0.92; fruit drinks 0.91; fruit juices 0.98; coffee 0.81; tea 0.89.

Both compensated and uncompensated own-price elasticities were negative for all non-alcoholic beverages, showing the theoretical coherence with demand theory. All, own-price elasticities were significant at 10% level, but high-fat milk. Isotonics, regular soft drinks, coffee and tea exhibited an elastic own-price elasticity of demand (compensated elasticities). Regular soft drinks were the most elastic non-alcoholic beverage category, having own-price elasticity of demand of -1.70. The next highest was isotonics with compensated own-price elasticity of demand of -1.35. Calculated compensated own-price elasticity of demand for coffee and tea was -1.20 and -1.14 respectively. Bottled water was the most price inelastic non-alcoholic beverage category, where the calculated own-price elasticity of demand was -0.28.

Table 6.7: Houthakker and Taylor Model Short-Run Uncompensated Elasticity Estimates[39]

	iso	Rsd	dsd	Hfm	Lfm	Fd	fj	Bw	cof	Tea	exp
iso	**-1.3555**	0.1098	1.4794	0.4628	-0.3101	**-3.2978**	**2.0750**	0.2790	**0.7176**	0.0457	**0.8643**
	0.0115	0.9293	0.2403	0.7651	0.8374	0.0005	0.0152	0.5367	0.0311	0.8696	0.0007
rsd	0.1480	**-1.9197**	-0.3564	0.0422	-0.5397	**-1.0149**	**0.4595**	0.0123	**0.6106**	**0.3154**	**1.1318**
	0.3106	0.0000	0.4114	0.9425	0.3416	0.0000	0.1026	0.9371	0.0000	0.0017	0.0000
dsd	**-0.3597**	**-1.0403**	**-1.0891**	**1.0192**	**-1.0807**	-0.2101	**-0.3997**	-0.1373	**0.5368**	**0.3182**	**1.2026**
	0.0333	0.0422	0.0506	0.1380	0.1075	0.3990	0.1294	0.4634	0.0000	0.0087	0.0000
hfm	**0.1314**	**0.3697**	-0.1984	-0.2712	0.0072	**0.2176**	**-0.5274**	**-0.1155**	**-0.2210**	**-0.3111**	**0.8375**
	0.1078	0.1644	0.4951	0.3517	0.9800	0.0799	0.0000	0.1851	0.0000	0.0000	0.0000
lfm	0.0848	**0.7487**	-0.3171	0.4425	**-0.6705**	**0.5409**	**-0.8628**	-0.1509	**-0.2395**	**-0.2975**	**0.9179**
	0.4585	0.0291	0.3440	0.3377	0.1333	0.0019	0.0007	0.2234	0.0378	0.0004	0.0000
fd	**-0.6881**	0.2152	**0.8542**	0.6963	**-1.1658**	**-0.7950**	-0.4787	0.1391	**0.2929**	**0.4156**	**0.9103**
	0.0011	0.6753	0.1151	0.3299	0.0922	0.0013	0.2133	0.4914	0.1365	0.0010	0.0000
fj	**-0.2967**	**0.7534**	0.3535	**-1.4267**	**1.2163**	**1.2618**	**-0.6173**	0.0826	**-0.6012**	**-0.2390**	**0.9821**
	0.0323	0.0407	0.4110	0.0189	0.0408	0.0000	0.0198	0.5879	0.0000	0.0123	0.0000
bw	-0.1751	-0.4254	-0.3713	**0.9196**	**-1.1574**	**-0.7717**	0.2552	**-0.2919**	**-0.1324**	**0.2941**	**0.1698**
	0.3022	0.4542	0.5439	0.1504	0.0811	0.0108	0.3502	0.1555	0.1983	0.0254	0.0242
cof	**0.5742**	**-1.1537**	0.2013	**-1.4992**	**1.3287**	**0.7649**	-0.1902	**-0.3918**	**-1.2696**	**-0.3258**	**0.8085**
	0.0194	0.0749	0.7479	0.0870	0.1175	0.0104	0.6672	0.1085	0.0000	0.0273	0.0000
tea	0.0981	**1.8331**	**-1.2808**	**1.6987**	**-1.9157**	**-1.2830**	**0.8686**	**0.5071**	**-0.5187**	**-1.1836**	**0.8886**
	0.6959	0.0078	0.1079	0.1081	0.0697	0.0003	0.0425	0.0651	0.0022	0.0000	0.0000

[39] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Table 6.8: Houthakker and Taylor Model Short-Run Compensated Elasticity Estimates[40]

	iso	rsd	dsd	hfm	lfm	fd	fj	Bw	cof	Tea
iso	**-1.3477**	0.2749	1.5926	0.5786	-0.2332	**-3.2321**	**2.2236**	0.3361	**0.7902**	0.0193
	0.0118	0.8242	0.2071	0.7083	0.8775	0.0005	0.0107	0.4586	0.0193	0.7533
rsd	0.1582	**-1.7036**	-0.2081	0.1939	-0.4390	**-0.9288**	**0.6542**	0.0870	**0.7056**	**0.3698**
	0.2788	0.0000	0.6311	0.7408	0.4385	0.0000	0.0214	0.5774	0.0000	0.0003
dsd	**-0.3489**	**-0.8106**	**-0.9315**	**1.1804**	**-0.9736**	-0.1187	-0.1928	-0.0580	**0.6379**	**0.3760**
	0.0387	0.1081	0.0928	0.0874	0.1458	0.6312	0.4599	0.7560	0.0000	0.0023
hfm	**0.1390**	**0.5297**	-0.0887	-0.1590	0.0817	**0.2813**	**-0.3833**	-0.0602	**-0.1506**	**-0.2709**
	0.0899	0.0483	0.7599	0.5828	0.7758	0.0255	0.0016	0.4880	0.0017	0.0000
lfm	0.0931	**0.9241**	-0.1968	0.5655	**-0.5888**	**0.6107**	**-0.7049**	-0.0903	**-0.1624**	**-0.2534**
	0.4165	0.0080	0.5557	0.2221	0.1859	0.0006	0.0046	0.4633	0.1521	0.0020
fd	**-0.6799**	0.3891	**0.9734**	0.8183	**-1.0848**	**-0.7258**	-0.3221	0.1991	**0.3694**	**0.4593**
	0.0013	0.4477	0.0740	0.2528	0.1165	0.0031	0.3985	0.3255	0.0624	0.0003
fj	**-0.2879**	**0.9410**	0.4822	**-1.2951**	**1.3037**	**1.3364**	**-0.4484**	0.1474	**-0.5187**	**-0.1918**
	0.0375	0.0110	0.2644	0.0320	0.0289	0.0000	0.0869	0.3357	0.0000	0.0428
bw	-0.1736	-0.3930	-0.3490	**0.9423**	**-1.1423**	**-0.7588**	0.2844	**-0.2807**	-0.1182	**0.2952**
	0.3057	0.4870	0.5683	0.1397	0.0854	0.0121	0.2975	0.1707	0.2463	0.0222
cof	**0.5815**	**-0.9993**	0.3072	**-1.3909**	**1.4006**	**0.8264**	-0.0511	**-0.3384**	**-1.2017**	**-0.2870**
	0.0181	0.1185	0.6247	0.1111	0.0996	0.0060	0.9080	0.1625	0.0000	0.0494
tea	0.1061	**2.0028**	**-1.1644**	**1.8178**	**-1.8366**	**-1.2154**	**1.0215**	**0.5657**	**-0.4441**	**-1.1410**
	0.6726	0.0037	0.1436	0.0856	0.0819	0.0006	0.0179	0.0406	0.0073	0.0000

[40] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Fifty five out of ninety (sixty one percent) compensated cross-price elasticities were significant at 0.20 level. Twenty seven out of ninety were significant and had negative sign indicating net complements. Fifty percent of significant compensated cross-price elasticities are indicative of net substitutes (positive sign). Fruit drinks act as net complements for both isotonics and regular soft drinks. Fruit juice and coffee are net substitutes for isotonics. Net substitutes associated with regular soft drinks are fruit juices, coffee and tea. Isotonics, regular soft drinks and low-fat milk are net complements for diet soft drinks, while high-fat milk, coffee and tea were net substitutes.

Isotonics, regular soft drinks and fruit drinks were net substitutes for high-fat milk, whereas fruit juices, coffee and tea act as net complements. This is not a surprising result since most of consumers drink fruit juices, coffee and/or tea together with milk during breakfast time. Net substitutes associated with low-fat milk were regular soft drinks and fruit drinks. Again, fruit juices, coffee and tea act as net complements for low-fat milk. Reasoning for this latter result may be similar to that of high-fat milk consumption.

Isotonics and low fat milk act as net complements for fruit drinks, while tea, coffee and diet soft drinks were net substitutes. Net complements associated with fruit juices were isotonics, high-fat milk, coffee, and tea. Regular soft drinks, low-fat milk and fruit drinks were net substitutes for fruit juices. Fruit drinks and low-fat milk were net complements for bottled water, whereas high-fat milk and tea were net substitutes.

Net Substitute for coffee was isotonics, low-fat milk and fruit drinks. Regular soft drinks, high-fat milk, bottled water and tea act as net complements for coffee. Regular soft drinks, bottled water, high-fat milk, and fruit juices were net substitute for tea. Net complements for tea were diet soft drinks, low-fat milk, fruit drinks, and coffee.

Long-Run Elasticity Estimates

Calculated *long-run* uncompensated and compensated price elasticities and expenditure elasticities are illustrated in Tables 6.9 and 6.10 respectively. All expenditure elasticities were significant at the 0.10 level. Isotonics, regular soft drinks, fruit drinks and fruit juices showed expenditure elasticities which are elastic (2.59, 1.26, 1.06 and 1.00 respectively). Bottled water was highly expenditure inelastic; resulting in an expenditure elasticity of 0.49. Other non-alcoholic beverages showed following expenditure elasticities: diet soft drinks 0.90; high-fat milk 0.94; low-fat milk 0.90; coffee 0.79; tea 0.59.

Both compensated and uncompensated own-price elasticities were negative for all non-alcoholic beverages, showing the theoretical coherence with demand theory. All, but high-fat milk, own-price elasticities were significant at the 0.20 level. Isotonics showed the highest own-price elasticity of demand (-4.05). Also, regular soft drinks and coffee are elastic with respect to own-price elasticity of demand. More specifically, they were -1.92 and -1.17 respectively. Fruit juices were the highly inelastic non-alcoholic beverage category resulting in an own-price elasticity of demand of -0.46. Other non-alcoholic beverages showed the following own-price elasticities of demand: diet soft drinks -0.66; low-fat milk -0.57; fruit drinks -0.85; bottled water -0.84; and tea -0.74.

Table 6.9: Houthakker and Taylor Model Long-Run Uncompensated Elasticity Estimates[41]

	iso	rsd	dsd	Hfm	Lfm	fd	fj	bw	Cof	tea	exp
iso	**-4.0590**	0.3288	4.4301	1.3857	-0.9287	**-9.8754**	**6.2136**	0.8356	**2.1490**	0.1368	**2.5882**
	0.0015	0.9289	0.2404	0.7653	0.8380	0.0000	0.0077	0.5304	0.0162	0.8702	0.0001
rsd	0.1647	**-2.1370**	-0.3967	0.0470	-0.6008	**-1.1297**	**0.5115**	0.0137	**0.6797**	**0.3886**	**1.2599**
	0.3095	0.0000	0.4121	0.9425	0.3395	0.0000	0.1062	0.9371	0.0000	0.0559	0.0000
dsd	**-0.2687**	**-0.7769**	**-0.8133**	**0.7612**	**-0.8071**	-0.1569	**-0.2985**	-0.1026	**0.4009**	**0.2377**	**0.8981**
	0.0391	0.0446	0.0539	0.1231	0.0961	0.3920	0.1249	0.4607	0.0000	0.0091	0.0000
hfm	**0.1483**	**0.4171**	-0.2237	-0.3059	0.0081	**0.2455**	**-0.5949**	**-0.1302**	**-0.2493**	**-0.3509**	**0.9447**
	0.0930	0.1608	0.4953	0.3545	0.9800	0.0789	0.0000	0.1913	0.0000	0.0000	0.0000
lfm	0.0831	**0.7331**	-0.3104	0.4333	**-0.6565**	**0.5297**	**-0.8448**	-0.1477	**-0.2345**	**-0.2913**	**0.8988**
	0.4564	0.0246	0.3441	0.3377	0.1348	0.0011	0.0006	0.2255	0.0350	0.0002	0.0000
fd	**-0.7987**	0.2498	**0.9916**	0.8083	**-1.3533**	**-0.9228**	-0.5556	0.1614	**0.3400**	**0.4824**	**1.0567**
	0.0007	0.6757	0.1137	0.3349	0.0993	0.0015	0.2033	0.4877	0.1380	0.0010	0.0000
fj	**-0.3037**	**0.7713**	0.3619	**-1.4605**	**1.2451**	**1.2916**	**-0.6319**	0.0845	**-0.6155**	**-0.2446**	**1.0053**
	0.0383	0.0429	0.4083	0.0219	0.0438	0.0000	0.0309	0.5884	0.0000	0.0138	0.0000
bw	-0.5083	-1.2349	-1.0778	**2.6695**	**-3.3599**	**-2.2403**	0.7409	**-0.8474**	**-0.3844**	**0.8538**	**0.4928**
	0.2765	0.4656	0.5349	0.1011	0.0394	0.0072	0.3833	0.1148	0.1520	0.0200	0.0498
cof	**0.5581**	**-1.1213**	0.1956	**-1.4571**	**1.2913**	**0.7434**	-0.1848	**-0.3808**	**-1.2339**	**-0.3167**	**0.7857**
	0.0152	0.0685	0.7468	0.0773	0.1065	0.0092	0.6683	0.1057	0.0000	0.0221	0.0000
tea	0.0651	**1.2160**	**-0.8497**	**1.1269**	**-1.2709**	**-0.8511**	**0.5762**	**0.3364**	**-0.3441**	**-0.7852**	**0.5895**
	0.6942	0.0072	0.1163	0.1000	0.0632	0.0011	0.0359	0.0593	0.0024	0.0000	0.0000

[41] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Table 6.10: Houthakker and Taylor Model Long-Run Compensated Elasticity Estimates[42]

	iso	rsd	dsd	Hfm	Lfm	fd	fj	bw	cof	tea
iso	**-4.0512**	0.4939	4.5433	1.5016	-0.8517	**-9.8097**	**6.3623**	0.8927	**2.2216**	0.1783
	0.0016	0.8933	0.2282	0.7461	0.8513	0.0000	0.0063	0.5027	0.0127	0.8310
rsd	0.1749	**-1.9208**	-0.2484	0.1987	-0.5001	**-1.0437**	**0.7062**	0.0884	**0.7747**	**0.4429**
	0.2807	0.0000	0.6072	0.7606	0.4260	0.0000	0.0269	0.6109	0.0000	0.0305
dsd	**-0.2578**	**-0.5472**	**-0.6558**	**0.9223**	**-0.7000**	-0.0654	-0.0916	-0.0232	**0.5019**	**0.2954**
	0.0474	0.1518	0.1191	0.0630	0.1477	0.7187	0.6361	0.8672	0.0000	0.0014
hfm	**0.1558**	**0.5770**	-0.1140	-0.1937	0.0826	**0.3091**	**-0.4508**	-0.0750	**-0.1789**	**-0.3107**
	0.0781	0.0534	0.7278	0.5561	0.7985	0.0282	0.0013	0.4515	0.0013	0.0000
lfm	0.0913	**0.9085**	-0.1902	0.5563	**-0.5748**	**0.5994**	**-0.6869**	-0.0872	**-0.1574**	**-0.2472**
	0.4133	0.0059	0.5616	0.2194	0.1896	0.0003	0.0045	0.4730	0.1528	0.0011
fd	**-0.7906**	0.4237	**1.1108**	0.9303	**-1.2722**	**-0.8536**	-0.3991	0.2215	**0.4165**	**0.5261**
	0.0007	0.4768	0.0774	0.2673	0.1209	0.0032	0.3581	0.3416	0.0705	0.0003
fj	**-0.2949**	**0.9588**	0.4905	**-1.3289**	**1.3325**	**1.3663**	**-0.4630**	0.1493	**-0.5330**	**-0.1975**
	0.0440	0.0121	0.2644	0.0361	0.0315	0.0000	0.1111	0.3410	0.0000	0.0455
bw	-0.5068	-1.2025	-1.0556	**2.6922**	**-3.3448**	**-2.2274**	0.7701	**-0.8362**	-0.3701	**0.8416**
	0.2777	0.4767	0.5434	0.0978	0.0404	0.0076	0.3644	0.1193	0.1661	0.0189
cof	**0.5653**	**-0.9669**	0.3015	**-1.3488**	**1.3633**	**0.8049**	-0.0458	**-0.3274**	**-1.1660**	**-0.2778**
	0.0140	0.1129	0.6196	0.1012	0.0887	0.0050	0.9156	0.1620	0.0000	0.0432
tea	0.0731	**1.3858**	**-0.7333**	**1.2460**	**-1.1918**	**-0.7836**	**0.7291**	**0.3950**	**-0.2695**	**-0.7426**
	0.6589	0.0022	0.1756	0.0688	0.0815	0.0027	0.0085	0.0277	0.0150	0.0000

[42] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

Out of ninety compensated cross-price elasticities, 56 were significant at the 0.20 level. Forty eight percent were substitutes and fifty two percent were complements. Fruit drinks were the only significant net complement for isotonics, whereas fruit juices and coffee were net substitutes. Again, fruit drinks were the only net complement that is significantly affecting regular soft drinks, while fruit juices, coffee and tea were net substitutes. High-fat milk, coffee and tea act as net substitutes for diet soft drinks. Net complements for diet soft drinks were isotonics, regular soft drinks and low-fat milk.

Isotonics, regular soft drinks and fruit drinks were net substitutes for high-fat milk, while fruit juices, coffee and tea were complements. Above complementarity of high-fat milk with fruit juice, coffee and tea can be directly attributable to breakfast choices of the U.S consumer. Fruit drinks and regular soft drinks were net substitutes for low-fat milk, where as fruit juices, coffee and tea were net complements.

Net substitutes for fruit drinks were found to be diet soft drinks, coffee and tea, while net complements were isotonics and low-fat milk. Regular soft drinks, low-fat milk and fruit drinks were net substitutes for fruit juices. Net complements for fruit juices were found to be isotonics, high-fat milk, coffee and tea. High-fat milk and tea were net substitutes for bottled water, whereas low-fat milk and fruit drinks function as net complements.

Net substitutes for coffee were identified to be isotonics, low-fat milk and fruit drinks. Regular soft drinks, high-fat milk, bottled water and tea were net complements to coffee. High-fat milk, regular soft drinks, fruit juices and bottled water were net substitutes for tea. Net complements for tea were identified to be diet soft drinks, low-fat milk, fruit drinks and coffee.

Comparison of Habit Persistence, Inventory Behavior with Short-Run and Long-Run Elasticities

We compare the relationship between habit persistence and/or inventory behavior has with short-run and long-run price and expenditure elasticity estimates in Table 6.11. In determining demand for non-alcoholic beverages, if habits dominate, we would expect to have larger price and expenditure elasticities in the long-run, because, it takes time for consumers to respond to a change in price or expenditure and establish a regular purchasing behavior (or develop a behavior into a habit).

This behavioral phenomenon is evident (dominance of habit persistence and larger long run elasticities) with respect to isotonics, regular soft drinks, high-fat milk, fruit drinks, fruit juices and bottled water. For example, long-run own-price elasticity of demand for isotonics is -4.05 in comparison to its short-run counterpart which is -1.35. The long-run expenditure elasticity with respect to regular soft drinks is 1.26 which is higher than its short-run estimate of 1.13. Similar trends of price and expenditure elasticities were evident with respect to non-alcoholic beverages that showed dominance in habit persistence behavior.

Table 6.11: Houthakker and Taylor Model: Comparison of Compensated Own-Price Elasticities and Expenditure Elasticities with Coefficient Associated with State Variable in the Structural Equation (Beta)[43]

		Iso	rsd	dsd	hfm	lfm	fd	fj	Bw	Cof	Tea
Own-price Elasticities	**Short Run**	**-1.3477**	**-1.7036**	**-0.9315**	-0.1590	**-0.5888**	**-0.7258**	**-0.4484**	**-0.2807**	**-1.2017**	**-1.1410**
	Long Run	**-4.0512**	**-1.9208**	**-0.6558**	-0.1937	**-0.5748**	**-0.8536**	**-0.4630**	**-0.8362**	**-1.1660**	**-0.7426**
Expenditure Elasticities	**Short Run**	**0.8643**	**1.1318**	**1.2026**	**0.8375**	**0.9179**	**0.9103**	**0.9821**	**0.1698**	**0.8085**	**0.8886**
	Long Run	**2.5882**	**1.2599**	**0.8981**	**0.9447**	**0.8988**	**1.0567**	**1.0053**	**0.4928**	**0.7857**	**0.5895**
Beta		**1.8092**	**0.2495**	**-0.5063**	0.3459	-0.1268	**0.2889**	0.0066	**0.7839**	-0.1026	**-0.8513**

[43] Numbers just below estimated coefficients represent *p*-values. Estimated coefficients in bold font show the parameters that are statistically significant at alpha level 0.10. Beverage abbreviations follow: iso=isotonics, rsd=regular soft drinks, dsd=diet soft drinks, hfm=high-fat milk, lfl=low-fat milk, fd=fruit drinks, fj=fruit juices, bw=bottled water, cof=coffee, and tea. Exp=Expenditure elasticity

On the other hand, if inventory behavior in demand for non-alcoholic beverages is dominant, we observed larger short-run price and expenditure elasticities compared to their long-run corresponding item. The reason for having such observation is that, if consumers stock-up goods (stock up inventory or inventory behavior) based on price or expenditure information, their response in the short-run is larger compared to long-run. In the long-run, such behavior fades away. Diet soft drinks, low-fat milk, coffee and tea show evidence to such inventory accumulation behavior. For example, the short-run own-price elasticity of demand for diet soft drinks was -0.93 where its long-run counterpart is -0.66. On the other hand, long-run expenditure elasticity with respect to tea was estimated to be 0.59 whereas its short-run counterpart was 0.89.

Comparison of Elasticity Estimates across LA/QUAIDS, Barten and Houthakker Models

We compare the compensated own-price and expenditure elasticities across LA/QUAIDS, Barten Synthetic and Houthakker and Taylor Sate Adjustment Model in Table 6.12. We do a beverage-by-beverage comparison.

Isotonics recorded to have the highest own-price elasticity of demand estimate in LA/QUAIDS model, Barten model and Houthakker long-run model. In numbers they are -3.85, -4.70 and -4.05 respectively. Own-price elasticity of demand for isotonics is low in the Houthakker short-run model. This may be due to the fact that short-run value does not include the movement of past stocks and habit that consumer had in consuming isotonics. Own-price elasticity of demand remains elastic across all models considered.

Table 6.12: Comparison of Elasticity Estimates from LA/QUAIDS, Barten Synthetic Model (BSM) and Houthakker and Taylor (HT) Model

	Compensated Own-Price Elasticity of Demand				Expenditure Elasticity			
Beverage	**LA/QUAIDS**	**BSM**	**HT Sort-Run**	**HT Long-Run**	**LA/QUAIDS**	**BSM**	**HT Sort-Run**	**HT Long-Run**
Isotonics	-3.85	-4.70	-1.35	-4.05	1.17	1.74	0.86	2.59
Regular Soft Drinks	-1.97	-1.52	-1.70	-1.92	1.52	1.21	1.13	1.26
Diet Soft Drinks	-1.11	-0.81	-0.93	-0.66	1.26	1.29	1.20	0.90
High Fat Milk	-0.65	-0.53	-0.16	-0.19	0.81	0.83	0.84	0.94
Low Fat Milk	-0.85	-0.84	-0.59	-0.57	0.86	0.86	0.92	0.90
Fruit Drinks	-0.59	-0.66	-0.72	-0.85	1.25	1.44	0.91	1.06
Fruit Juices	-1.03	-0.90	-0.45	-0.46	0.80	0.67	0.98	1.00
Bottled Water	-0.72	-0.26	-0.28	-0.84	0.53	1.12	0.17	0.49
Coffee	-1.61	-1.55	-1.20	-1.17	0.46	0.54	0.81	0.79
Tea	-0.87	-0.65	-1.14	-0.74	0.92	1.11	0.89	0.59

Isotonics expenditure elasticities were comparable across LA/QUAIDS and Barten models; however it is much higher with respect to Houthakker models. All expenditure elasticities were elastic irrespective to the model used. Compensated own-price elasticity of demand and expenditure elasticity is very comparable across three models for regular soft drinks. Calculated own-price elasticity demand is -1.97 and -1.92 for LA/QUAIDS and Houthakker long-run models respectively. It is slightly low for Barten model (-1.52). LA/QUAIDS model yields the highest expenditure elasticity for regular soft drinks, which is 1.52. It is slightly lower for all other models.

LA/QUAID model yields an elastic own-price elasticity of demand for diet soft drinks, which is -1.11. All other models give rise to an inelastic own-price elasticity of demand. With respect to expenditure elasticity, LA/QUAIDS, Barten and Houthakker short-run models give an elastic value. In numbers they are 1.52, 1.21 and 1.13 respectively. Hothakker long-run model recorded inelastic expenditure elasticity for diet soft drinks

Own-price elasticity of demand for high-fat milk was inelastic across all three models, where LA/QUAIDS and Barten model give similar values (-0.65 and -0.53 respectively). However, it was low for Houthakker model (-0.16 and -0.19 for short-run and long-run models respectively). Expenditure elasticities nevertheless, were inelastic and very similar across all three models, out of which Houthakker long-run model has the highest (0.94). Low-fat milk showed the exactly the same pattern as did with high-fat milk for own-price and expenditure elasticities. The only difference with low-fat milk was with respect to the model that generated the highest expenditure elasticity, which is the Houthakker short-run model. The latter gave the expenditure elasticity value of 0.92 for low-fat milk.

Fruit drinks were inelastic with respect to the own-price elasticity of demand where LA/QUAIDS model recorded the lowest value (-0.59). LA/QUAIDS, Batern and Houthakker long-run models gave elastic expenditure elasticity values for fruit drinks while Houthakker short-run model recorded an inelastic value. The difference between two Houthakker models can be attributable to the habit forming/inventory behavior embodied in those models. Fruit juices showed an elastic own-price elasticity of demand for LA/QUAIDS model. However, it was inelastic with respect to other models. Both Houthakker models showed low price elasticity values compared to other two models. Calculated expenditure elasticities were similar across LA/QUAIDS, Barten and Houthakker short-run models (all were inelastic), however, it was unitary elastic with respect to Houthakker long-run model.

Own-price elasticity of demand for bottled water is -0.72 and -0.84 for LA/QUAIDS and Houthakker long-run model respectively. However, they were low for Barten and Hothakker short-run models. Barten model showed elastic expenditure elasticity for bottled water while other models gave inelastic expenditure elasticities. Houthakker short-run model gave the lowest expenditure elasticity for bottled water, which is 0.17.

Coffee showed elastic own-price elasticity of demand across all three models. LA/QUAIDS model and Barten model gave higher elasticity values compared to Houthakker model. In numbers, former two models gave -1.61 and -1.55 and latter models gave -1.20 and -1.17 respectively. Again, LA/QUAIDS model and Barten model showed expenditure elasticity values that are very similar to each other (0.46 and 0.54). Houthakker models gave slightly higher expenditure elasticity numbers for coffee (they were 0.81 and 0.79 for short-run and long-run model respectively).

Calculated own-price elasticities of demand for tea were -0.87 and -0.65 for LA/QUAIDS and Barten model respectively. Houthakker short-run model gave elastic demand (-1.14) for tea while the long-run model gave -0.74. This latter result is directly attributable to tea showing an inventory behavior in its demand. Barten model gave elastic expenditure elasticity for tea (1.11) whereas other model gave inelastic values.

Comparison with Previous Studies in the Literature

The purpose of Table 6.13 is to compare our results with similar studies done on non-alcoholic beverages in the past (we compare ours with four past studies). It should be stressed that to our knowledge, ours is the first study that models demand for non-alcoholic beverages in a systemwide framework with such a rich delineation of non-alcoholic beverages categories. All past studies had only up to 5 non-alcoholic beverage categories, namely, milk, juice, soft drinks, bottled water and tea/coffee (combined). Our study has 10 non-alcoholic beverage categories and other than bottled water (which is cited in the past literature), our study has 9 unique categories that have not studied in the past. We have two separate categories each for milk (high-fat milk and low-fat milk), soft drinks (regular soft drinks and diet soft drinks), and fruit beverages (fruit drinks and fruit juices). We also treat tea and coffee in two separate categories. Inclusion of isotonics (sport drinks) in our beverage list is a very unique move.

Three out of four past studies used annual time series data (Zheng and Kaiser, 2008 and Kinnucan et al. 2001) and one study used a cross sectional data set from 1996-

1997 (Yen et al. 2004). Our unique data set spans over 72 monthly observations starting at January 1998 and ending at December 2003. Given the 6 year period, our data set is more immune to effects from structural change compared to data spanning over a 30 year period as used in previous studies. In addition to that, given the nature of monthly observations in our possession, we were in a position to explore quarterly seasonal variability of data, which we found highly significant.

The overall implication of Table 6.13 is that all compensated and uncompensated own-price elasticities gave theoretically consistent negative sign and statistical significance at 1% and 5% level except for bottled water in Zheng and Kaiser (2008) Rotterdam model with respect to sign and statistical significance. Note that all of uncompensated and compensated price elasticities and expenditure elasticities in our model is highly significant at 1% level. Owing to the short time-series studied in our data set, we observe consistently higher own-price elasticities compared to other models that used time series data with a longer time span. Own-price elasticities calculated for soft drinks in past models turned out to be inelastic in nature, however ours were elastic. That difference may be due to, on one hand the long time span considered in past studies compared to our analysis, and on the other hand, our data disaggregated soft drinks into two categories, such as regular soft drinks and diet soft drinks. Our own-price elasticities for high-fat milk and low-fat milk is similar to such elasticities generated through Yen et al., (2004) model, even though Yen et al., (2004) did not disaggregate milk into high-fat milk and low-fat milk.

Table 6.13: Comparison of Price and Expenditure Elasticities with other Studies in the Literature

	Model	Data	Products	Own-price elasticities: Compensated Price	Own-price elasticities: Uncompensated Price	Expenditure Elasticities
Our Study	Linearized Quadratic AIDS model	Monthly time series January 1998-December 2003 (derived from Nielsen HomeScan scanner data)	Isotonics	-3.854***	-3.865***	1.174***
			Regular soft drinks	-1.965***	-2.255***	1.518***
			Diet soft drinks	-1.108***	-1.272***	1.256***
			High-fat milk	-0.651***	-0.759***	0.806***
			Low-fat milk	-0.848***	-0.924***	0.855***
			Fruit drinks	-0.595***	-0.689***	1.246***
			Fruit juices	-1.035***	-1.173***	0.804***
			Bottled water	-0.719***	-0.754***	0.530***
			Coffee	-1.607***	-1.646***	0.462***
			Tea	-0.867***	-0.910***	0.915***
Zheng and Kaiser (2008)	LA-AIDS model	Annual time series 1974-2005 US-Bureau of Labor Statistics, Beverage Marketing Corp USDA-ERS	Soft drinks	-0.151**	-0.521**	0.997
			Milk	-0.154**	-0.301**	0.614**
			Juice	-0.172**	-0.272	0.656
			Bottled water	-0.498**	-0.501**	0.029
			Coffee/tea	-0.083**	-0.462**	3.144**
Zheng And Kaiser 2008	Rotterdam model	Annual time series 1974-2005 US-Bureau of Labor Statistics, Beverage Marketing Corp USDA-ERS	Soft drinks	-0.164**	-0.306**	0.381**
			Milk	-0.102**	-0.161**	0.243**
			Juice	-0.458**	-0.898**	2.891**
			Bottled water	0.044	0.051	0.062**
			Coffee/tea	-0.260**	-0.628**	3.049**

Table 6.13: continued

				Own-price elasticities		
	Model	**Data**	**Products**	**Compensated Price**	**Uncompensated Price**	**Expenditure Elasticities**
Kinnucan et al. 2001	Rotterdam model	Annual time series	Soft drinks	-0.137**	-0.675**	1.238**
		1970-1994	Milk	-0.169**	-0.283**	0.406**
		Putman & Allshouse,	Juice	-0.361**	-0.471**	0.698
		US Dept of Labor	Bottled water	--	--	--
		CPI reports, AD$SUMMARY Leading National Advertisers Inc	Coffee/tea	-0.249**	-0.487**	1.876**
Yen et al. 2004	Translog demand system	National Food Stamp Program Survey,	Soft drinks	-0.520**	-0.800**	1.010**
		1996-97, 908 obs	Milk	-0.590**	-0.690**	0.800**
			Juice	-0.350**	-0.520**	0.900**
			Bottled water	--	--	--
			Coffee/tea	-0.470**	-0.890**	1.130**

All past studies considered in Table 6.13 had inelastic demands for juices. However, our study disaggregates juices into fruit juices and fruit drinks. Therefore, our elasticities are different from those of past studies, in particular for fruit juices. We find that fruit juices are price elastic compared to juices category considered in all past studies. Bottled water was inclided only in Zheng and Kaiser (2008) study where it had inelastic price elasticity of demand around -0.50 for LA/AIDS model. Our finding is slightly higher than that (-0.75) owing to the time span of the data available to us. Bottle water variable considered in the Rotterdam model used by Zheng and Kaiser (2008) neither gave the right sign for own-price elasticity of demand nor significant. Coffee and tea were a combined category in all past studies considered, however we have them separated in our analysis. We find coffee to be price elastic and tea to be price inelastic. All other past studies found that combined coffee/tea category to be price inelastic.

We found highly significant expenditure elasticities for both regular soft drinks and diet soft drinks and they were expenditure elastic. Kinnucan et al., (2001) and Yen at al., (2004) found expenditure elasticity to be elastic for soft drinks, however, Zheng and Kaiser (2008) found them to be expenditure inelastic in both Rotterdam and LA/AIDS models, even though the former was not significant. All models, including our model gave rise to inelastic expenditure elasticity estimates for milk and they all were significant. However, our study provided more information due to disaggregation of milk category into high-fat milk and low-fat milk and their respective expenditure elasticity estimates. Zheng and Kaiser (2008) found a highly elastic juice category; however our study found elastic expenditure elasticity for fruit drinks and inelastic expenditure elasticity for fruit juices. Rotterdam model used by Zheng and Kaiser

(2008) gave very small expenditure elasticity for bolted water (0.062) whereas we found it to be higher (0.530). Bottled water expenditure elasticity calculated by Zheng and Kaiser (2008) through LA/AIDS model was not significant. Our tea and coffee expenditure elasticities are more comparable with Kinnucan et al. (2001) and Yen et al. (2004) than to Zheng and Kaiser (2008).

CHAPTER VII

NUTRITIONAL CONTRIBUTIONS OF NON-ALCOHOLIC BEVERAGES

In this chapter, we discuss the model development, data analysis and discussion of the *nutrition study*. Main objective of our *nutrition study* is to find out demographic factors affecting intake of calories, calcium, vitamin C and caffeine derived from consumption of non-alcoholic beverages at home. Extensive cross-tabulations and regression analysis are used to achieve above objectives. Also, we ascertain the impact of the year 2000 USDA dietary guidelines for Americans on the intake of aforementioned nutrients and calories derived through consumption of non-alcoholic beverages using yearly dummy variables introduced into regressions.

Model Development: Nutrition Study

In this section, we offer an extensive narrative on the regression and cross-tabulation procedure used in analyzing data to achieve objectives of the *nutrition study*. We also specify the variables used in the study along with expected results. We are using Nielsen HomeScan scanner data for calendar years 1998 through 2003 for this analysis. First we perform regression and cross-tabulation analysis for each nutrition category and calories for each year. Second, we stack the household data from each year one-on-top of the other to create a pooled/stacked dataset of 41,071 households. Then, we do regression and cross-tabulation analysis for each beverage using the pooled/stacked dataset. In all, each nutrition category is subjected to seven regressions and in total it will be 28 regressions for four categories of nutrients. In regression analysis, we use a price variable on the right-hand-side. It is neither price of nutrients nor calories. It is the weighted average price of non-alcoholic beverages taken all.

Therefore, we develop and explain a conceptual framework to model the effect of price of non-alcoholic beverages to the intake of nutrients and calories derived from the intake of non-alcoholic beverages.

Each nutrition category (caffeine, calcium and vitamin C) and caloric intake is regressed on price of non-alcoholic beverages and all of other demographic factors listed in Table 4.1 in Chapter IV for each year from 1998 through 2003. The regression equation for each nutrient and calories is given as follows:

$$
\begin{aligned}
Q_{ht} = {} & \beta_0 + \beta_1 PRICE_{ht} + \beta_2 PRICE_{ht}^2 + \beta_3 AGEHH2529_{ht} + \\
& \beta_4 AGEHH3034_{ht} + \beta_5 AGEHH3544_{ht} + \beta_6 AGEHH4554_{ht} + \\
& \beta_7 AGEHH5564_{ht} + \beta_8 AGEHHGT64_{ht} + \\
& \beta_9 EMPHHPT_{ht} + \beta_{10} EMPHHFT_{ht} + \beta_{11} EDUHHHS_{ht} + \\
& \beta_{12} EDUHHU_{ht} + \beta_{13} EDUHHPC_{ht} + \beta_{14} REG\_CENTRAL_{ht} + \\
& \beta_{15} REG\_SOUTH_{ht} + \beta_{16} REG\_WEST_{ht} + \beta_{17} RACE\_BLACK_{ht} + \\
& \beta_{18} RACE\_ORIENTAL_{ht} + \beta_{19} RACE\_OTHER_{ht} + \beta_{20} HISP\_YES_{ht} + \\
& \beta_{21} AGEPCLT6\_ONLY_{ht} + \beta_{22} AGEPC6\_12ONLY_{ht} + \\
& \beta_{23} AGEPC13\_17ONLY_{ht} + \beta_{24} AGEPCLT6\_6\_12ONLY_{ht} + \\
& \beta_{25} AGEPCLT6\_13\_17ONLY_{ht} + \beta_{26} AGEPC6\_12AND13\_17ONLY_{ht} + \\
& \beta_{27} AGEPCLT6\_6\_12AND13\_17_{ht} + \beta_{28} MHONLY_{ht} + \\
& \beta_{29} FHONLY_{ht} + \beta_{30} POV185_{ht} + \\
& \beta_{31} D2001_{ht} + \beta_{32} D2002_{ht} + \beta_{33} D2003_{ht}
\end{aligned}
\tag{7.1}
$$

where k= the number of households and t= the year (1998, 1999, 2000, 2001, 2002 and 2003); Q_{ht} corresponds to the amount of caloric intake (kilocalories per person per day) and nutrient intake (caffeine, calcium and vitamin C in milligrams per person per day) derived from the consumption of non-alcoholic beverages for a given time period. The right-hand side variables pertain to the weighted price of non-alcoholic beverages and to the various demographic factors discussed previously.

We considered different functional forms such as linear, linear-log, quadratic, log-log and log-linear. During this exercise, first we estimated ordinary least squares (OLS) regressions for calories and each nutrient category for each year (1998 through 2003) for each functional form explained above. Then we corrected them for heteroskedasticity using Harvey (1976) test to obtain weighted least squares (WLS) estimates and tested for appropriate functional form via Schwarz loss function and Box-Cox transformation approaches. We found that the quadratic functional form outperformed other functional forms.

Next, we ran a series of seemingly unrelated regressions (SUR) for calories and each nutritional category for the six-year period to check for any efficiency improvements over single equation WLS models. To perform SUR, we randomly picked 6000 observations for calories and each nutritional category for each year (random sampling of 6000 observations was done due to the fact that the number of households participated in the survey was different for each year).

Also given the data structure associated with stacked/pooled analysis, we used ordinary least squares regressions using Newey and West (1987) procedure to circumvent potential autocorrelation and heteroscedasticity issues. The level of significance chosen for this analysis is 0.05.

It is noteworthy to address the marginal impact of price on the level of caloric or nutrient intake given the fact that a quadratic functional form is used for the econometric models. Let the intake of calories, calcium, caffeine and vitamin C be denoted by Q_i. The quantity of non-alcoholic beverages associated with each of the respective intakes is represented by Q_{NAB}. P_{NAB} is the weighted average price of non-alcoholic beverages.

Then it follows that:

$$(7.2) \qquad \frac{\partial Q_i}{\partial P_{NAB}} = \frac{\partial Q_i}{\partial Q_{NAB}} * \frac{\partial Q_{NAB}}{\partial P_{NAB}}$$

In words, the change of intake of calories and other nutrients with respect to a change of price of non-alcoholic beverages (i.e. $\frac{\partial Q_i}{\partial P_{NAB}}$) can be decomposed into the product of change of intake of calories and other nutrients due to a change in the quantity consumed of non-alcoholic beverages (i.e. $\frac{\partial Q_i}{\partial Q_{NAB}}$) as well as the change in the quantity consumed of non-alcoholic beverages due to a change in price of the corresponding non-alcoholic beverage category (i.e. $\frac{\partial Q_{NAB}}{\partial P_{NAB}}$). Considering all non-alcoholic beverages as a single good, from the law of demand we know that $\frac{\partial Q_{NAB}}{\partial P_{NAB}}$ must have a negative sign (the own-price effect). As the quantity of non-alcoholic beverages consumed changes, caloric and nutrient (calcium, caffeine and vitamin C) intakes may either increase, decrease, or remain the same. That is, the sign of $\frac{\partial Q_i}{\partial Q_{NAB}}$ depends on the composition of the non-alcoholic beverages consumed. Therefore, the sign of $\frac{\partial Q_i}{\partial P_{NAB}}$ is indeterminate.

Empirical Results: Nutrition Study

Following section begins with an account on summary statistics of price, demographic variables and caloric and nutrient intakes used in the study. Next we talk about average intakes of calories and each nutrient category from 1998 through 2003. Demographic analysis with respect to intake of calories and each nutrition category is taken up next. This is followed by a regression analysis to delineate the factors affecting the intake of calories and each nutrition category derived from consumption on non-alcoholic beverages at home. Regression analysis is further extended to ascertain the impact of year 2000 USDA Dietary Guideline for Americans.

Summary Statistics

Following Tables 7.1 through 7.4 shows the summary statistics of the intake of calories, calcium, vitamin C and caffeine derived from the consumption of non-alcoholic beverages in the USA from 1998 through 2003. According to them, on average for the six-year period (1998 through 2003), at-home consumption of non-alcoholic beverages accounts for 220 kilo calories of caloric intake, 190 milligrams of calcium, 34 milligrams of vitamin C and 83 milligrams of caffeine per head per day. To give above descriptive statistics more perspective, when the daily recommended values for each nutrition category is concerned, through consumption of non-alcoholic beverages at home, one derives 11% of calories, 19% of calcium, 34% of vitamin C and 41% of caffeine (daily recommended/tolerable values are; 2000 kilo calories of energy, 1000 milligrams of calcium, 155 milligrams of vitamin C and 200 milligrams of caffeine).

As shown is Table 7.1 and Figure 7.1, there is a decreasing trend in the caloric intake derived from the consumption of non-alcoholic beverages over the period of 1998 through 2003. In 1998, it was 231.99 kilo calories per head per day and it dropped to 198.9 kilo calories per head per day in year 2003. We observe a drastic drop in the caloric intake after year 2001 (see Figure 7.1). The large standard deviation (SD) for caloric intake for all the years considered show the high degree of variability in the data. Coefficient of variation (CV) ranges from 67.21 kilo calories per head per day in 1999 to 89.13 kilo calories per head per day in year 2000.

Table 7.1: Summary Statistics of Intake of Calories per Person per Day: Derived from Consumption of Non-alcoholic Beverages in United States At-home Markets: 1998-2003[44]

	Calories (kcal/head/day)						
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**Six Year Average**
Mean	231.99	232.55	235.63	226.41	199.41	198.9	220.815
Med	204.23	202.02	200.32	194.57	166.76	162.76	
SD	157.83	156.3	210	158.61	146.95	151.49	
Min	0	0.412	0.37	0.216	0	0.394	
Max	3276.62	3482.61	11297.95	2506.44	1968.18	1721.52	
CV	68.03	67.21	89.13	70.05	73.69	76.17	
DR	2000	2000	2000	2000	2000	2000	

Intake of calcium derived from the consumption of non-alcoholic beverages for the period 1998 through 2003 is explained in Table 7.2 and Figure 7.2. According to Figure 7.2, we observe a downward trend in average intake of calcium during the time period considered. Just as in the case of caloric intake, there is a considerable drop of calcium intake after year 2001. Again, we observe very large standard deviations associated with calcium intake indicating high variability in the data. Coefficient of

[44] Med=Median, SD=Standard Deviation, Min=Minumum, Max=Maximum, CV=Coefficient of Variation, DR=Daily Recommended

variation is highest in year 2000 with 92.42 mg per head per day and lowest in 1998 with 80.91 mg per head per day.

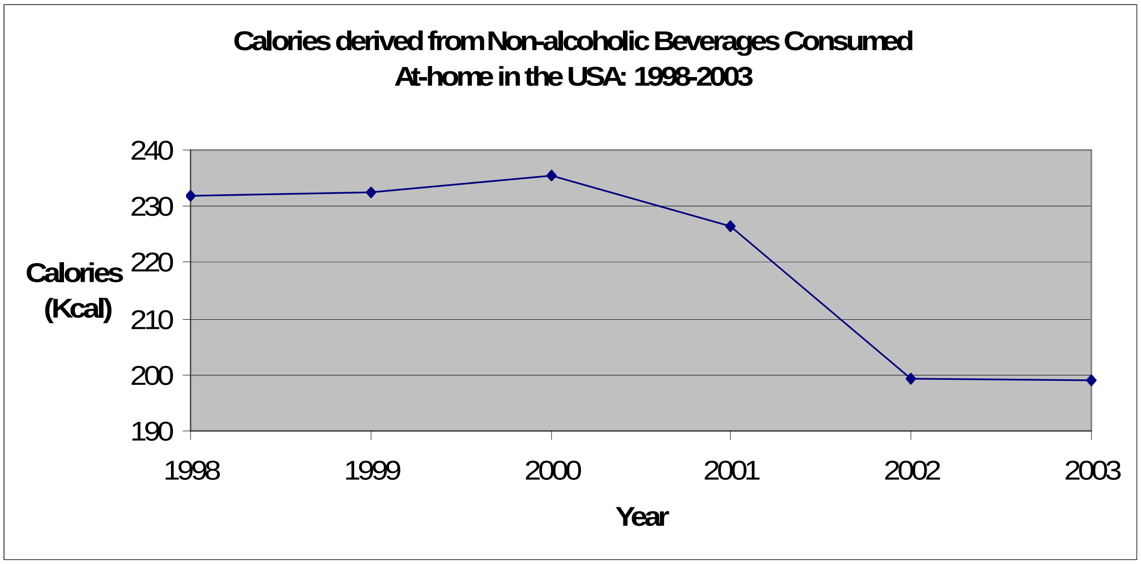

Figure 7.1: Calories derived from non-alcoholic beverages consumed at home in the United States: 1998-2003

Table 7.2: Summary Statistics of Intake of Calcium per Person per Day: Derived from Consumption of Non-alcoholic Beverages in United States At-home Markets: 1998-2003

	Calcium (mg/head/day)[45]						
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**Six Year Average**
Mean	207.53	202.88	203.81	191.16	167.05	167.21	189.94
Med	165.53	158.24	156.01	148.36	124.95	125.71	
SD	167.91	167.6	188.36	168.8	150.54	154.94	
Min	0	0	0.13	0	0	0	
Max	2536.22	2120.71	6254.1	2443.53	1604.69	2026.67	
CV	80.91	82.6	92.42	88.3	90.11	92.67	
DR	1000	1000	1000	1000	1000	1000	

[45] Med=Median
SD=Standard Deviation
CV=Coefficient of Variation
DR=Daily Recommended

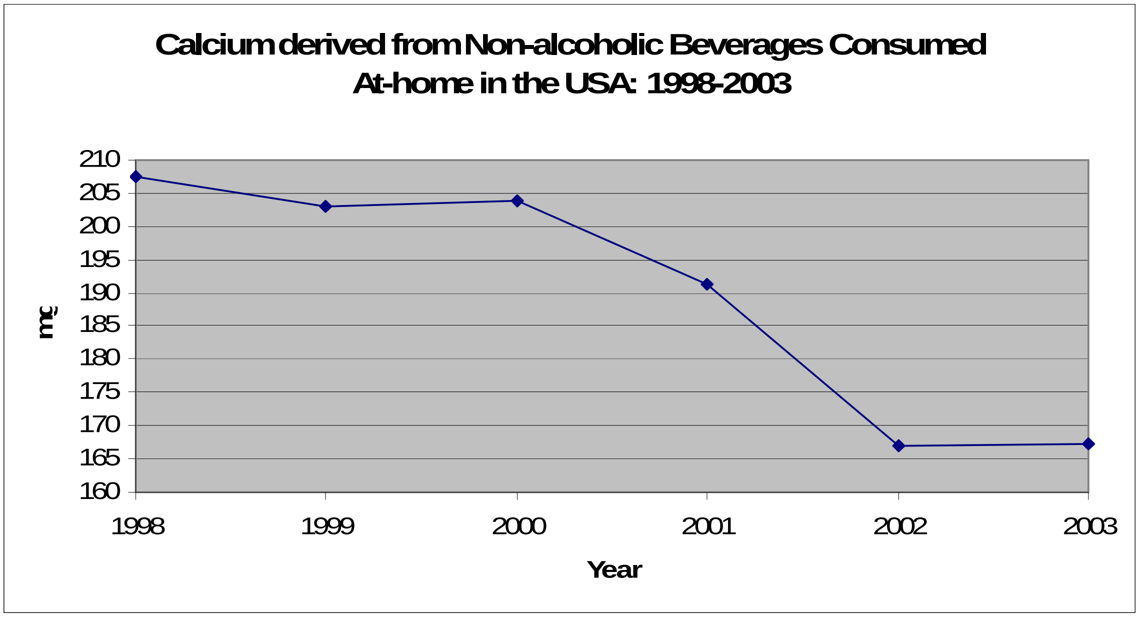

Figure 7.2: Calcium derived from non-alcoholic beverages consumed at home in the United States: 1998-2003

Vitamin C intake derived from the consumption on non-alcoholic beverages has an increasing trend toward year 2000 and then it drops toward year 2003. These trends are shown in Table 7.3 and Figure 7.3. We observe a considerable drop of vitamin C intake after year 2001. Vitamin C intake data too are associated with large standard deviations indicating the high variability of the data considered.

Table 7.3: Summary Statistics of Intake of Vitamin C per Person per Day: Derived from Consumption of Non-alcoholic Beverages in United States At-home Markets: 1998-2003

Vitamin C (mg/head/day)[46]							
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**Six Year Average**
Mean	53.91	54.91	56.47	54.95	48.98	48.45	52.945
Med	41.22	42.14	41.7	40.76	35.62	34.36	
SD	49.88	49.64	53.34	51.75	49.13	50.09	
Min	0	0	0	0	0	0	
Max	712.53	633.75	878.03	614.77	785.94	649.64	
CV	92.53	90.4	94.46	94.19	100.29	103.37	
DR	155	155	155	155	155	155	

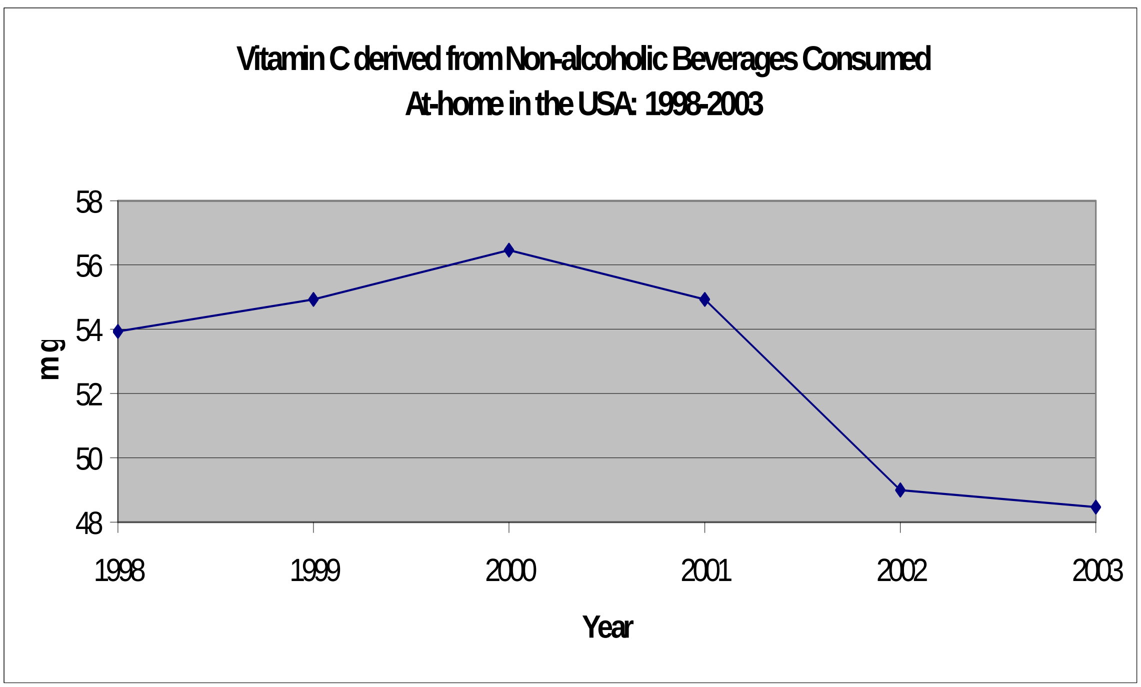

Figure 7.3: Vitamin c derived from non-alcoholic beverages consumed at home in the United States: 1998-2003

[46] Med=Median
SD=Standard Deviation
CV=Coefficient of Variation
DR=Daily Recommended

According to Table 7.4 and Figure 7.4, we see an increasing trend in the intake of caffeine toward year 2000 and then a downward trend toward year 2003. Similar to trending behavior observed with calories, calcium and vitamin C intake, there is a considerable drop in caffeine intake after year 2001.

Table 7.4: Summary Statistics of Intake of Caffeine per Person per Day: Derived from Consumption of Non-alcoholic Beverages in United States At-home Markets: 1998-2003[47]

	Caffeine (mg/head/day)						
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**Six Year Average**
Mean	84.81	86.82	89.65	88.91	73	76.03	83.20333
Med	54.31	53.44	53.83	53.94	43.71	45.4	
SD	100.07	107.14	181.53	109.86	92.79	97.53	
Min	0	0	0	0	0	0	
Max	1444	2448.03	11633.19	1867.76	1838.32	2407.24	
CV	117.99	123.4	202.49	123.55	127.09	128.29	
DR	200	200	200	200	200	200	

[47] Med=Median
SD=Standard Deviation
CV=Coefficient of Variation
DR=Daily Recommended

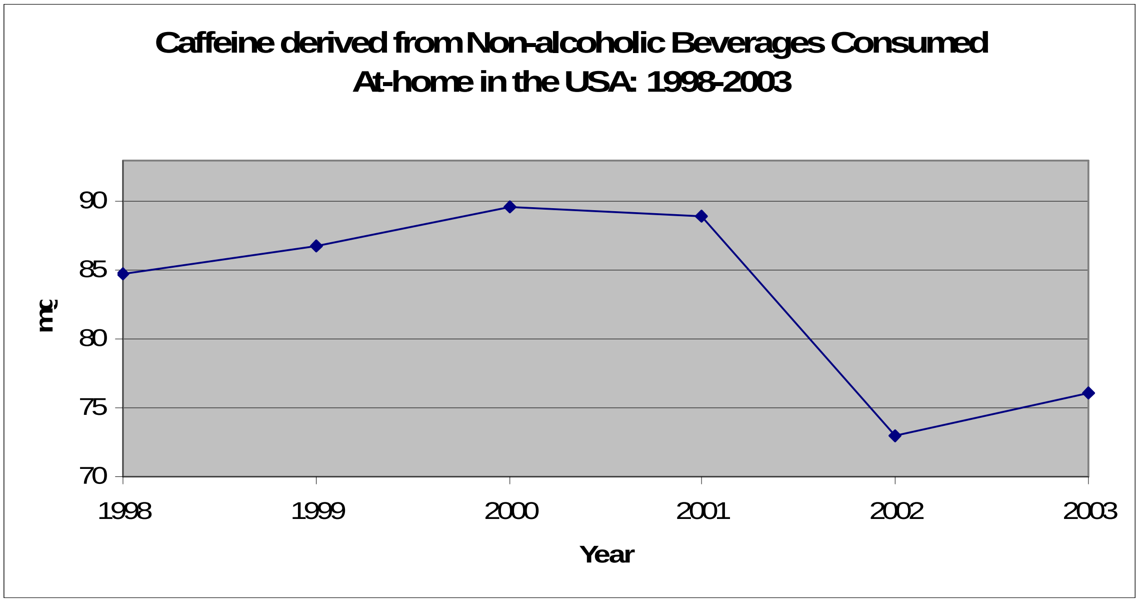

Figure 7.4: Caffeine derived from non-alcoholic beverages consumed at home in the United States: 1998-2003

Average Intakes of Calories, Calcium, Vitamin C and Caffeine: 1998-2003

Generally, the average intake of calories, calcium, vitamin C and caffeine derived from the consumption of non-alcoholic beverages in at-home markets follow a similar trend from year 1998 through 2003. There is a very sizeable drop in the intake of calories, calcium, vitamin C and caffeine derived from the consumption of non-alcoholic beverages in the calendar year 2001. Preceding behavior in the intake of those nutrients is in accordance with the dietary guidelines set forth by the United States Department of Agriculture (USDA) in year 2000 in their report "Dietary Guidelines for Americans, 2000". In that, USDA emphasized on cutting down on extra calories and caffeine intake from food and beverages. One of their major objectives was to help people choose beverages and foods sensibly to moderate the intake of sugars. Sugars contribute to the extra calories that people intake when they drink a beverage (other than water) to quench their thirst. These beverages contain not only sugars, but also caffeine. Therefore, if people choose a beverage that does not have added sugars and caffeine in it to quench their thirst than they did before, they seem to have paid attention to the dietary guidelines set forth by USDA.

According to the USDA report on “Dietary Guidelines for Americans” (2000), major sources of added sugars, hence calories are soft drinks (carbonated non-diet soft drinks) and fruit juices (like fruitades and fruit punch). Carbonated soft drinks also contribute to the added caffeine to the diet. Other caffeine sources are coffee and tea. Vitamin C mainly comes from the fruit juices and fruit drinks and to some degree from isotonics. Milk and calcium fortified fruit juices are major contributors of calcium to the diet derived from beverages.

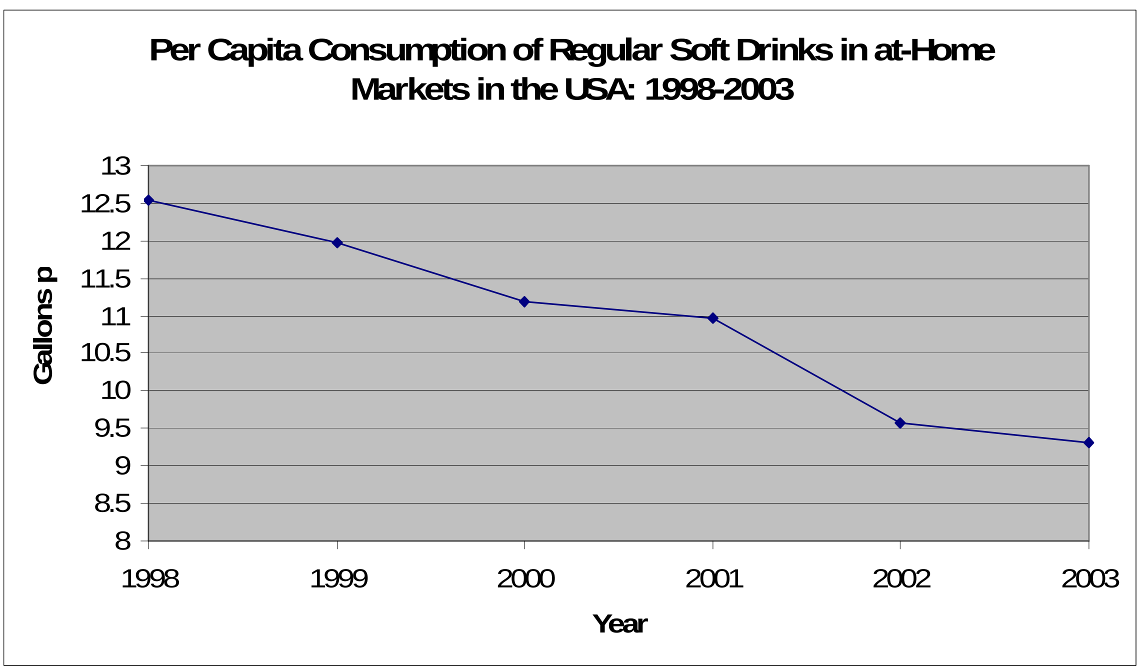

Figure 7.5: Per capita consumption of regular soft drinks in at-home markets in the United States: 1998-2003

Following Figures 7.5 through 7.14 show the consumption of selected non-alcoholic beverages in gallons per person per year basis for at-home markets in the USA for the period 1998 through 2003. As shown in Figure 7.5, per capita consumption of regular soft drinks is about 11 gallons per year in 2001 and it dropped to about 9.4 gallons per year in 2003. Also, according to Figure 7.8, per capita consumption of fruit drinks (fruitades and fruit punch) is about 2.9 gallons per year in 2001 and it dropped to about 2.7 gallons per year in 2003. As stated earlier, regular soft drink (or in other words carbonated non-diet soft drinks) and fruit drinks are two major contributors of added sugars and hence extra calories to the diet, derived from beverages.

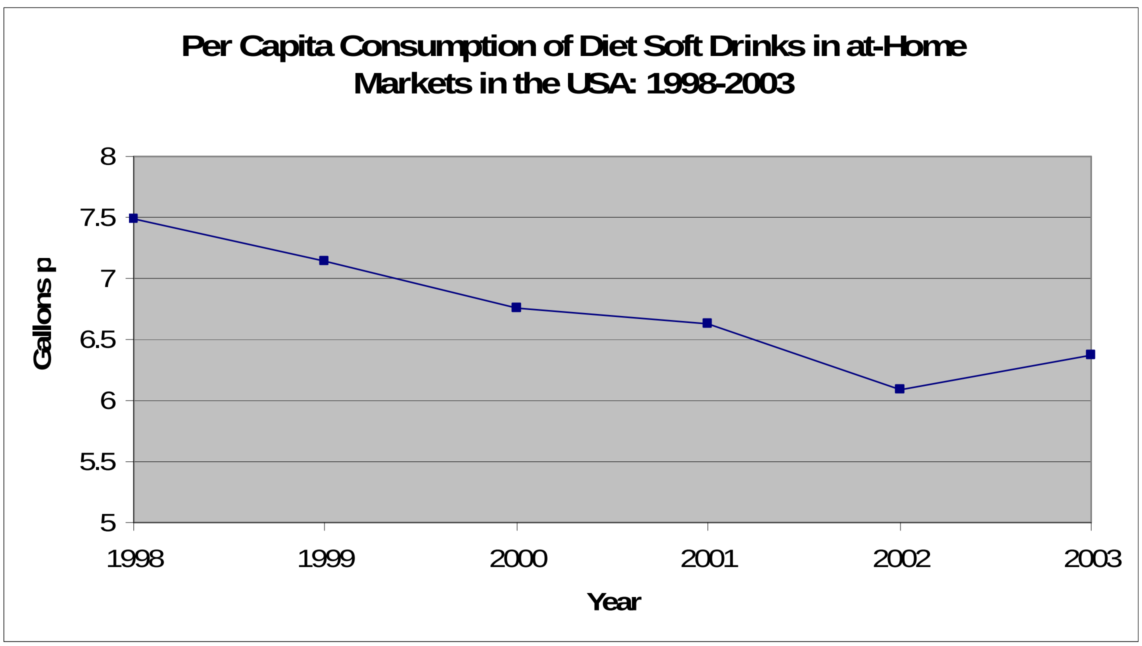

Figure 7.6: Per capita consumption of diet soft drinks in at-home markets in the United States: 1998-2003

Drop in the consumption of regular soft drinks and fruit drinks by the US consumer is indicative of the drop in the intake of calories derived from non-alcoholic beverages from 2001 through 2003; the time period immediately followed by the implementation of the dietary guidelines for Americans by USDA.

Major contributors for caffeine intake derived from consumption of non-alcoholic beverages are regular soft drinks, coffee and tea. According to Figures 7.5, 7.11 and 7.12, per capita consumption of regular soft drinks, tea and coffee respectively show a decreasing trend more specifically after year 2001. Per capita consumption of tea dropped from about 4.3 gallons per person per year in year 2001 to about 3.6 gallons per person per year in 2003. Coffee consumption was about 12 gallons per person per year in 2001 and it deceased up to about 9 gallons per person per year in 2003. These decreasing trends in consumption of regular soft drinks, tea and coffee by the US consumer goes hand-in-hand with the decreasing trends in the intake of caffeine derived from the consumption of non-alcoholic beverages for the same time period (2001 through 2003).

Even though USDA dietary guidelines and food guide pyramid advocate increased consumption of calcium and vitamin C, interestingly enough we find that the intake of calcium and vitamin C derived from consumption of non-alcoholic beverages are decreasing over the time from 1998 through 2003. Milk (high-fat and low-fat) and calcium fortified fruit juices are the major contributors for calcium intake derived from beverages.

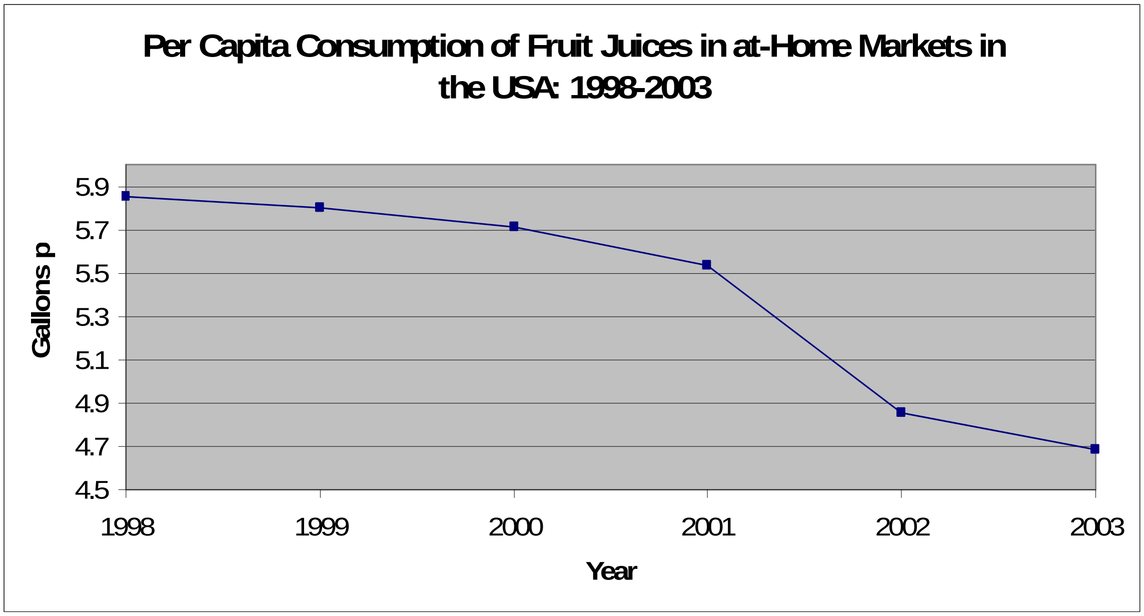

Figure 7.7: Per capita consumption of fruit juices in at-home markets in the United States: 1998-2003

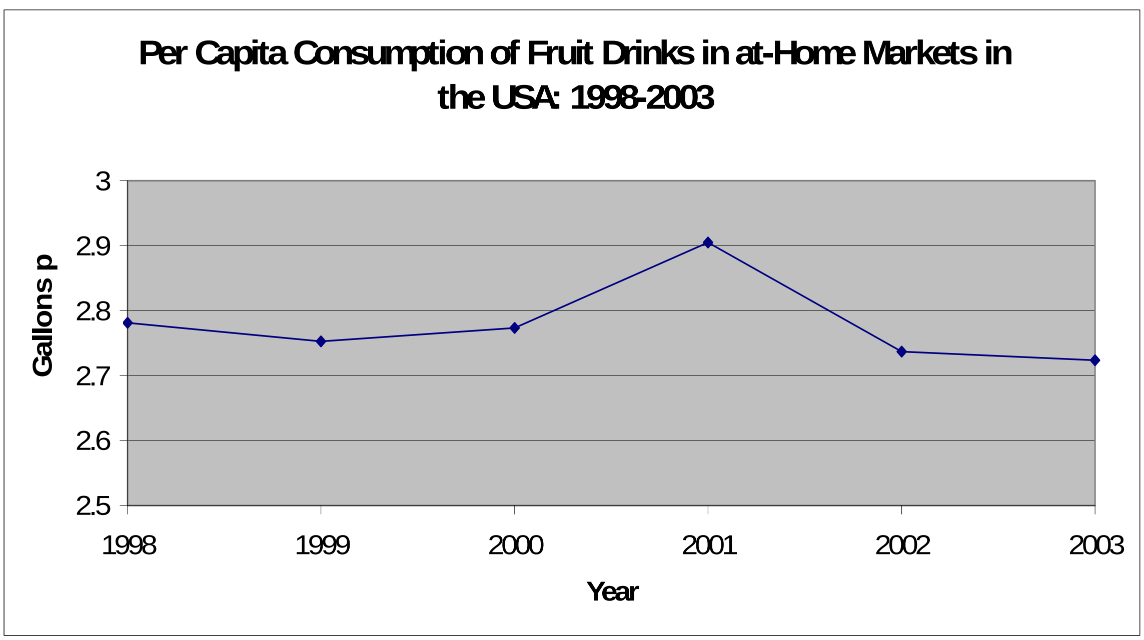

Figure 7.8: Per capita consumption of fruit drinks in at-home markets in the United States: 1998-2003

As shown in Figure 7.9, we find that, per capita high fat milk consumption in at-home markets was a little above 7 gallons per year in 1998 and drops up to about 5.5 gallons per person per year. Figure 7.10 shows the per capita at-home consumption of low fat milk by a US consumer. According to that, low fat milk consumption was about 5.7 gallons per year in 1998. It dropped to about 3.6 gallons in year 2003. Overall, there is a drop in the total milk consumption, hence a drop in calcium intake derived from milk. Decreasing trend in per capita consumption of fruit juices in at-home markets during the same time period also may be contributing to the low intake of calcium derived from beverages.

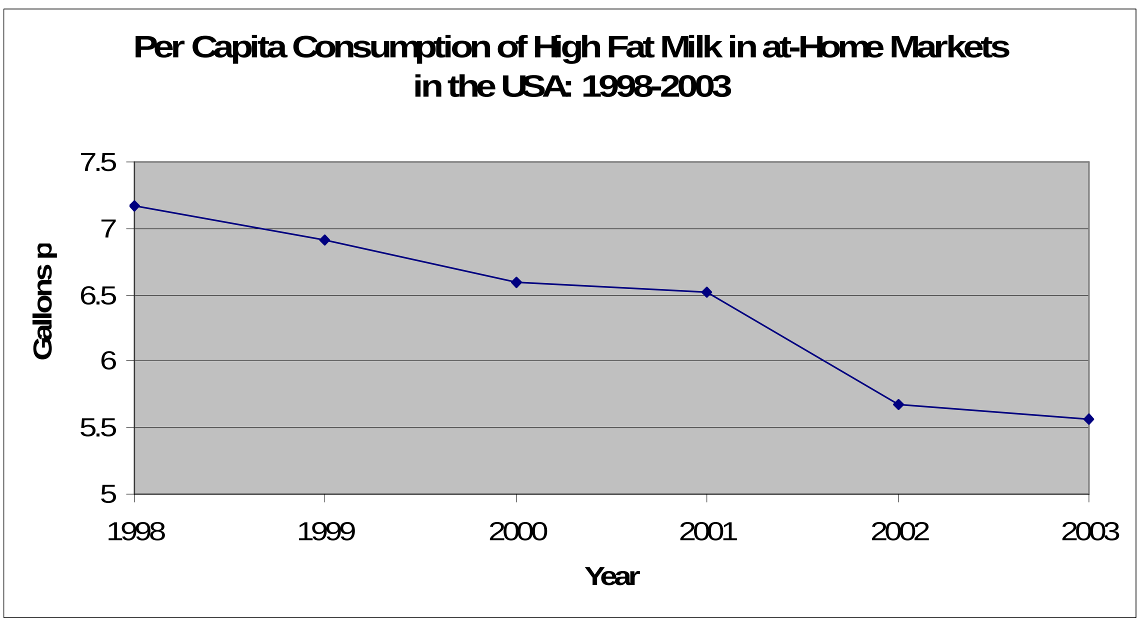

Figure 7.9: Per capita consumption of high fat milk in at-home markets in the United States: 1998-2003

Drop in the intake of vitamin C derived from consumption of non-alcoholic beverages in at-home markets can be directly attributed to the decreasing trend in the consumption of fruit juices and isotonics. Per capita fruit juice consumption is about 5.8 gallons per year in 1998 in at-home markets and it dropped to about 4.6 gallons per person per year in 2003. Per capita isotonics consumption too shows a decreasing trend during the time period concerned.

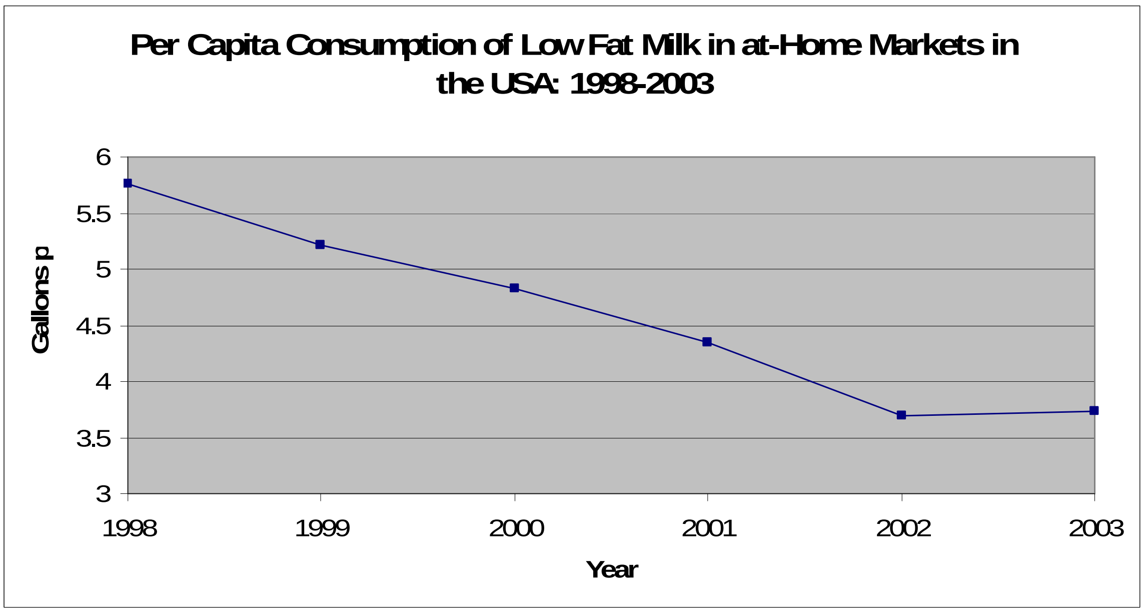

Figure 7.10: Per capita consumption of low fat milk in at-home markets in the United States: 1998-2003

To add more perspective to above trends in different types of beverages consumed at home, we can state that, caloric and caffeine intake derived from consumption of non-alcoholic beverages were decreasing as a consequence of decreasing consumption of soft drinks, fruit drinks, tea and coffee in at-home markets, fulfilling one of the objectives set forth by the USDA year 2000 dietary guidelines for Americans.

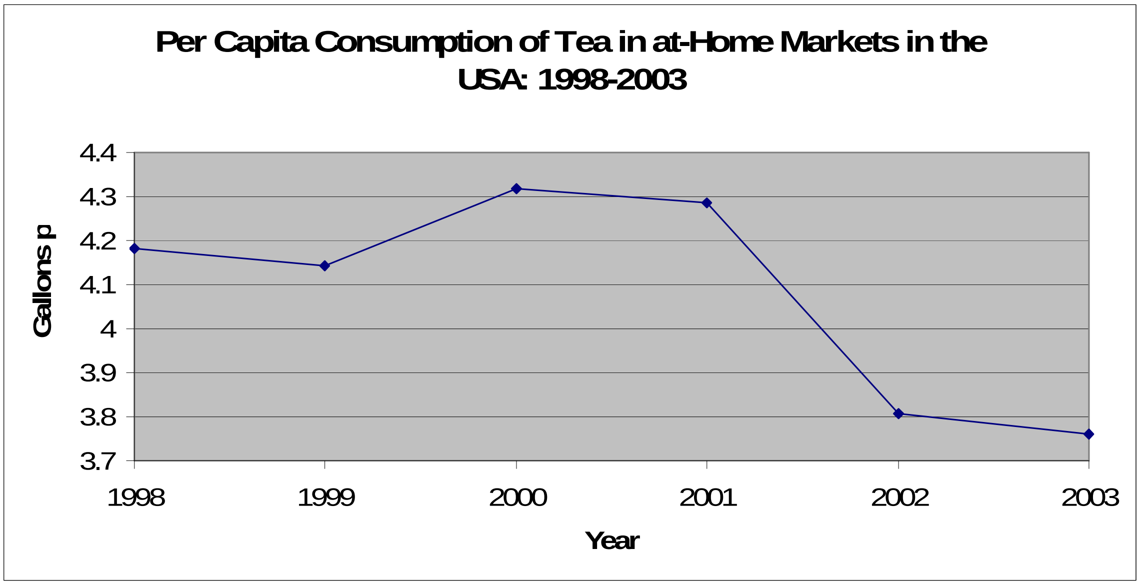

Figure 7.11: Per capita consumption of tea in at-home markets in the United States: 1998-2003

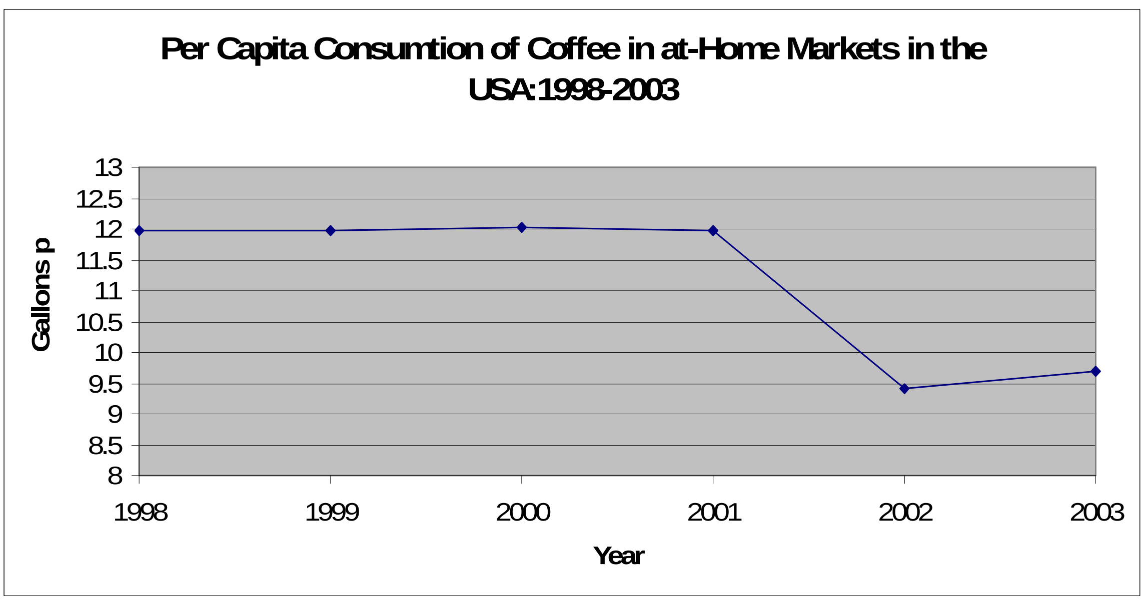

Figure 7.12: Per capita consumption of coffee in at-home markets in the United States: 1998-2003

Furthermore, USDA year 2000 dietary guidelines promote the consumption of water as a means of thirst quencher and advise the US consumer to substitute away specifically from beverages with added sugars like soft drinks. The trend in per capita bottled water consumption in the US at-home markets as shown in Figure 7.14 would testify to the behavioral change in the US consumer in drinking increasing amounts of water in lieu of soft drinks to quench their thirst. For example, in 1998, per capita bottled water consumption was 3 gallons per year in at-home markets and it increased up to more than 5 gallons per year in 2003. According to USDA disappearance data on bottled water consumption that accounts for both at-home and away-from-home markets, per capita consumption of bottled water was 14.4 gallons per year in 1998. It increased up to 21.6 gallons per year in 2003.

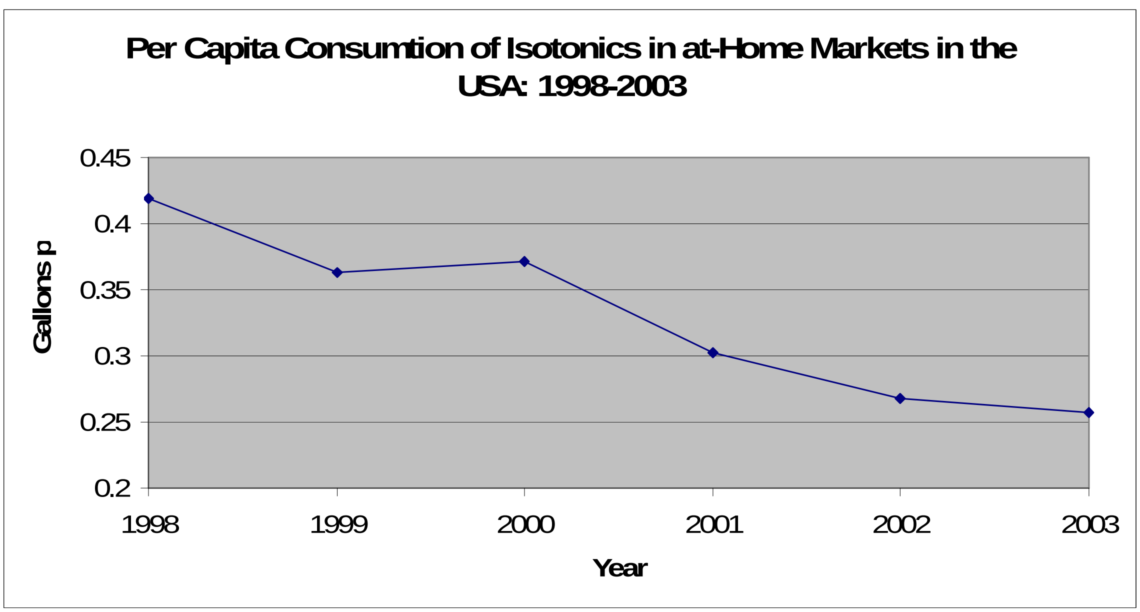

Figure 7.13: Per capita consumption of isotonics in at-home markets in the United States: 1998-2003

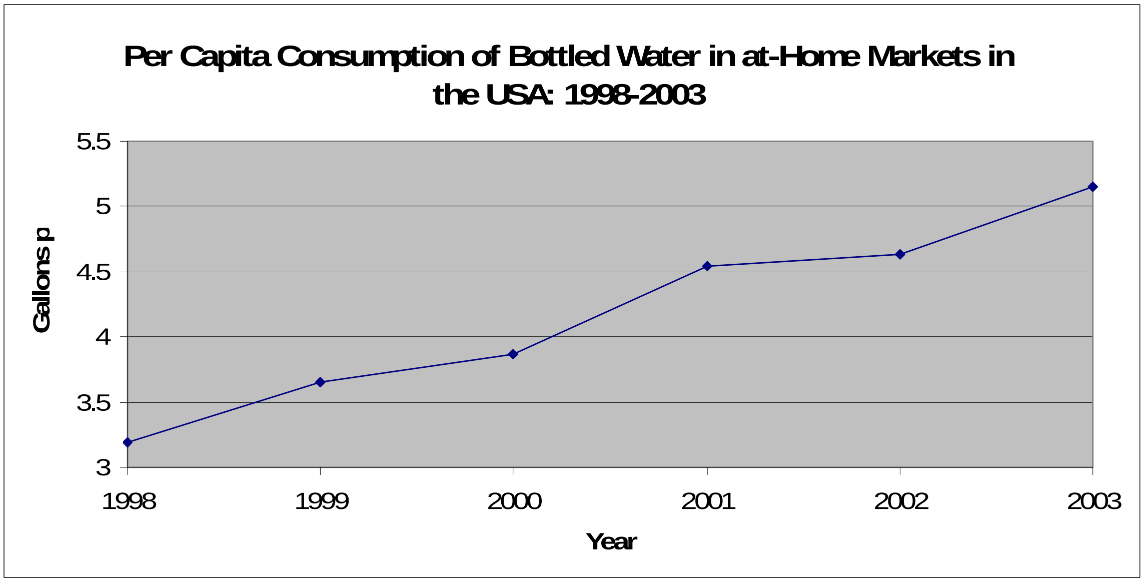

Figure 7.14: Per capita consumption of bottled water in at-home markets in the United States: 1998-2003

Decreasing intake of calcium and vitamin C derived from non-alcoholic beverages consumed in at-home markets can be directly attributed to dwindling trends in milk, fruit juice, and isotonics consumption by the US consumer. From this latter result, we can infer that beverage choices have a lesser value placed on by the US consumer in obtaining calcium and vitamin C to their diet. A testable hypothesis that derives from this latter result would be to find out the products that consumer is substituting away from beverage choices to gain calcium and vitamin C into their diet.

Demographic Analysis of Calorie and Nutrient Intake

Caloric, Calcium, Vitamin C and Caffeine intake derived from non-alcoholic beverage consumption is varied by different demographic characteristics. Identification of such demographic characteristics is important to help identify the appropriate target group for government's nutrition enhancement programs and household that are nutritionally at-risk. Following section includes a discussion of factors including age, employment status and education status of the household, region, race, Hispanic origin, age and presence of children, gender of household head and poverty status of the household.

Age of the Household Head

Figure 7.15 shows the per capita caloric intake per day by age category of household head derived through consumption of non-alcoholic beverages from 1998 through 2003. The noteworthy result is that the caloric intake has an increasing trend for those households where the household head is under the age of 25. More specifically, in year 1998, the per capita caloric intake for the aforementioned age category was 212 kilo calories per day and it increased up to about 250 kilo calories per day by the year 2003.

To give more perspective to above result, we say that even though the per capita caloric intake derived from non-alcoholic beverages are at a decreasing trend as a whole, as shown in Figure 7.1, households with younger household heads still do intake more calories derived from non-alcoholic beverages consumed at home. All other households with household heads above 25 years of age show a decreasing trend in their caloric intake derived from consumption of non-alcoholic beverages at home.

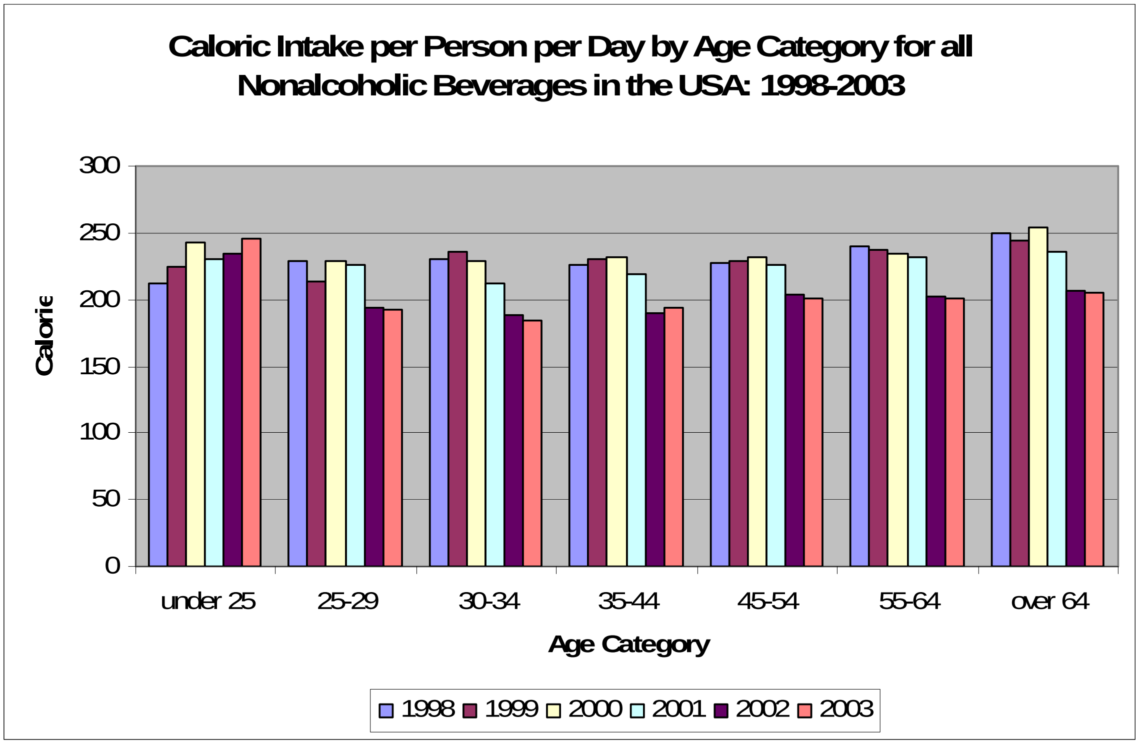

Figure 7.15: Per capita caloric intake per day by age category for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Figure 7.16 shows the per capita caffeine intake per day by age category of household head derived through consumption of non-alcoholic beverages at home from 1998 through 2003. Overall, there is a decreasing trend in caffeine intake from 1998 through 2003, however, more older the household head is, the more intake of caffeine derived through consumption of non-alcoholic beverages. For example, in year 2000, average per capita intake of caffeine derived from consumption of non-alcoholic beverages is about 45 mg per day for household heads under age 25 years and it is as high as 105 mg per day for household heads over 64 years of age.

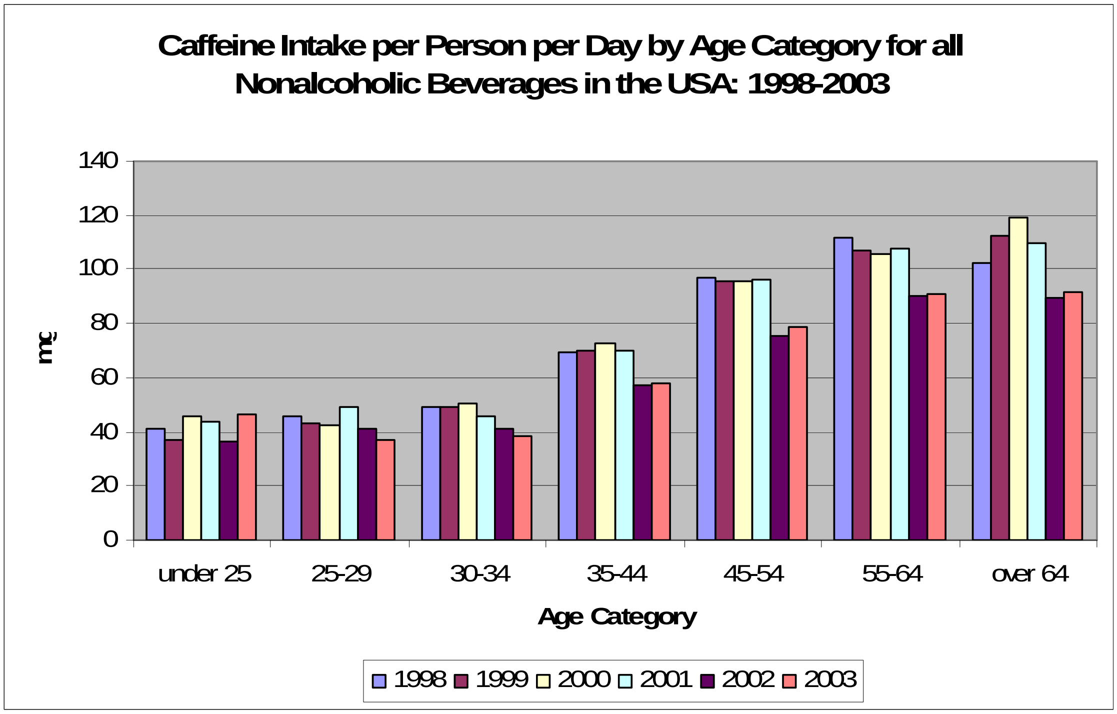

Figure 7.16: Per capita caffeine intake per day by age category for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Per capita vitamin C intake derived from consumption of non-alcoholic beverages at home is explained in Figure 7.17. According to that, there is an increasing trend in vitamin C intake for those households where the household head is below 25 years of age for the time period considered. For all other households where the household head's age is above 25 years, there is a decreasing trend in the vitamin C intake derived from consumption of non-alcoholic beverages at home.

Intake of calcium per person per day derived from consumption of non-alcoholic beverages at home is shown is Figure 7.18. Generally, we see a decreasing trend of calcium intake from beverages for all age categories. Nevertheless, like in the case of intake of caffeine from beverages, in a given year, the older the household head is, the more calcium taken in from beverages, even though there is a drop of intake over the time period considered.

Employment Status of Household Head

In households where the household head is not employed for pay, average per-capita intakes of calories, caffeine, calcium and vitamin C derived from consumption of non-alcoholic beverages are higher in comparison to those household where the household head is employed for pay (either part-time or full-time).

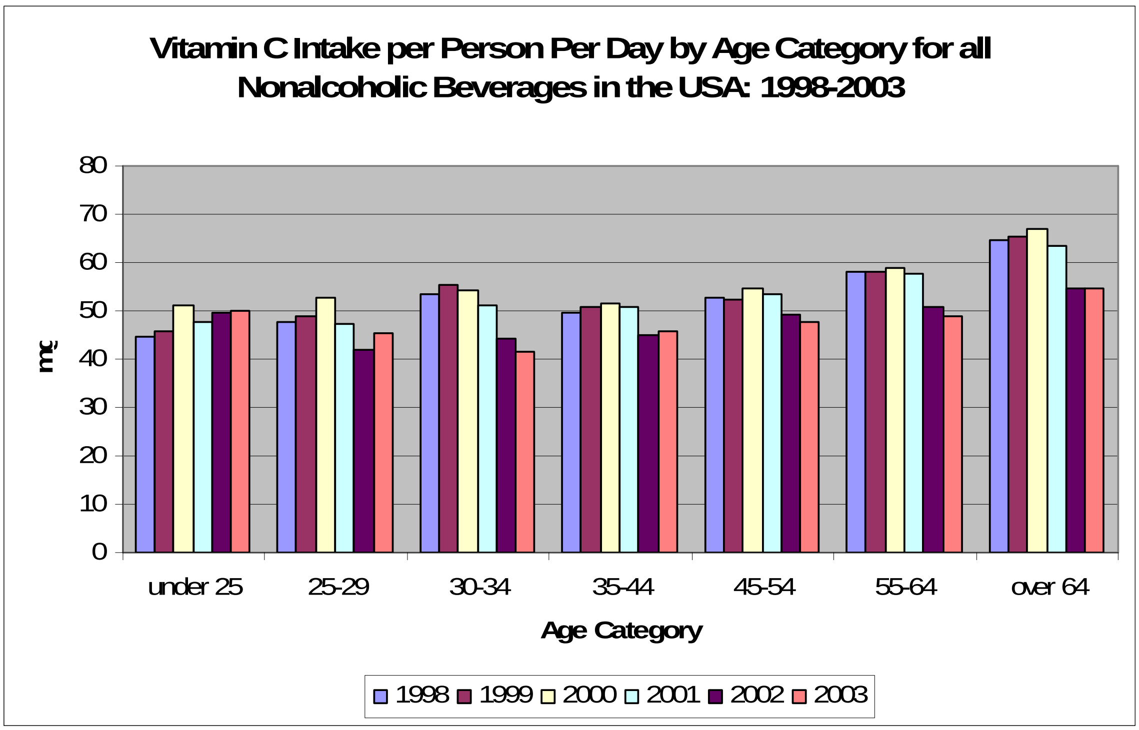

Figure 7.17: Per capita vitamin c intake per day by age category for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

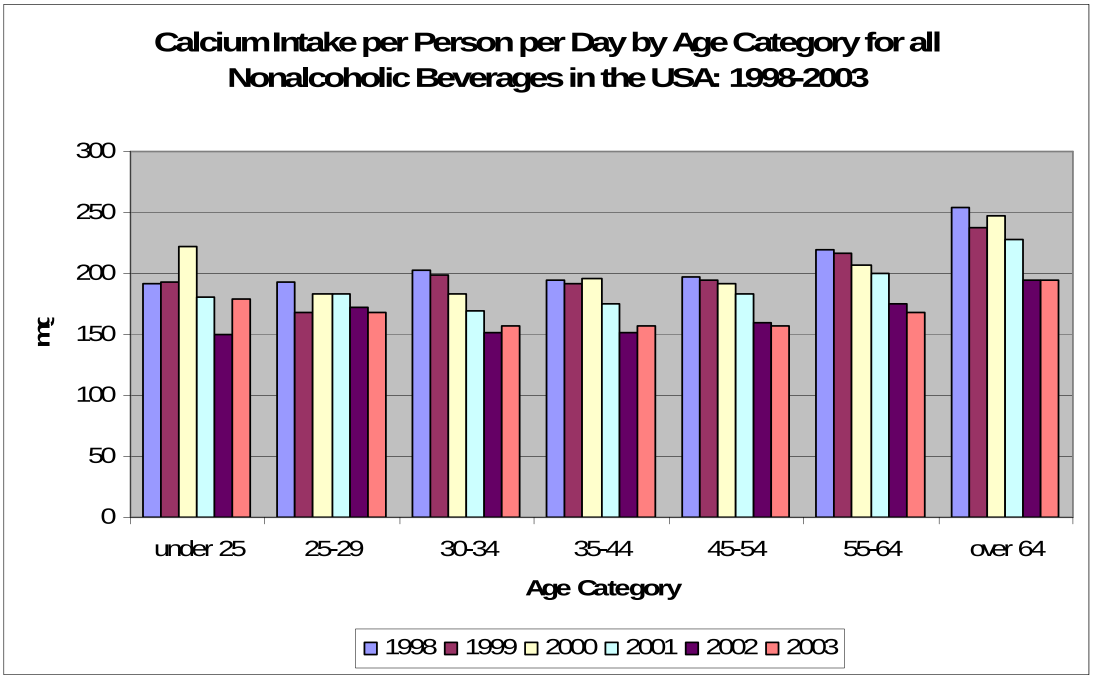

Figure 7.18: Per capita calcium intake per day by age category for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

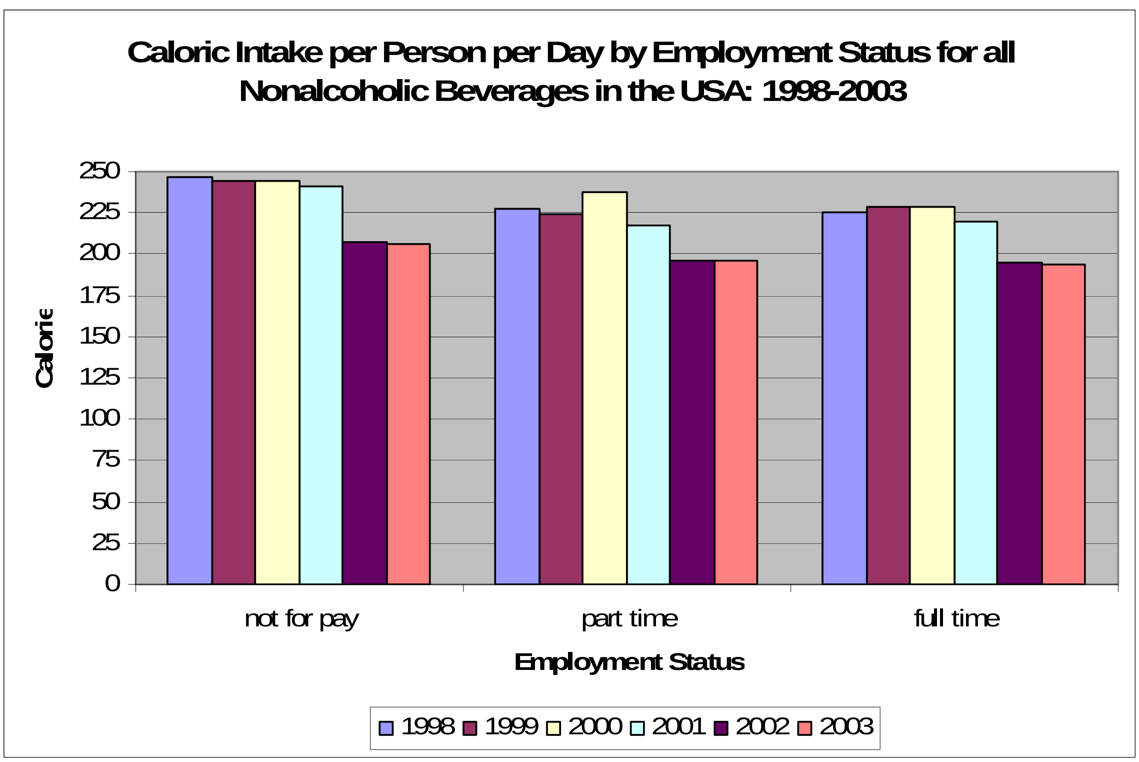

Figure 7.19: Per capita caloric intake per day by employment status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Figures 7.19 through 7.22 show such behavior for caloric, caffeine, vitamin C and calcium intakes derived from consumption of non-alcoholic beverages respectively.

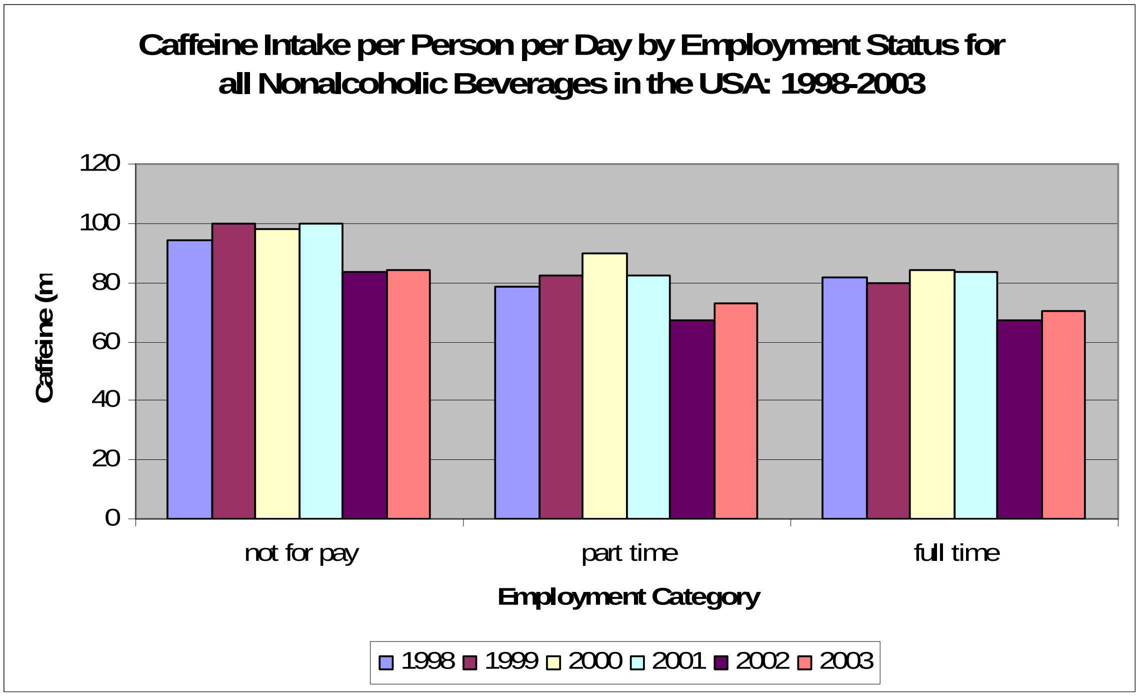

Figure 7.20: Per capita caffeine intake per day by employment status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

These data, however, are associated with household at-home consumption of non-alcoholic beverages. Therefore, one cannot be too surprising because we suspect that households with employed household head eat more away-from-home than households where the household head is not employed for pay.

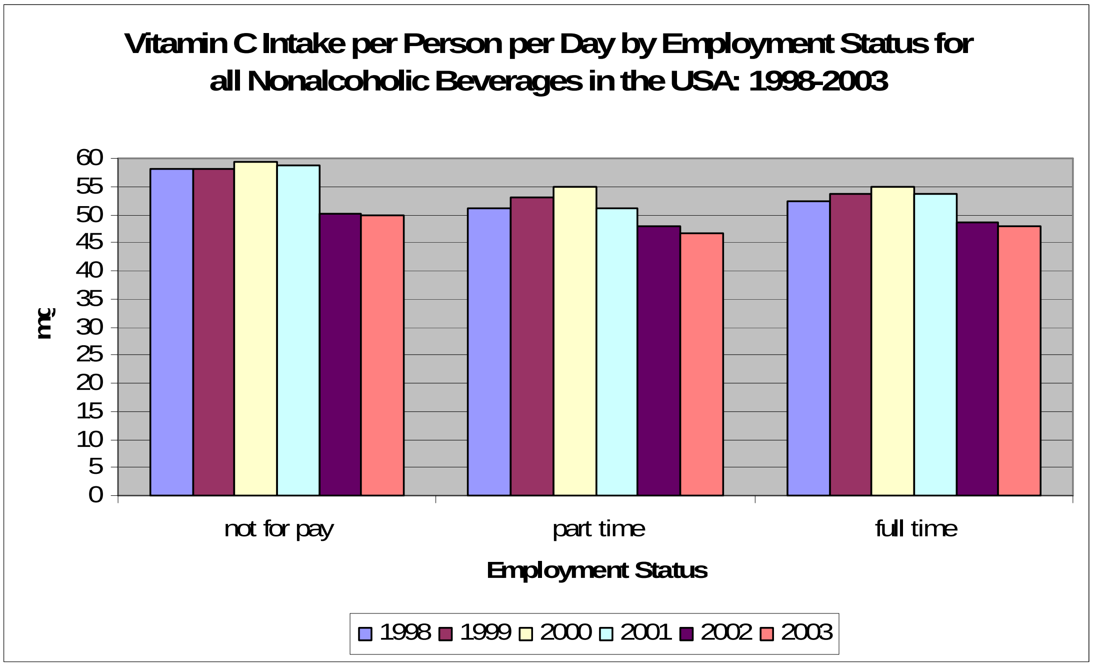

Figure 7.21: Per capita vitamin c intake per day by employment status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

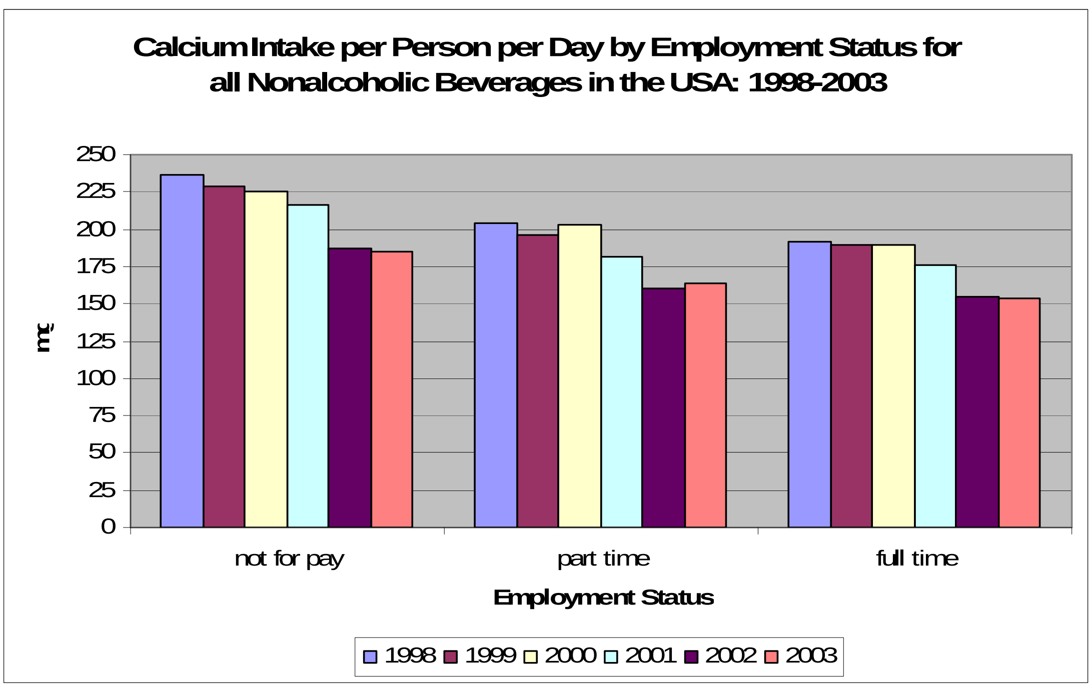

Figure 7.22: Per capita calcium intake per day by employment status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Overall, we find a decreasing trend in the intake of calories, caffeine, vitamin C and calcium derived from non-alcoholic beverages for all households irrespective of their employment status.

Education Status of Household Head

As shown is Figure 7.23, per capita caloric intake derived from non-alcoholic beverages consumed at home is higher for those households with household heads have less than high school education in comparison to those households where household head is educated at high school level or better (at undergraduate and post college education).

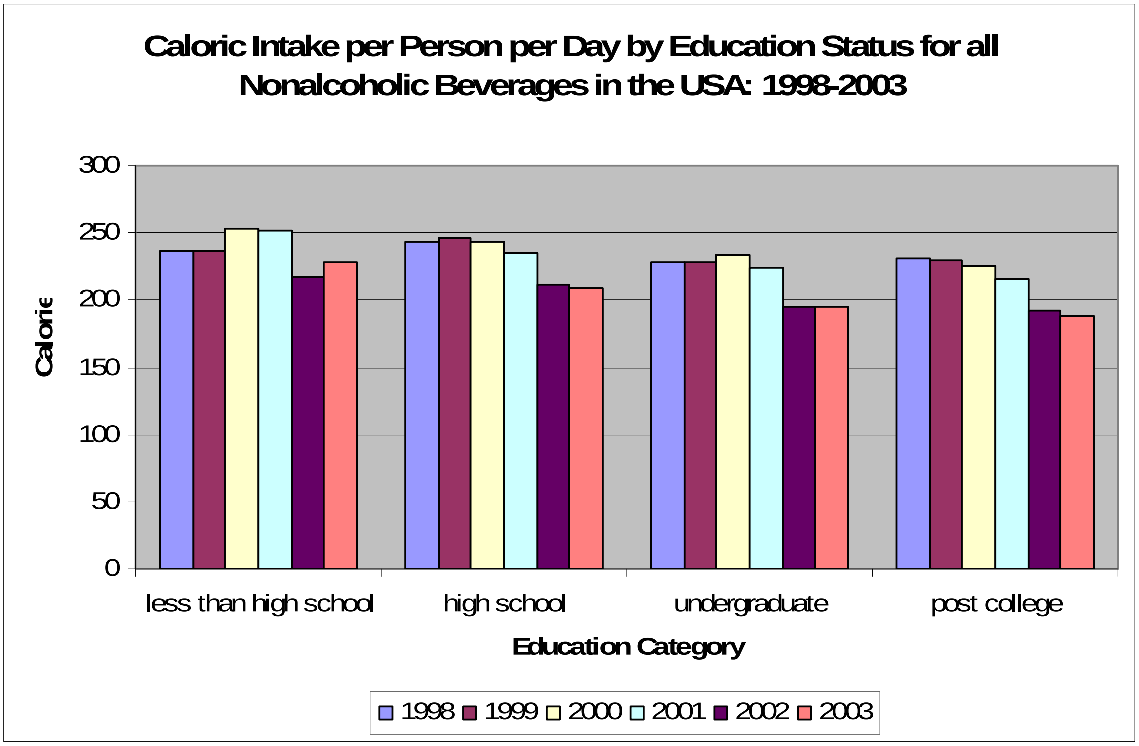

Figure 7.23: Per capita caloric intake per day by education status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

According to Figure 7.24, caffeine intake derived from consumption of non-alcoholic beverages at home is notably higher for those households with household head are educated up to high school level, in contrast to other households with household heads are educated at undergraduate or post college level.

The more educated the household head is (at undergraduate and post college level), the more the average intake of vitamin C derived from consumption of non-alcoholic beverages at home. This result is shown in Figure 7.25. Households where household head is educated at less than high-school level show an increasing intake of vitamin C derived from non-alcoholic beverages over the time period considered, even though their overall intake of vitamin C is lower than that of households with more educated household heads.

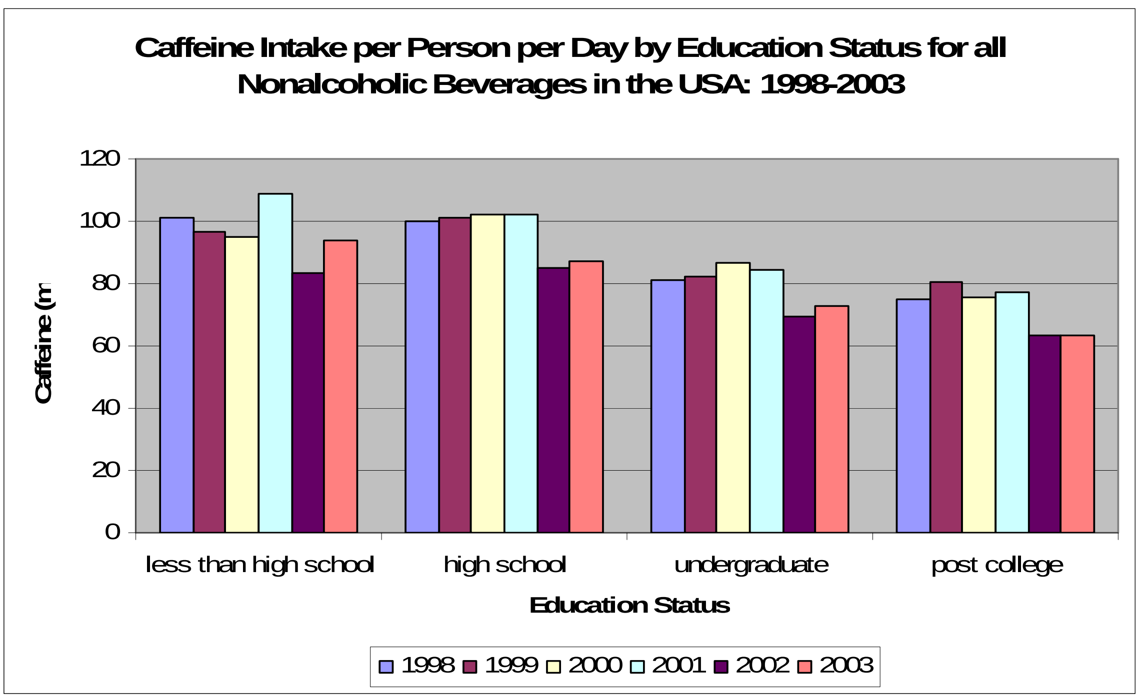

Figure 7.24: Per capita caffeine intake per day by education status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

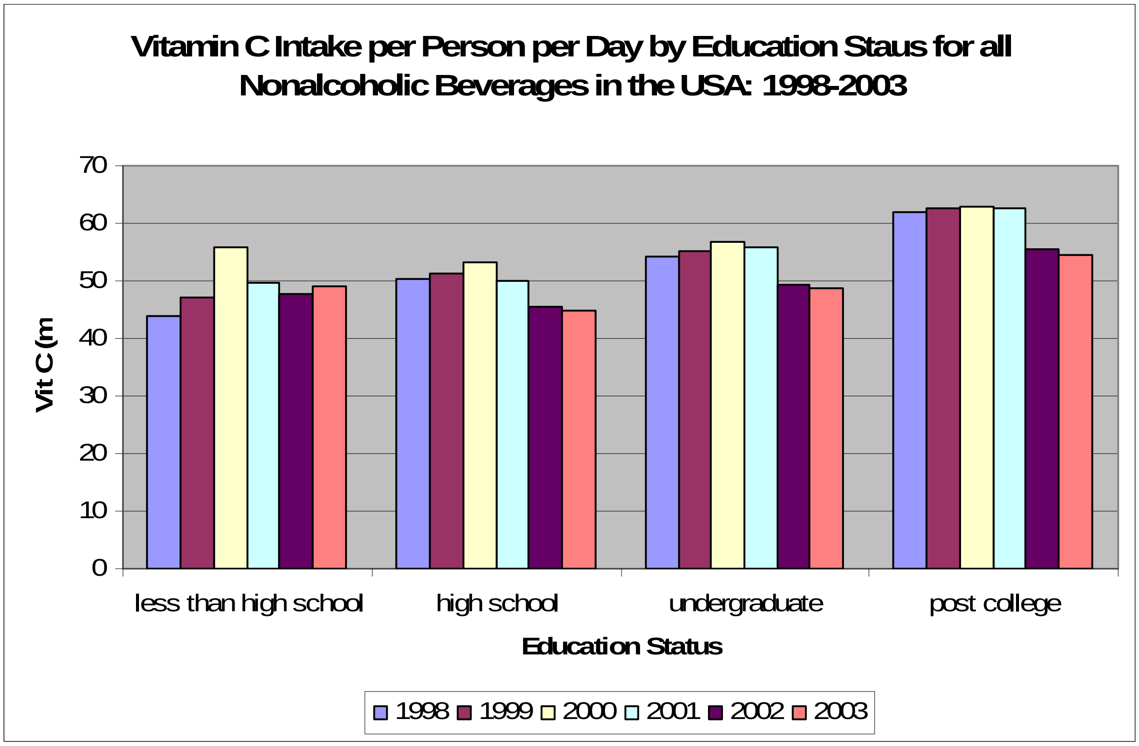

Figure 7.25: Per capita vitamin c intake per day by education status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

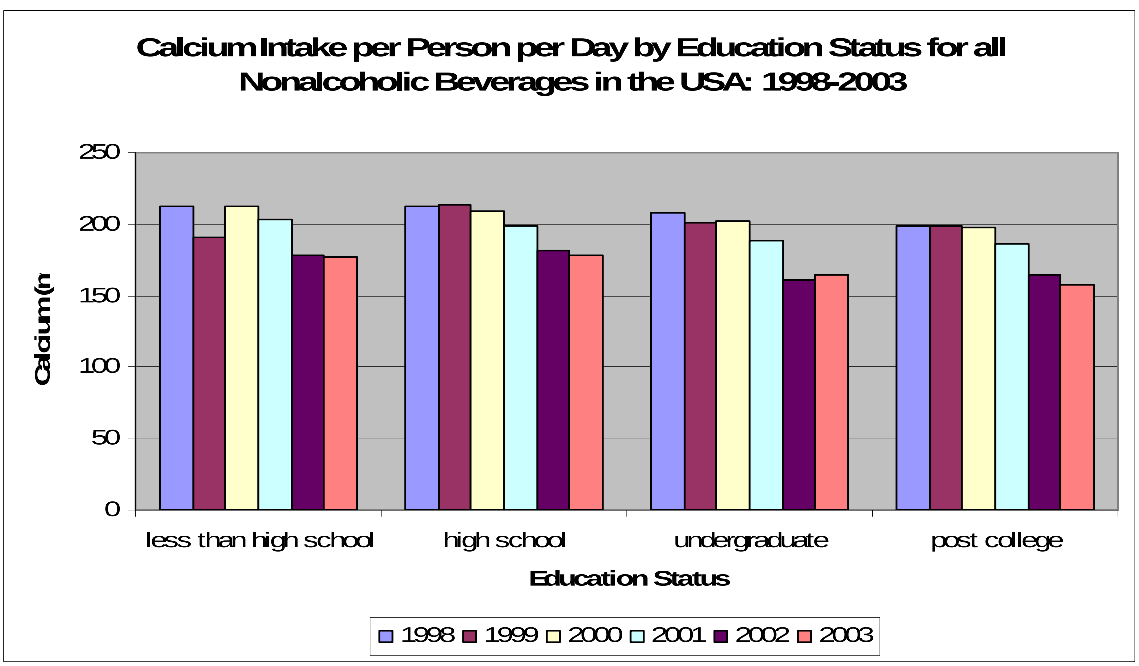

Figure 7.26: Per capita calcium intake per day by education status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Calcium intake derived from non-alcoholic beverages are higher for those households where the household head is educated at most at high school level (see Figure 7.26). Quite surprisingly, intake of calcium from beverages is low for those households with more educated household heads. Probably they are substituting away from beverage choices into non-beverages choices like cheese to gain calcium to their bodies. This is a testable proposition.

Region

According to Figure 7.27, households live in the Midwest and South regions of the United States account for higher average per capita intake of calories derived from consumption of non-alcoholic beverages at home in comparison to other regions (East, and West). For example, in the year 2000, per capita caloric intake per day was 250 kilo calories in the MidWestern U.S., while it was 216 kilo calories in the Western U.S.

Average caffeine intake derived from consumption of non-alcoholic beverages is highest in the Eastern U.S. (98 mg per person per day in 2001), whereas the second highest region being the MidWestern U.S. (see Figure 7.28).

Figure 7.29 reveals that, average intake of vitamin C resulting from consumption on non-alcoholic beverages is higher for those households live in the East and the Southern part of the US in comparison to those live in West and Midwest. Intake of calcium derived from consumption of non-alcoholic beverages are the highest in the Midwest part of the US.

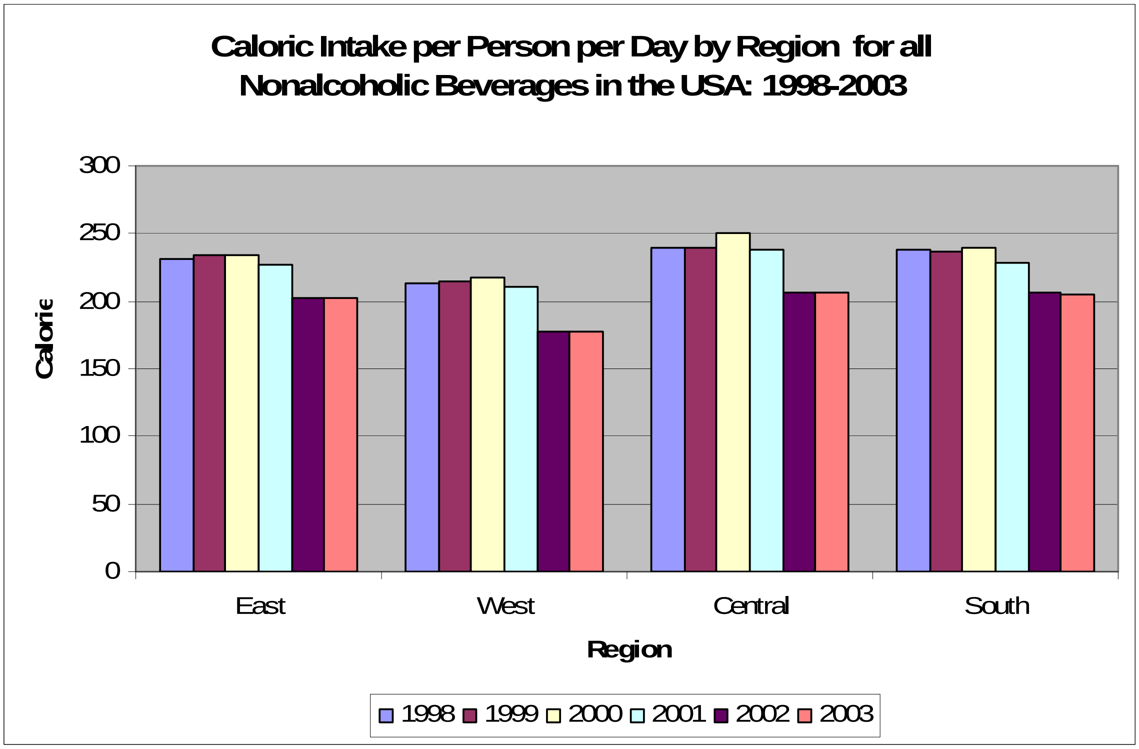

Figure 7.27: Per capita caloric intake per day by region for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

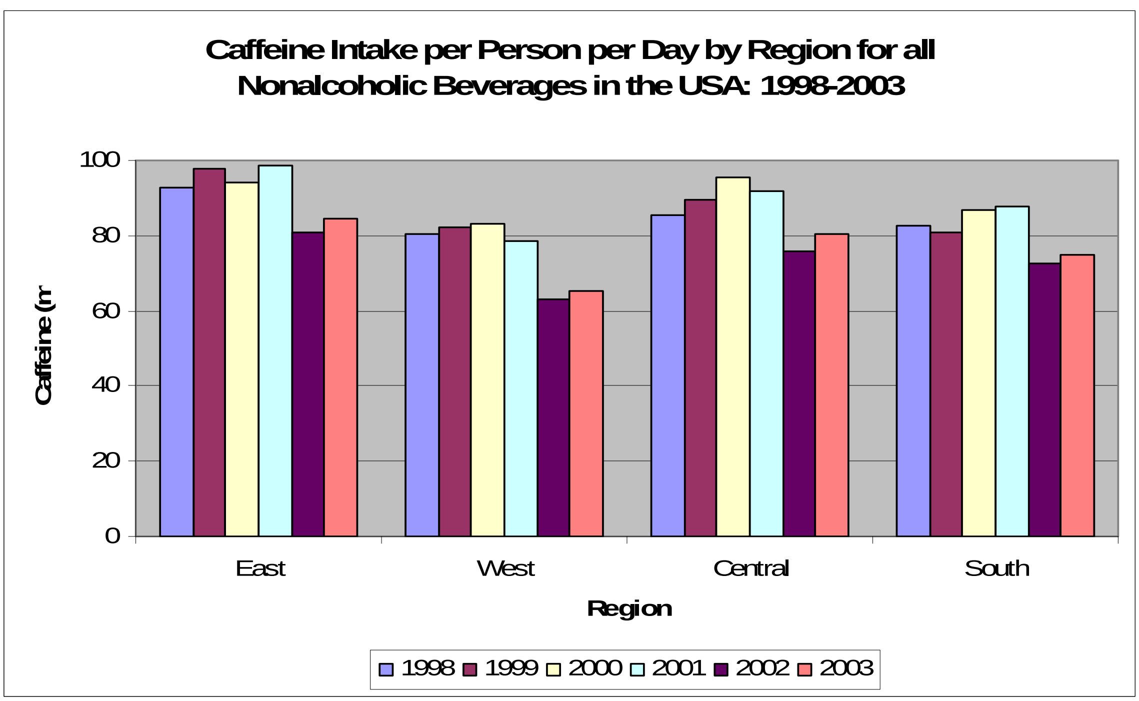

Figure 7.28: Per capita caffeine intake per day by region for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

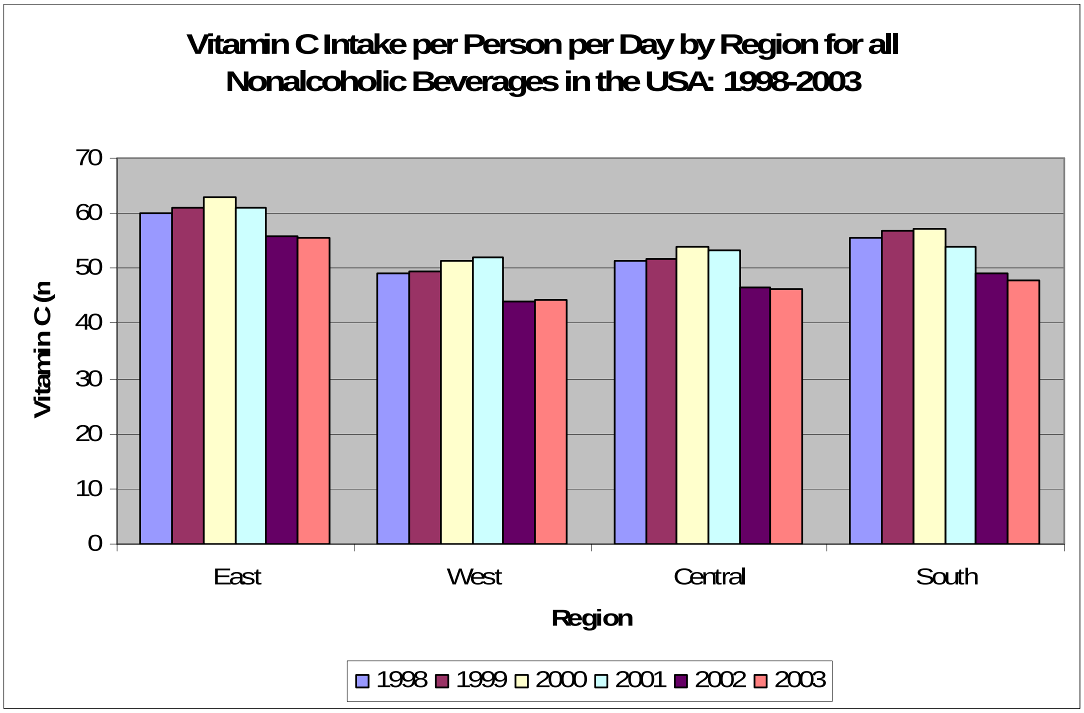

Figure 7.29: Per capita vitamin c intake per day by region for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

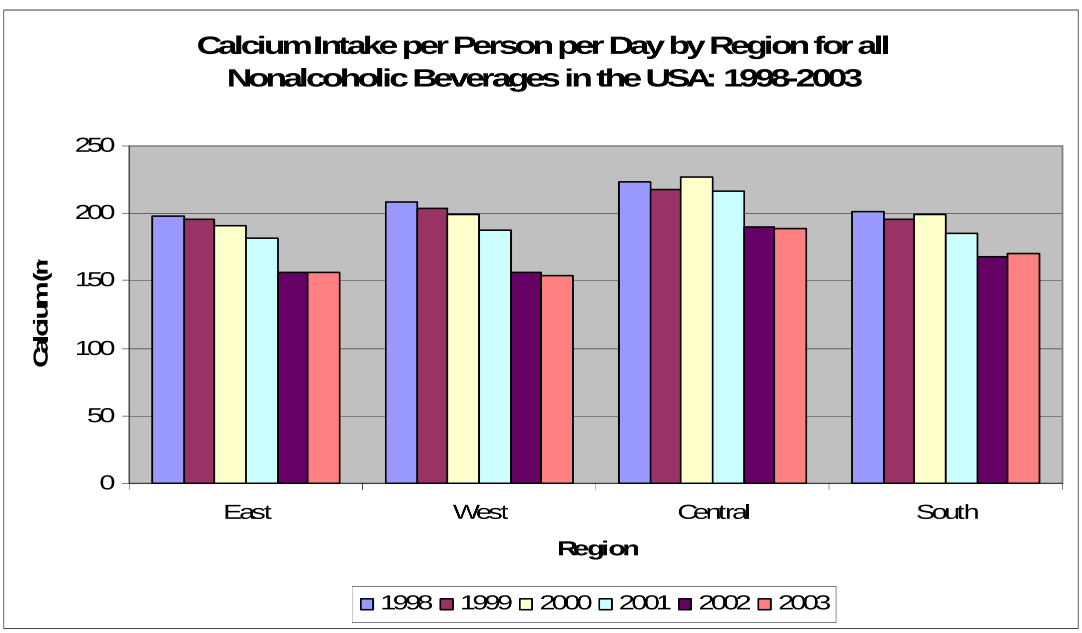

Figure 7.30: Per capita calcium intake per day by region for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

Race

As indicated by Figure 7.31, those who are classified as White and Black intake more calories derived from consumption of non-alcoholic beverages on average than those classified as Asian and Other. For example, per capita intake of calories by a Black individual is 212.6 kilo calories per day in year 2003, while that is for an Asian is 145 kilo calories. Asians consume consistently low amount of calories per person per day for all the six years (1998 through 2003) compared to other racial groups.

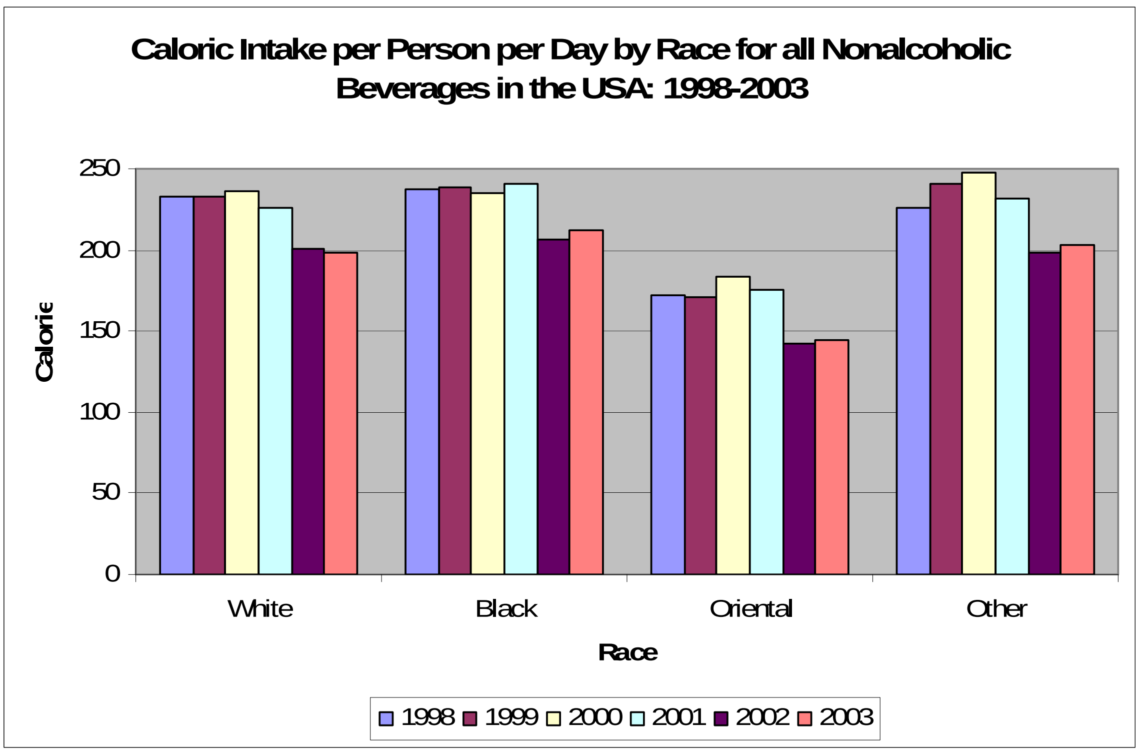

Figure 7.31: Per capita caloric intake per day by race for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

As depicted in Figure 7.32, those who classify as Whites are amongst the group of households that intake highest amount of caffeine derived from consumption of non-alcoholic beverages at home. It is as high as 83.65 mg per capita per day. Asians intake a very low amount of caffeine taken from beverages for all years and it is as low as 39 mg per capita per day.

Figure 7.33 shows the information pertaining to intake of calcium per capita per day for all race categories. It is clear that Whites account for the highest amount of calcium intake derived from non-alcoholic beverages compared to any other racial category. Those who classify as Black do intake the lowest amount of calcium from beverages. To give more perspective to the above calcium intake, in the year 2003, whites' intake of calcium was 181 mg per person per day and in contrast those who classify as blacks ingested only 104 mg of calcium per person per day in 2003.

As explained in Figure 7.34, those who classify as Black has the all time high average intake of vitamin C derived from non-alcoholic beverages at home compared to all other race categories. For example, they consumed 65 mg of vitamin C per person per day in 2003, in comparison to those who classify as oriental who consumed only 39 mg per person per day in the same year.

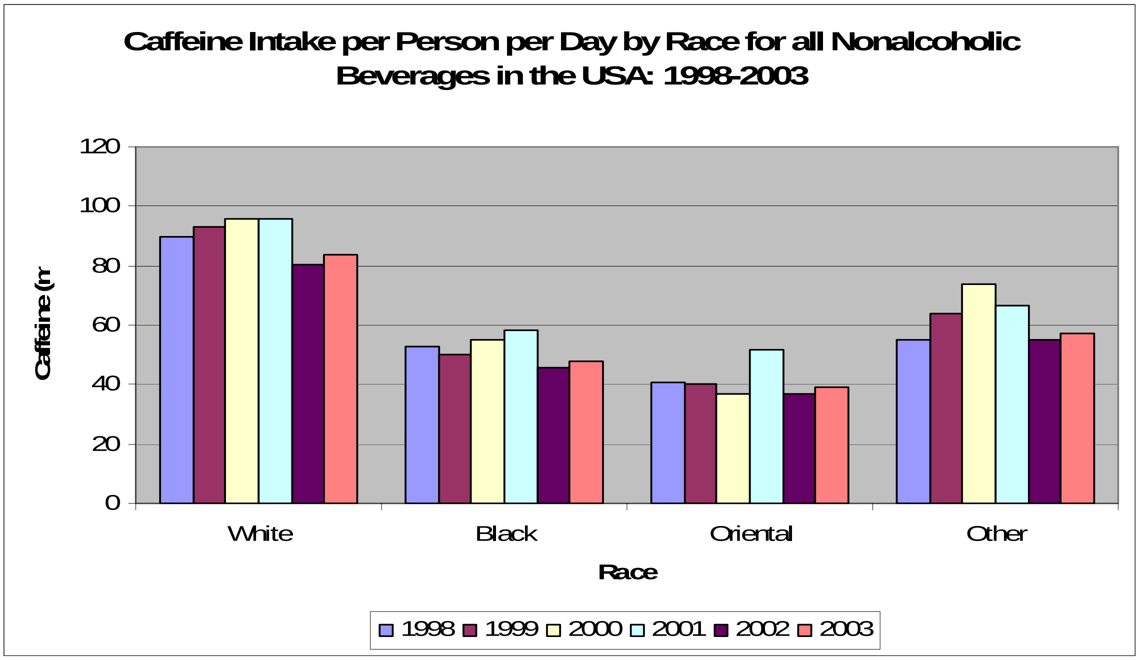

Figure 7.32: Per capita caffeine intake per day by race for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

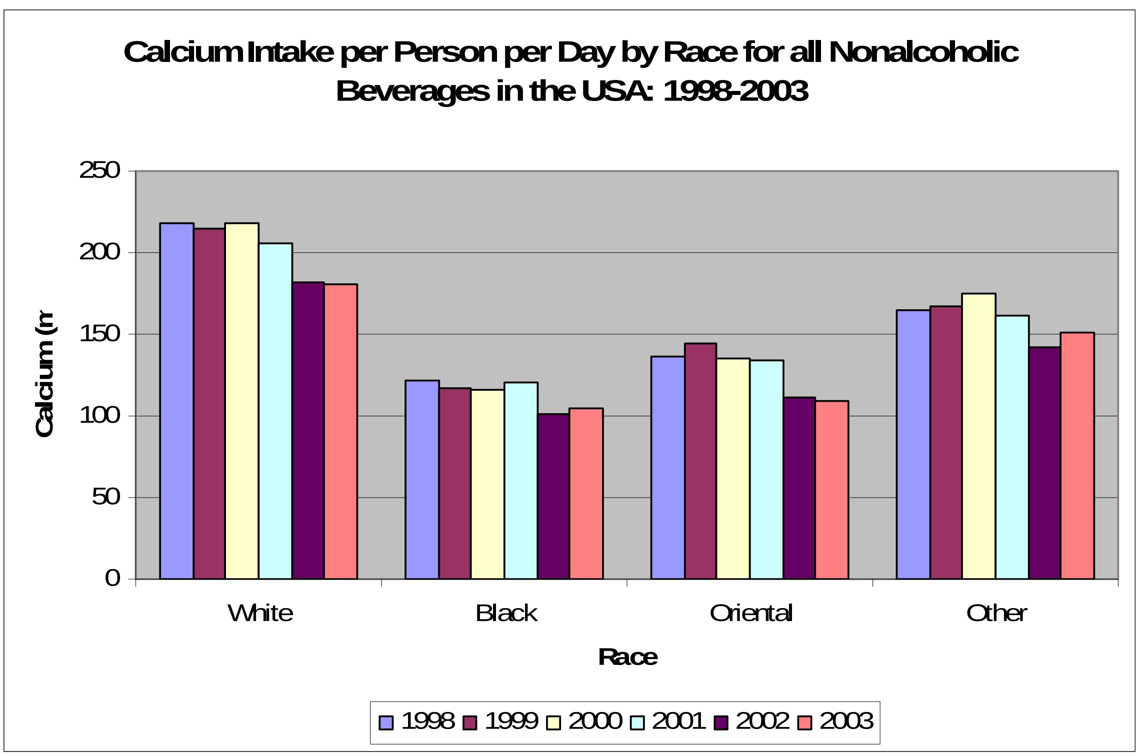

Figure 7.33: Per capita calcium intake per day by race for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

This lower intake of calcium derived from beverages amongst those who classify Blacks is accounted for by lower milk/dairy products consumption by them due to their inherent intolerance for milk/dairy products. They may be adding calcium to their diet through non-dairy beverages/products, which is a testable proposition.

Hispanic Origin of Household

On average, per capita daily intake of calories, caffeine, calcium and vitamin C derived from consumption of non-alcoholic beverages are lower for Hispanics than that for non-Hispanics for all years from 1998 through 2003 (see Figures 7.35 through 7.38). According to Figures 7.36 and 7.37, calcium and caffeine intake for Hispanics are considerably lower than that for non-Hispanics for all 6 years under study.

The six-year average per capita intake of caffeine for Hispanics is about 62 mg per day and that for Non-Hispanics is about 85 mg per day. On a 6-year average basis, Hispanics consume about 28 mg less calcium per person per day compared to that of non-Hispanics. This difference may be attributed to lower milk consumption by Hispanics.

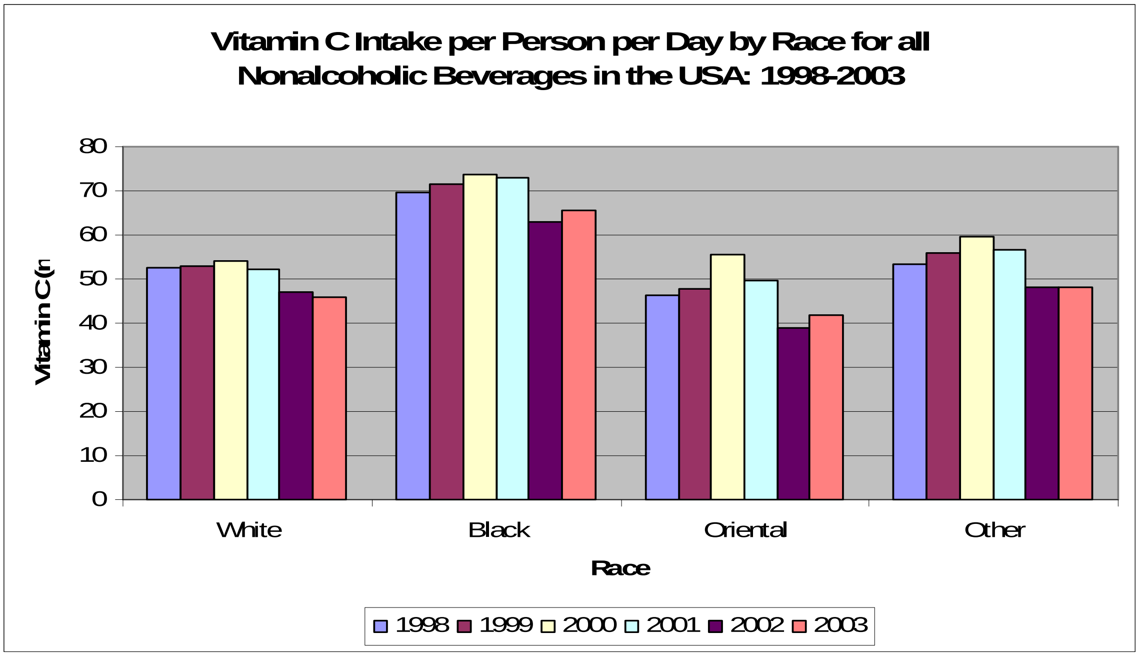

Figure 7.34: Per capita vitamin c intake per day by race for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

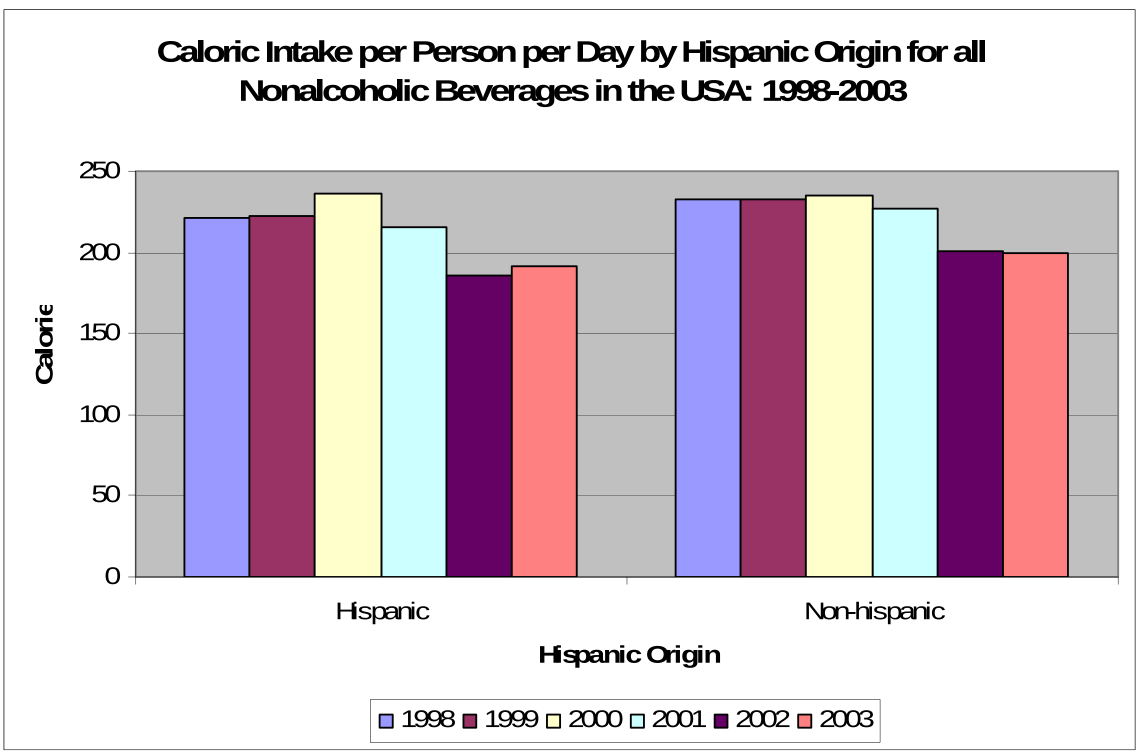

Figure 7.35: Per capita caloric intake per day by hispanic origin for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

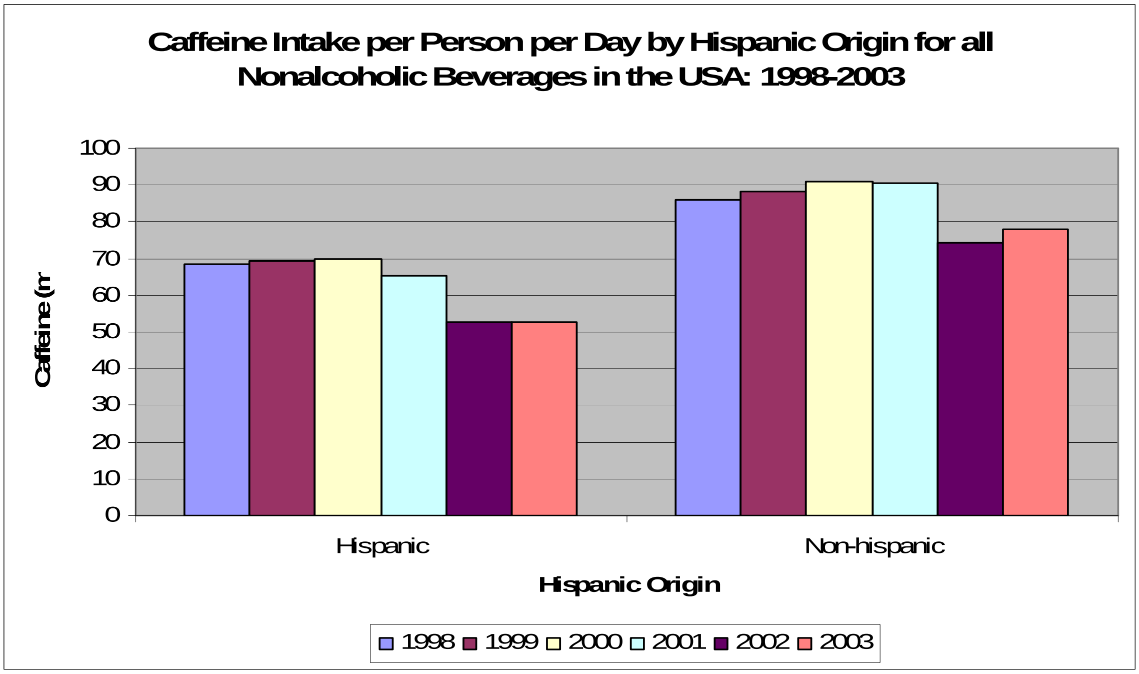

Figure 4.36: Per capita caffeine intake per day by hispanic origin for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

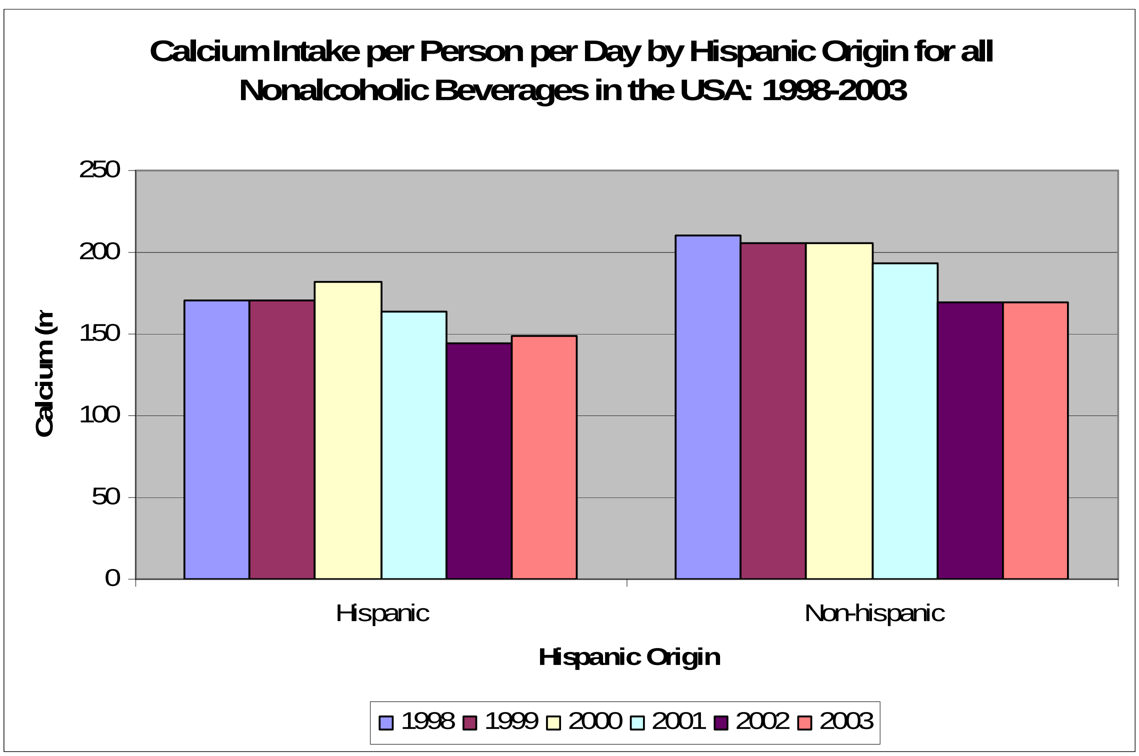

Figure 7.37: Per capita calcium intake per day by hispanic origin for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

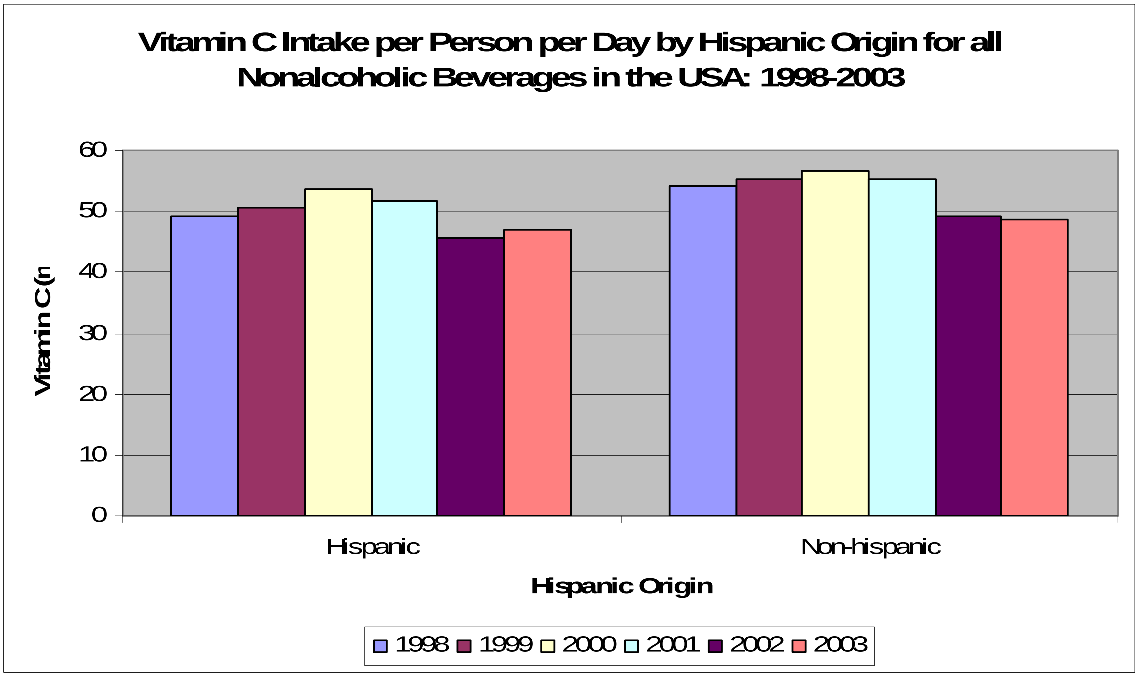

Figure 7.38: Per capita vitamin c intake per day by hispanic origin for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

<u>Age and Presence of Children in the Household</u>

According to Figures 7.39 through 7.42, average per capita intake of calories, caffeine, calcium and vitamin C per day derived through consumption of non-alcoholic beverages at home for the six-year period (1998 through 2003) is higher for households' with-out children compared to those households with children. Figure 7.39 reveals that the six-year average intake of per capita calories for those households' with-out children is 227 kilo calories per day.

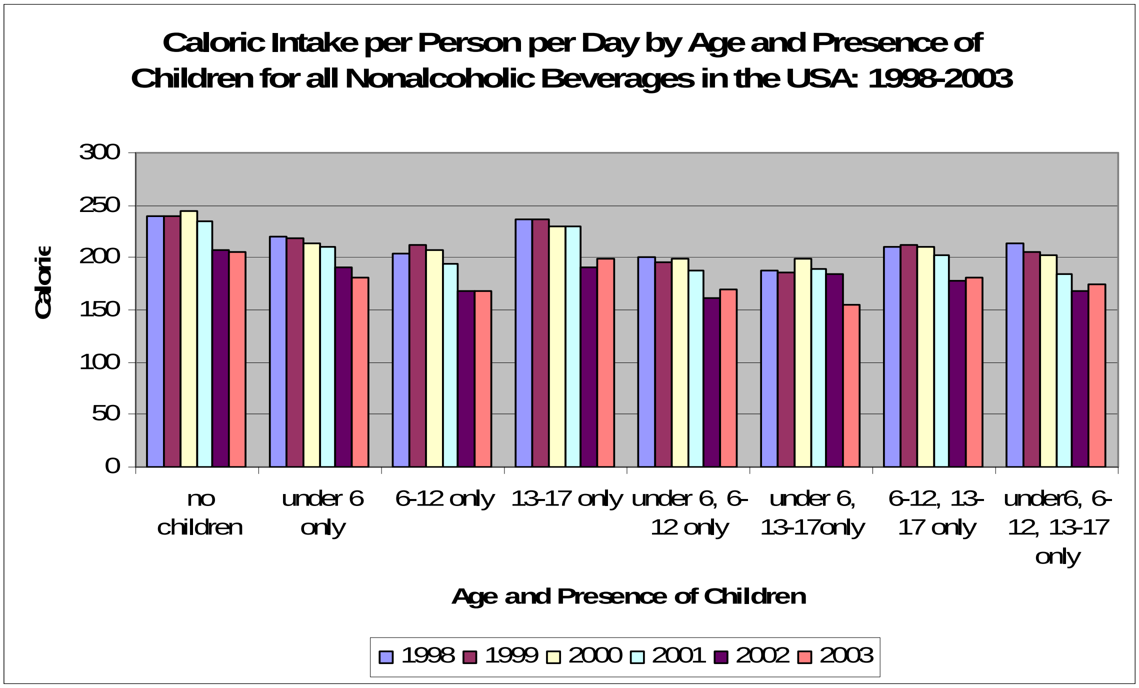

Figure 7.39: Per capita caloric intake per day by age and presence of children for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

Presence of children, more specifically households with 13 to 17 year-olds have a higher per capita intake of calories derived from consumption of non-alcoholic beverages (221 kilo calories per day) in comparison to households with children who are lesser than 13 years. This probably is due to the reason that 13-17 year-olds drink a lot of carbonated soft drinks to quench their thirst than any other age category.

Average per capita caffeine intake derived from consumption of non-alcoholic beverages at home is shown in Figure 4.40. According that, households with children aging 13 to 17 years do consume the highest amount of caffeine (61 mg per person per day) compared to children of all other age categories and it is only 37 mg lower than for those households' with-out children. This result again may be due to the fact that 13-17 year-olds consume more caffeinated soft drinks (carbonated soft drinks).

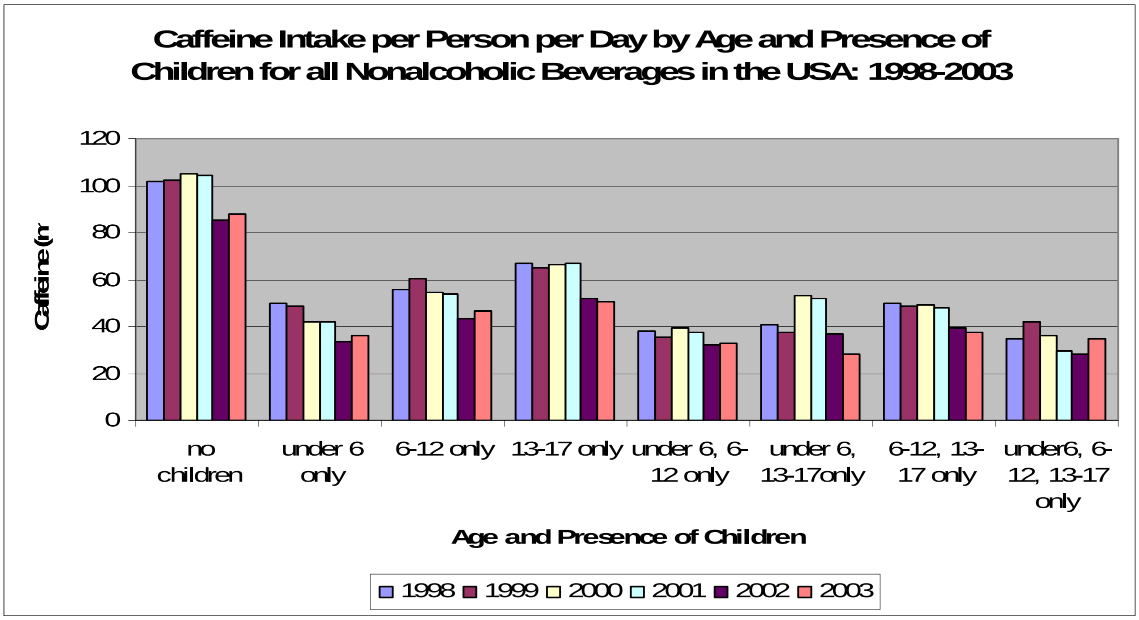

Figure 7.40: Per capita caffeine intake per day by age and presence of children for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

Per capita calcium intake derived from consumption of non-alcoholic beverages is supped to be higher for those households with small children possibly below 6 years of age. It is evident from the findings from this study, such that the highest 6-year average intake of calcium derived from beverages are amongst households with children under age 6 (183 mg of calcium per person per day) (see Figure 7.41). As children grow, it is clear that the average intake of calcium derived from consumption of beverages is low, possibly substituting away from beverages to other non-beverage categories for calcium. This is a testable proposition.

As explained in the Figure 7.42, six-year average vitamin C intake derived from beverages for those households with children is about 45 mg per person per day on average. It is about 10 mg per person per day lesser (based on six-year average) than for those households' with-out children.

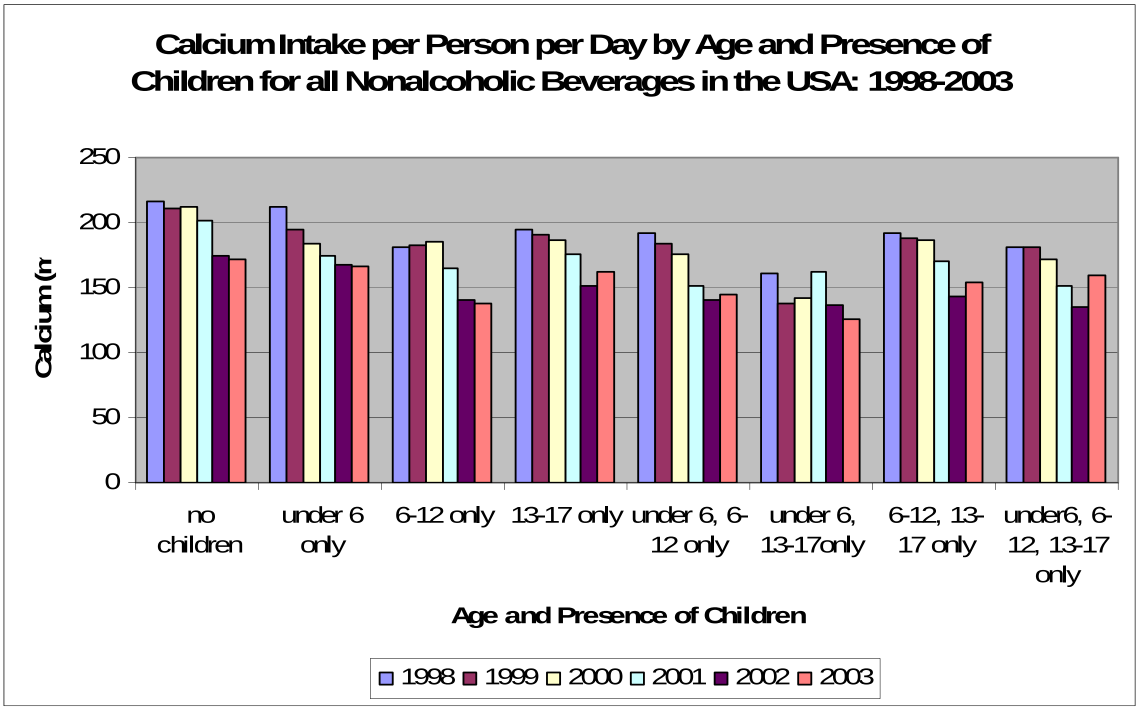

Figure 7.41: Per capita calcium intake per day by age and presence of children for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

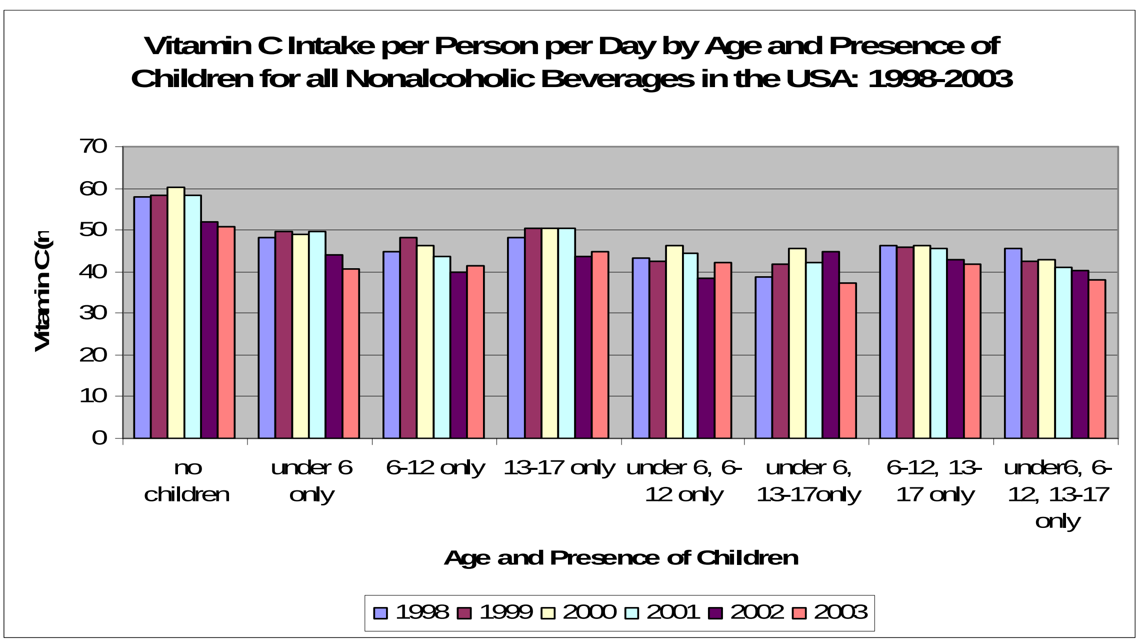

Figure 7.42: Per capita vitamin c intake per day by age and presence of children for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

Gender of the Household Head

Households with male household head as the decision maker show higher average per capita intake of calories, caffeine, calcium and vitamin C derived from consumption of non-alcoholic beverages at home compared to those households headed by a female head and those with both male and female heads. As shown in Figures 7.43 through 7.46, above result is consistent throughout the six-year period considered in this study.

For example, six-year average per capita intake of calories for a male headed household is about 296 kilo calories per day; this is compared to that of 224 kilo calories per day for a female headed household. More per capita caloric and caffeine intake in male headed households may be due to the reason that they consume more carbonated soft drinks than a female headed household.

Poverty Status of the Household

Figure 7.47 shows the per capita average intake of calories per day derived from consumption of non-alcoholic beverages at home by poverty status of the household.

Households which are below 185% poverty status (poverty households) do intake slightly more calories from beverages than those households that are categorized as non-poor. The six-year average per capita intake of calories for poverty households is 227 kilo calories per day and that is only 7 kilo calories higher than that for non-poverty households. As shown in Figures 7.48 through 7.50, per capita average intake of caffeine, calcium and vitamin C respectively, derived from consumption of non-alcoholic beverages is slightly lower for poverty households compared to that of non-poverty households for the entire period considered.

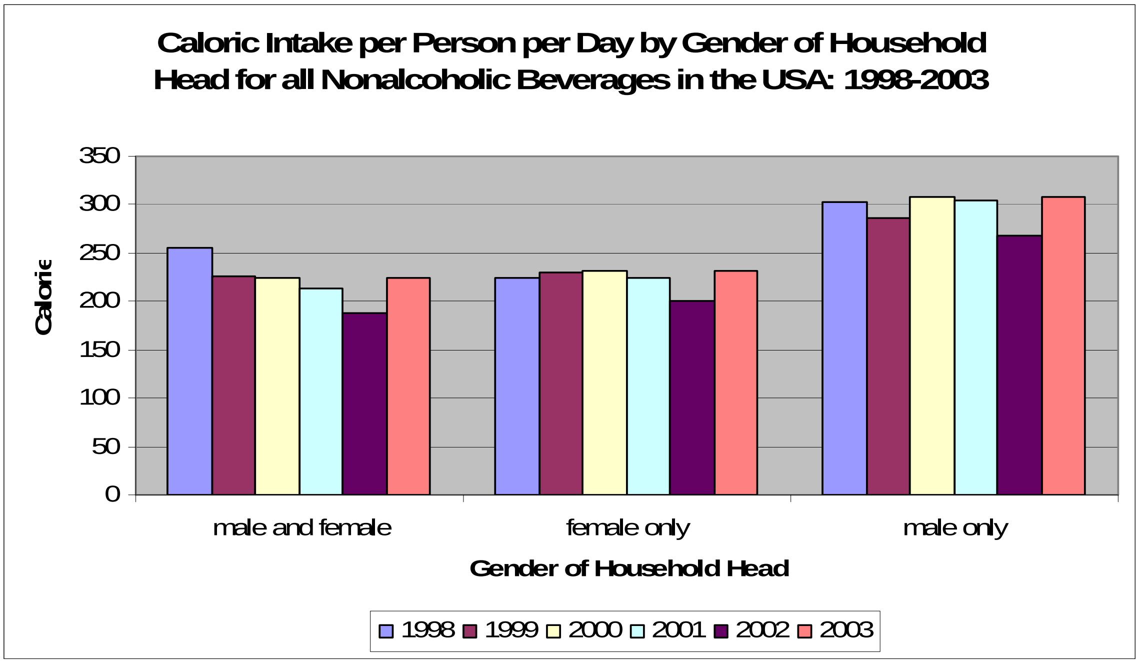

Figure 7.43: Per capita caloric intake per day by gender of household head for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

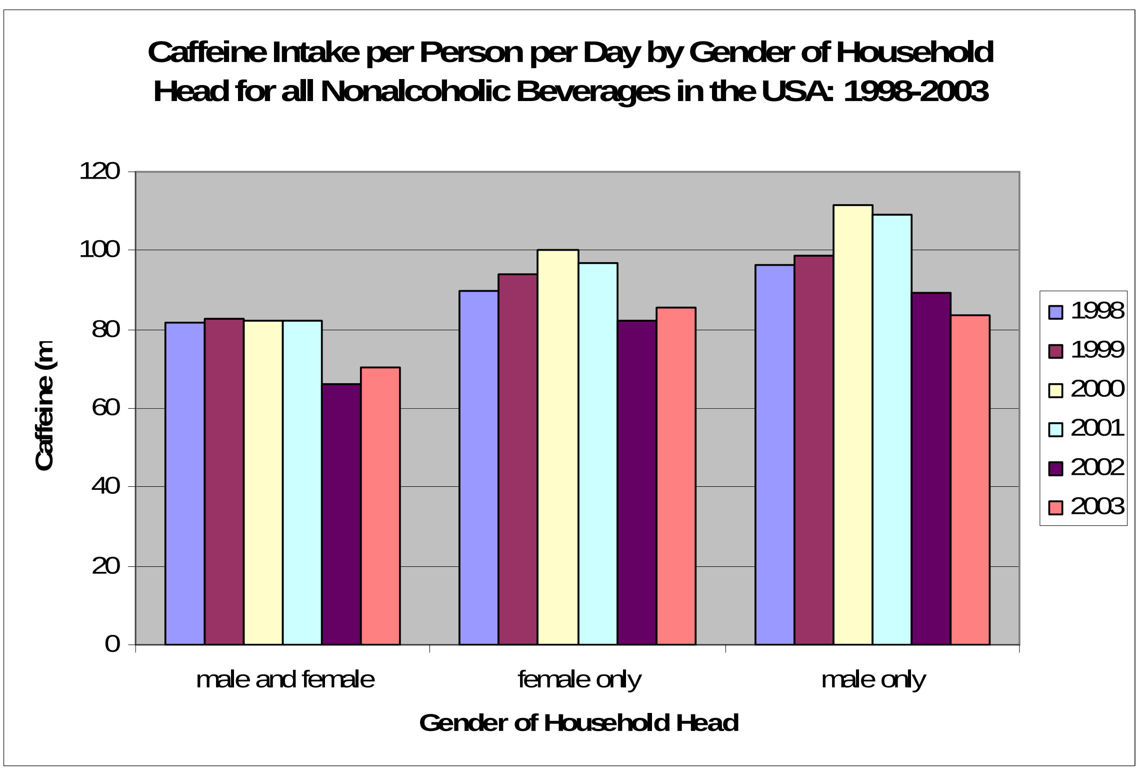

Figure 7.44: Per capita caffeine intake per day by gender of household head for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

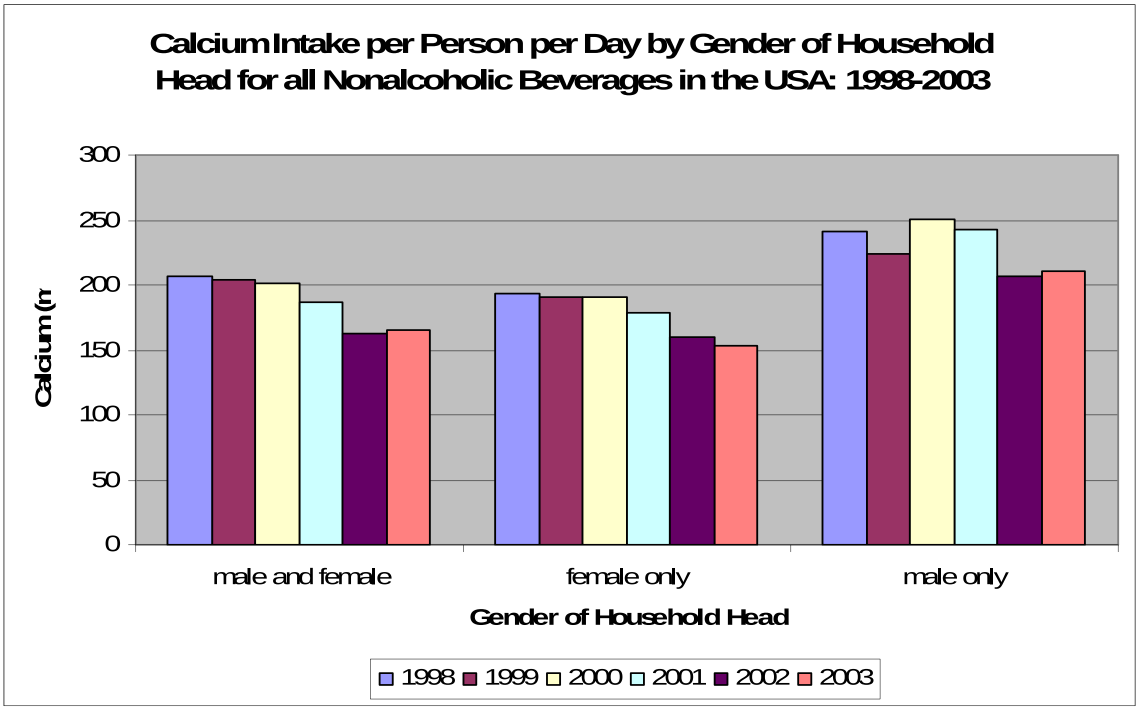

Figure 7.45: Per capita calcium intake per day by gender of household head for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

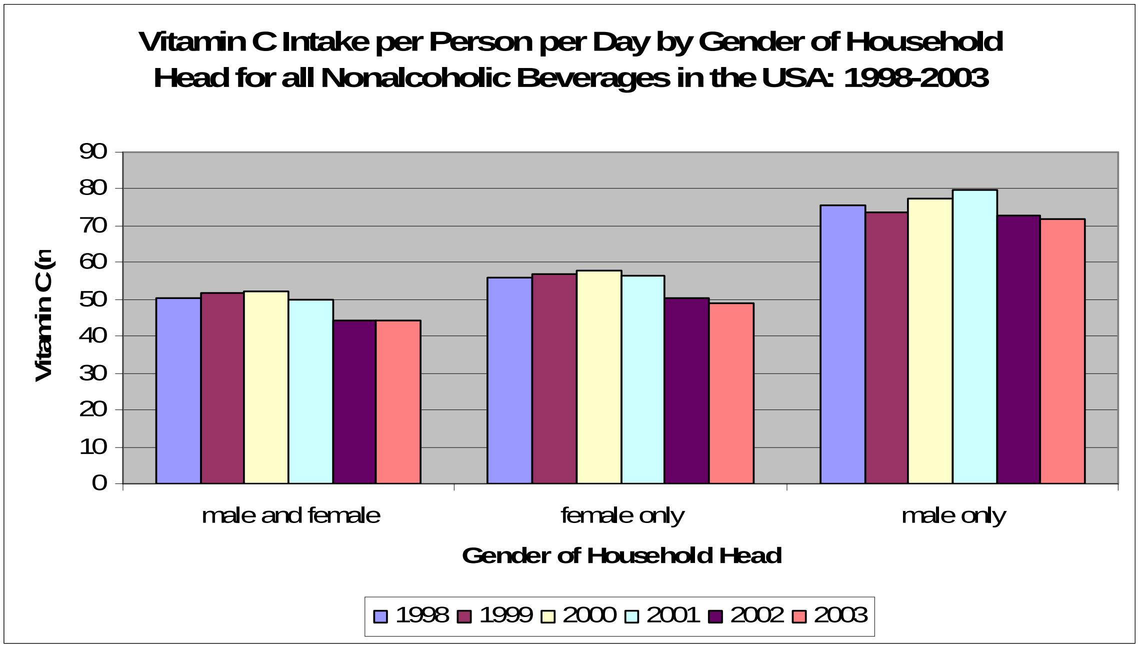

Figure 7.46: Per capita vitamin c intake per day by gender of household head for all non- alcoholic beverages in the U.S. at-home markets: 1998-2003

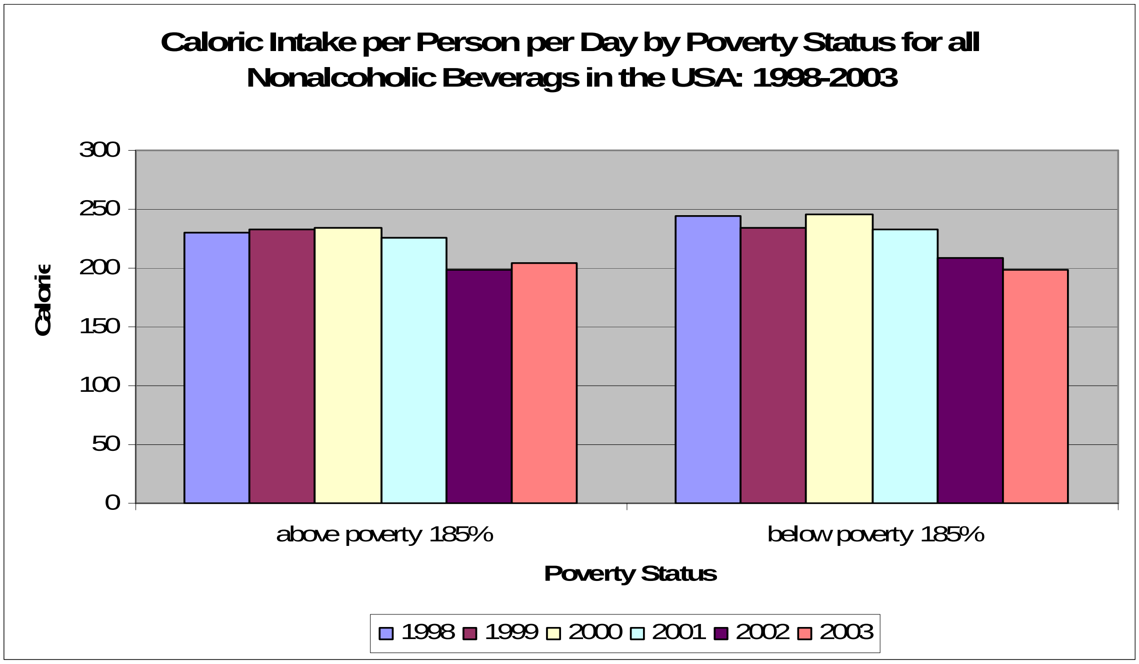

Figure 7.47: Per capita caloric intake per day by poverty status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

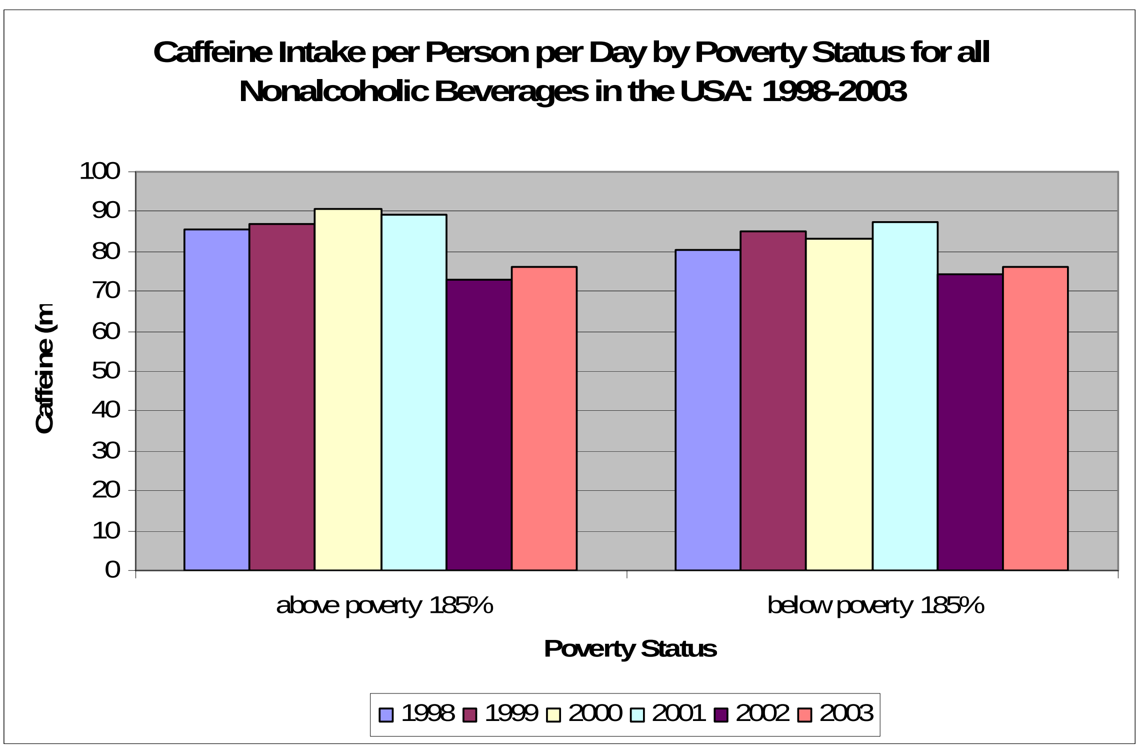

Figure 7.48: Per capita caffeine intake per day by poverty status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

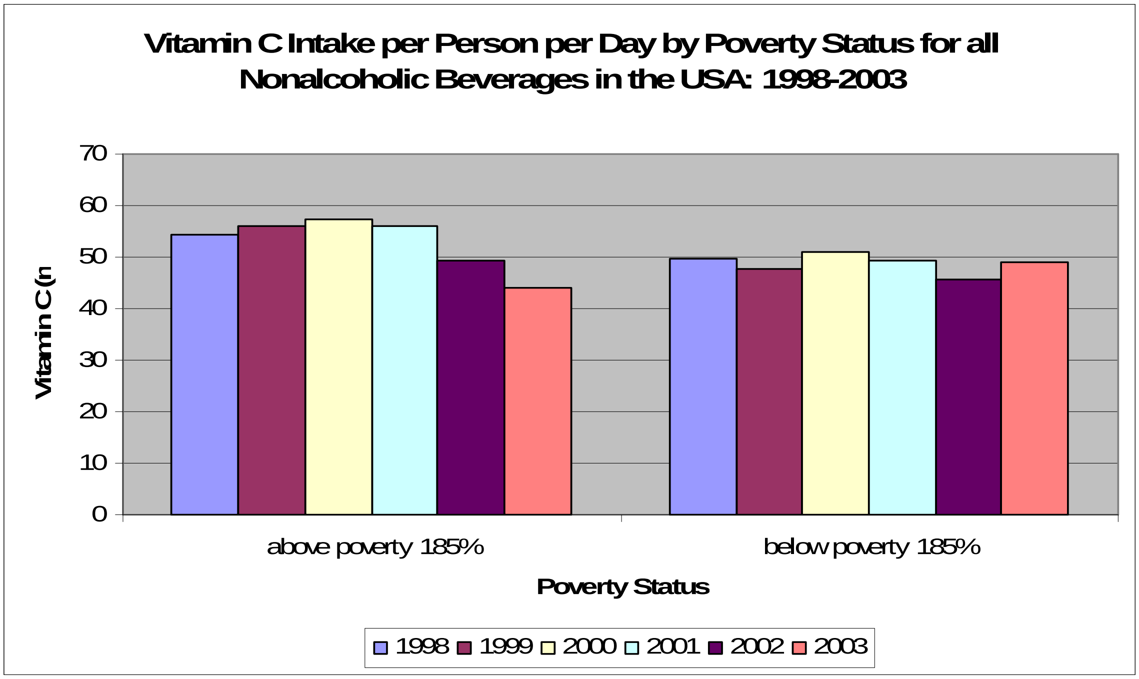

Figure 7.49: Per capita calcium intake per day by poverty status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

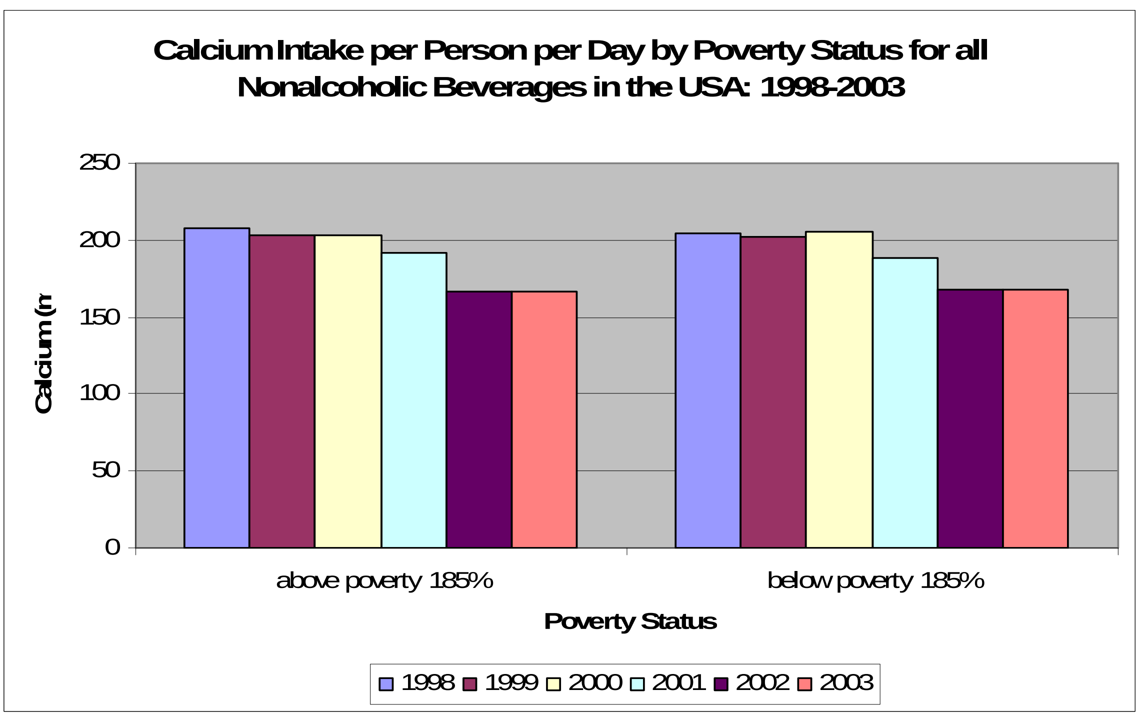

Figure 7.50: Per capita vitamin c intake per day by poverty status for all non-alcoholic beverages in the U.S. at-home markets: 1998-2003

Regression Analysis of Calorie and Nutrient Intake

In this section we discuss results from three different type of regression work done to achieve our objectives. First, we discuss the outcome of single equation models developed to ascertain the factors affecting the intake of calories, caffeine, calcium and vitamin C derived from consumption of non-alcoholic beverages at home by the U.S. consumer for the period of 1998 through 2003. Next, we offer a narrative for results from seemingly unrelated regressions (SUR) performed for caloric and nutrient intake to find out any efficiency improvement over single-equation models. Finally, we discuss single equation models estimated for the entire macro sample (pooled sample) of observations for calories and other nutrient intake (with 41071 observations) along with yearly dummies as additional explanatory variables to learn about potential impact of USDA year 2000 dietary.

In our analyses of all nutrient and calorie models, we find that, quadratic functional form outperforms other functional forms tested (tests of functional forms are carried out using Schwarz information criteria (SIC) and Box-Cox transformation method). It is important to note that, in our analyses we use the *p-value* 0.05 as the level of significance.

Factors Affecting Caloric Intake: 1998 through 2003

In the following section we discuss the factors affecting caloric intake derived from consumption of non-alcoholic beverages at home by the U.S. consumer on a year-by-year basis from 1998 through 2003. At the end, we offer a commentary on the factors affecting caloric intake taking the entire sample from 1998 through 2003 as a whole.

Caloric Intake 1998

Regression results for the factors affecting the caloric intake in the calendar year 1998 are depicted in Appendix 6. Price, employment status of the household head, region, race, age and presence of children, gender of the household head and poverty status of the household are statistically important in the determination of daily caloric intake.

Owing to the quadratic functional form, the marginal effect of price on caloric intake is a function of price, namely 71.59-21.52*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.33 per gallon, all other factors invariant.

Households where the household head is employed either full time or part time, have significantly lower caloric intake derived from consumption of non-alcoholic beverages than households where the household head is not employed for pay. In particular, households with household head that is employed full time consume 30 kilo calories per person per day lesser than those households that are with a household head that is not employed for pay. It is 15 kilo calories less for households with a household heat that is employed on a part time basis.

Caloric intake derived from the consumption of non-alcoholic beverages are lesser by 21 kilo calories per person per day for those households live in the Western regions of U.S. in comparison to those live in the Eastern parts of United States. Asians consume 48 kilo calories per person per day derived from non-alcoholic beverages compared to Whites.

Households with children consume anywhere from 20-55 kilo calories per person per day lesser than those without children. Households managed only by a male household head have 77 kilo calories per person per day more caloric intake derived from non-alcoholic beverages compared those managed by both a male and a female. Poverty households consume 17 kilo calories more from consumption of non-alcoholic beverages relative to non-poverty households.

Caloric Intake 1999

Factors affecting the intake of calories derived from consumption of non-alcoholic beverages for year 1999 are shown in Appendix 6. Price, employment status of the household head, region, race and age and presence of children are found to be significant factors affecting the caloric intake.

The marginal effect of price on caloric intake is a function of price, namely 86.39-22.98*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.76 per gallon, all other factors invariant.

Households where the household food manger is employed either full-time or part-time have a higher intake of calories (26 and 19 kilo calories respectively) derived from non-alcoholic beverages compared to those households where the household head is not employed for full pay. Households live in the Western UnitedStates consume 26 kilo calories per person per day lesser than those live in the Eastern UnitedStates.

Asian’s intake of calories derived from non-alcoholic beverages is 54 kilo calories per person per day lower than that for Whites. Races categorized as other (non-White, non-Black and non-Asian) consume 22 kilo calories more than that of Whites. Households with children consume significantly lower amounts of calories (anywhere from 25-58 kilo calories per person per day) from beverages than those households without children.

Households where the household food manager is only a male consume 52 kilo calories more derived from beverages than those households that are managed by both a male and a female. Poverty status is not a significant driver of caloric intake from non-alcoholic beverages in 1999.

Caloric Intake 2000

Factors affecting per capita caloric intake derived from consumption of non-alcoholic beverages in year 2000 is depicted in Appendix 6. Price, employment status of the household head, region, race, age and presence of children and gender of the household food manager are significant factors driving the intake of calories obtained from consumption of non-alcoholic beverages.

The marginal effect of price on caloric intake is a function of price, namely 79.23-22.96*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.45 per gallon, all other factors held constant.

Households where household head is employed full time have a lower intake of calories (22 kilo calories per person per day lower) compared to those households where the household head is not employed for pay. Households in the Central part of U.S. consume 16.75 kilo calories per person per day more through non-alcoholic beverages than those in the East. Caloric consumption is lower by 21 kilo calories per person per day for those households who are in the Western part of United States compared to those in East.

Households with children have a lower caloric intake derived from consumption of non-alcoholic beverages, ranging from about 30-48 kilo calories per person per day than those households without children. Male only food manager's household has a higher caloric intake (83 kilo calories per person per day more) than a household where the food mangers are a male and a female. Poverty status of the household is not a significant factor determining the caloric intake drawn from consumption of non-alcoholic beverages at home in year 2000.

Caloric Intake 2001

Factors driving caloric intake obtained from consumption of non-alcoholic beverages in at-home markets in 2001 are shown in Appendix 6. Price, employment and education status of the household head, region, race, age and presence of children and gender of the household food manger are significant factors affecting the caloric intake from non-alcoholic beverages.

Given the fact that we have a quadratic functional form, the marginal effect of price on caloric intake is a function of price, namely 83.09-23.96*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.47 per gallon, all other factors invariant.

Households where the household head is employed full time or part time have significantly lower caloric intake compared to those households where the household head is not employed for pay. In particular, the caloric intake is 24 kilo calories per person per day lower for those households with a part-time employed household head and it is 37 kilo calories per person per day lower with a full-time employed household head.

More educated the household head is, the lower the caloric intake derived from consumption of non-alcoholic beverages. Household with a household head having a college degree (undergraduate) or post college level education consume 22 and 35 kilo calories per person per day respectively lower than those households with less than high school education.

Households in the Central part of the U.S. consume 13 kilo calories per person per day more than those in Eastern part of US. Furthermore, households in the Western US consume 19 kilo calories lower compared to those households in the East.

Those who are classified as Black consume 20 kilo calories per person per day more calories derived from consumption of non-alcoholic beverages compared to Whites and that is lower by about 35 kilo calories per person per day for households who are classified as Asian relative to Whites.

Households with children consume about 25 to 50 kilo calories per person per day through consumption of non-alcoholic beverages compared to those without children. More specifically, households with children who are less than twelve years of age consume lesser calories from non-alcoholic beverages compared to those households with children who are in between 13-17 years of age. In fact, households with children who are 13-17 years of age consume more calories (7 kilo calories per person per day) than those households without children, even though it is statistically not significant at 0.05 level.

For those households where the household food manager is only a male consume 91 kilo calories per person per day more than those households where the food manager are a male and a female. Poverty status of the household is not a significant determinant for caloric intake derived from non-alcoholic beverages in 2001.

Caloric Intake 2002

Factors affecting the caloric intake derived from the consumption of non-alcoholic beverages at home by the U.S. consumer in year 2002 is depicted in Appendix 6. Price, age, employment and education status of the household head, region, race, age and presence of children and gender of the household food manager are significant factors driving the caloric intake from beverages in 2002.

Owing to the quadratic functional form, the marginal effect of price on caloric intake is a function of price, namely 60.80-16.50*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.68 per gallon, all other factors invariant.

Households where the household head is over 64 years consume 55.5 kilo calories per person per day less calories derived from consumption of non-alcoholic beverages compared to those households where the household head is below 25 years of age. Looking at the signs and magnitudes of the coefficients related to age of the household head (even though some are not significant at the level of significance we desire) we can say that, the older the household head is, the lesser the calories consumed through non-alcoholic beverage consumption at home.

Caloric intake is lower for those households where the household head is employed full-time or part-time by 24 and 11 kilo calories per person per day respectively compared to those households where the household head is not employed for full pay. The more educated the household head is, lower the caloric intake drawn from consumption of non-alcoholic beverages compared to those household where the household head is educated only at less than high-school level. In particular, a household where the household head is educated at post-college level consume 30 kilo calories less compared to a household head who is educated at below high-school level.

Households in the Western US consume 25 kilo calories per person per day lower than those in the East. Those households classified as Asian consume 37 kilo calories per person per day lower than those classified as White.

Households with children consume 7 to 45 kilo calories per person per day lower calories derived from consumption of non-alcoholic beverages than those households that do not have children. Especially, households with children who are blow 12 years of age consume 45 kilo calories lower than those households without children, which is the highest.

Households where the household food manager is male only consume 80 kilo calories per person per day more compared to those households with both a male and a female. It is only 12 kilo calories per person per day more for a household where the food manager is female only. Poverty status of the household is not a significant driver in determining the caloric intake derived from consumption of non-alcoholic beverages in 2002.

Caloric Intake 2003

Factors affecting the caloric intake derived from consumption of non-alcoholic beverages are described in Appendix 6. Price, employment and education status of the household head, region, race, age and presence of children and gender of the household food manager are significant drivers in determining caloric intake in year 2003.

Due to the quadratic functional form, the marginal effect of price on caloric intake is a function of price, namely 45.48-12.36*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.70 per gallon, all other factors invariant.

Households where the household head is employed full-time have 24 kilo calories per person per day lower caloric intake from beverage consumption compared to those households where the household head is not employed for full pay. The more educated the household head is, the lower the caloric intake from consumption of beverages. In particular, households where the household head is educated at post-college level consume 45 kilo calories per person per day lower than those households where the household head is educated at sub high-school level.

Households in the Western U.S. consume 26 kilo calories per person per day lower calories from non-alcoholic beverages than those who are in the East. Those households who are classified as Black and Other consume 16 and 19 kilo calories per person per day respectively more than those households that are classified as White. However, for those households that are classified as Asian have a lower caloric consumption (34 kilo calories per person per day less) than White households.

Households where the household food manager is male only have 85 kilo calories per person per day more calories consumed compared to households where the food managers are both a male and a female. If the household food manager is only a female, the caloric intake goes up only by 10 kilo calories per person per day in comparison to a household with both male and female food managers. Poverty status of the household head is not a significant factor for caloric intake in 2003.

Caloric Intake 1998-2003

Regression results for factors affecting the caloric intake derived from consumption of non-alcoholic beverages at home by the U.S. consumer for the time period 1998 through 2003 is depicted in Appendix 6. We have taken the whole data set from 1998 through 2003 to get a comprehensive idea about the factors driving the caloric intake from the consumption of non-alcoholic beverages. Price, employment and education status of the household, region, race, age and presence of children, gender of the household food manager and poverty status are significant factors determining the intake of calories from consumption of beverages for the period 1998 through 2003 (significance of yearly dummies is discussed in the section *7.2.6* below).

Owing to the quadratic functional form, the marginal effect of price on caloric intake is a function of price, namely 64.93-17.68*price. Given that the average price paid for non-alcoholic beverages during the period in question is $2.38 per gallon, this marginal impact is positive. Also from this result, the price of non-alcoholic beverages associated with the maximum intake of calories is $3.67 per gallon, all other factors held constant.

Households where household head is employed full-time or part-time have significantly lower caloric intake in comparison to those households where the household head is not employed for full pay. In particular it is lower by 27 and 13 kilo calories per person per day for full-time and part-time employed households respectively.

More educated the household head is, the lower the calories taken in by consuming non-alcoholic beverages. It is 27 kilo calories lower for those households that have some post-college education compared to those had only some high-school education below the high school level and it is lower by about 18 kilo calories for those households with a household head that had some college education.

Households in the Central United States consume about 10 kilo calories per person per day more calories derived from consumption of non-alcoholic beverages than those live in the East. However, households live in the Western United States consume about 23 kilo calories per person per day lower than those live in the East.

Those who are classified as Black and Other in race categories consume 11 and 15 kilo calories per person per day respectively more than those classified as White. Asians consumes about 40 kilo calories per person per day lower than that of Whites.

Age and presence of children is a very significant factor determining the caloric intake derived from non-alcoholic beverages. More specifically, caloric intake is lower for those households with children compared to those without children. Households with children lower than 12 years of age have the lowest caloric intake of 46 kilo calories per person per day in comparison to those households without children.

Households where the household food manager is only a male consume 79 kilo calories per person per day more than those households where the food managers are both male and a female. Poverty households consume 6 kilo calories per person per day higher than that of non-poverty households. Age and Hispanic or non-Hispanic status of the household head is not an important factor determining the caloric intake derived from non-alcoholic beverages during 1998 through 2003.

Factors Affecting Caffeine Intake: 1998 through 2003

In this section we elaborate on the factors affecting caffeine intake obtained from consumption of non-alcoholic beverages at home for each year from 1998 through 2003. Finally, we offer an explanation for factors affecting caffeine intake taking the entire sample from 1998 through 2003.

Caffeine Intake: 1998

Factors affecting caffeine intake derived from the consumption of non-alcoholic beverages at home by a U.S. consumer in 1998 are shown in Appendix 6. Price, age of the household head, region, race, age and presence of children and gender of household food manager are significant factors in determining the caffeine intake.

The marginal effect of price on caffeine intake is expressed as $-144.51 + 35.38 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. From this finding, one may calculate the weighted average price of non-alcoholic beverages to minimize caffeine intake. This price is found to be $4.08 per gallon.

Households where household head is above 25 years of age consume significantly more caffeine from non-alcoholic beverages compared to those households where the household head is below 25 years. In particular, households where the household head is between 55 to 64 years of age consume 32mg of more caffeine per person per day in comparison to those households where the household head is below 25 years of age, which is the highest amongst any age category. Households with older household heads (above 64 years of age) intake significantly least amount of caffeine per person per day for all age categories considered. Southern households consume about 5mg of caffeine per person per day lesser than those in the Eastern U.S. Those who are classified as Black, Asian and Others consume about 25, 17 and 13mg of less caffeine per person per day respectively derived from consumption on non-alcoholic beverages compared to Whites.

Households with children consume appreciably lower amount of caffeine from non-alcoholic beverages compared to those households who do not have children. For example, households with children less than 12 years of age intake 35mg of less caffeine per person per day in contrast to those without children. Households with a food manager who is a male and a female only consume 15 and 5mg of caffeine more per person per day respectively than those households with both male and female food managers.

Caffeine Intake: 1999

Regression results pertaining to factors affecting the intake of caffeine derived from consumption of non-alcoholic beverages are depicted in the Appendix 6. Price, age and employment status of the household head, region, race, age and presence of children and gender of the household food manager are significant factors in determining the caffeine intake.

The marginal effect of price on caffeine intake can be shown as $-139.43 + 33.88 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. From this finding, one may calculate the weighted average price of non-alcoholic beverages to minimize caffeine intake. This price is found to be $4.11 per gallon.

Households with older household heads (more than 64 years of age) intake 20mg of caffeine per person per day compared to those with the head lesser than 25 years. This is amongst the lowest in comparison to caffeine intake of all other age categories. The highest intake of caffeine is reported with households where the household head is in between 55-64 years (26mg per person per day higher than those who are less than 25 years of age).

Part-time employed household head consume 7mg of caffeine lower than those who are not employed for full pay. Households in the Central and Southern U.S. consume about 6 and 9mg of less caffeine derived from non-alcoholic beverages, respectively compared to those in the East.

Those who are classified as Black and Asians intake respectively 26 and 22mg less caffeine per person per day compared to those who are classified as White.

Households with children who are below 12 years of age intake the lowest amount of caffeine (about 37mg of caffeine per person per day) amongst all age categories, compared to those who do not have children in the household.

Households managed exclusively by a male head consume 20mg more caffeine per person per day relative to those managed by both a male and a female head. If the household is managed by a female head, they consume about 13mg lesser than those managed by a male only head.

Caffeine Intake: 2000

Factors affecting caffeine intake derived from consumption of non-alcoholic beverages by U.S. consumer in year 2000 is depicted in Appendix 6. Significant factors that are driving the intake of caffeine are price, region, race, age and presence of children and gender of the household food manager.

The marginal effect of caffeine with respect to price can be expressed as $-152.30 + 37.28 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. Weighted average price of non-alcoholic beverages to minimize caffeine intake is calculated to be $4.09.

Southern households consume about 7mg of less caffeine compared to that of Eastern households. Those who are classified as Black consume 25mg less caffeine derived from non-alcoholic beverages than those classified as White.

It is important to note that, households with children (below 17 years of age) intake about 38mg of caffeine lesser than those households without children. Thirteen to seventeen year-olds have the highest amount of caffeine per person per day intake amongst the children from all age categories. Households with 13-17 year-olds consume 19mg of less caffeine per person per day in comparison to those who do not have children.

Households where the household food manager is exclusively male only have 26mg of more caffeine per person per day compared to those households with both male and female food managers. Poverty status of the household is not a significant factor determining the intake of caffeine through the consumption of non-alcoholic beverages in the U.S. in 2000.

Caffeine Intake: 2001

Factors affecting the intake of caffeine derived from consumption of non-alcoholic beverages at home by the U.S. consumer in year 2001 is shown in Appendix 6. Price, age and employment status of the household head, region, race, age and presence of children, gender of the household head and poverty status of the household are significant factors affecting the intake of caffeine.

The marginal effect of price on caffeine intake is expressed as $-130.71 + 30.66 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. The weighted average price of non-alcoholic beverages that minimizes the caffeine intake is $4.26 per gallon.

A household where the household head is in between 45-50 years of age has the highest intake of caffeine amongst all other age categories. More specifically, it is 21mg of more caffeine per person per day compared to a household where the household head is below 25 years of age. Full and part-time employed household heads consume about

5mg of less caffeine per person per day in comparison to those who are not employed for full pay.

Central and Southern households consume about 6mg of caffeine per person per day lesser than those live in the Eastern part of the United States. Those who are classified as Black and Asian consume about 20 and 11mg of less caffeine respectively than that for Whites.

Households with children consume about 44mg of less caffeine per person per day than those without children. However, in those households where the children are in between 13-17 years of age have relatively higher consumption of caffeine than those with other age categories. In particular, households with children who are 13-17 years consume 18mg of less caffeine compared to those without children and it is 11mg per person per higher than households with children who are below 12 years.

Households where the household food manager is solely a male consume 26mg more caffeine per person per day than those households where the food managers are both male and female and it is 15mg of more caffeine than those households where the household food manager is exclusively a female. Poverty households consume 6mg of caffeine per person per day lesser than non-poverty household s.

Caffeine Intake: 2002

Factors affecting the intake of caffeine derived from consumption of non-alcoholic beverages at home in year 2002 are shown in Appendix 6. Price, education status of the household head, region, race, Hispanic origin, age and presence of children, gender of the household food manager are significant drivers of caffeine intake.

The marginal effect of price on caffeine intake is expressed as $-87.65 + 18.36 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. Caffeine minimizing weighted average price of non-alcoholic beverages is $4.78 per gallon.

Households where the household head is employed full-time consume about 5mg less caffeine per person per day that those households where the household head is not employed for full pay.

Households in the Central and Southern part of the U.S. consume about 6-8mg low caffeine per person per day than those households in the Eastern part of the United States. Those who are classified as Asian and Black consume about 11 and 19 mg of less caffeine respectively than those who are classified as White.

Households with Hispanic origin consume about 10mg of less caffeine derived from non-alcoholic beverages than that of non-Hispanics. Households with children intake about 39mg of less caffeine compared to those households without children. More specifically, households that have children below the age of 12 years consume 25mg of less caffeine than those households without children. However, presence of teenagers (13 to 17 year-olds) in the household increase the intake of caffeine by about 10mg per person per day more compared to that of households that have children lesser than 12 years.

Households where the household food manager is a male, consume 21mg more caffeine compared those households where food managers are both male and female and it higher by about 12mg more than those households where the food manager is exclusively a female.

Poverty status of the household is not a significant factor affecting the caffeine intake derived from consumption of non-alcoholic beverages in 2002.

Caffeine Intake: 2003

Factors affecting caffeine intake derived from consumption of non-alcoholic beverages at-home markets in 2003 are shown in Appendix 6. Price, education status of the household head, region, race, age and presence of children, gender of the household head and poverty status of the household are significant factors affecting caffeine intake in 2003.

The marginal effect of price on caffeine intake is expressed as $-76.69 + 14.56 * price$. Using the averages price of non-alcoholic beverages over the 1998 to 2003 period; \$2.38 per gallon, we can show that this marginal impact is negative. Weighted average price of non-alcoholic beverages that minimizes caffeine intake is \$5.26 per gallon.

More educated a household head is, the lesser the caffeine consumed derived from consumption of non-alcoholic beverages at home. More specifically, households where household head has post college level education intake 15mg more caffeine in contrast to those households that have below high-school level education and it is about 3 and 6mg respectively more than that of households that have college level and high-school level education.

Central, Southern and Western households consume 8, 5 and 4mg less caffeine per person per day, respectively relative to those in the Eastern part of the United States. Those who are classified as Black consume 21mg less caffeine than Whites and it is about 8mg more per person per day in comparison to Asians.

Households with children consume about 34mg of caffeine less than those without children. In particular, households with children less than 12 years consume 26mg of caffeine less than those who do not have children and it is lower than about 7mg of caffeine per person per day than those households with 13 to 17 year-olds.

Poverty households consume 5mg of caffeine per person per day less than that of non-poverty households.

Caffeine Intake: 1998 through 2003

Regression results from factors affecting caffeine intake derived from consumption of non-alcoholic beverages at home taking entire sample of observations from 1998 through 2003 are depicted in Appendix 6. Variables that are significantly affecting caffeine intake are, price, age, employment and education status of the household, region, race, age and presence of children, gender of the household head and poverty status of the household (significance of the yearly dummy will be discussed in section *7.2.6*).

The marginal effect of price on caffeine intake is expressed as $-106.85 + 23.08 * price$. Given that the average price of non-alcoholic beverages over the 1998 to 2003 period is $2.38 per gallon, this marginal impact is negative. The weighted average price of non-alcoholic beverages that minimizes caffeine intake is $4.63 per gallon.

Older the household head is, the higher the per capita intake of caffeine per day, except for those households where the household head is over 64 years of age. Latter group consume about 20mg of caffeine per person per day more compared to those households where the household head is below 25 years. The highest caffeine intake is amongst the households where the household head is in between 55 to 64 years old (it is 25mg higher than those households where the household head is below the age of 25).

Full and part-time employed households consume about 3mg of caffeine lesser that those households who are not employed for full pay. More educated a household head is, the less the caffeine consumed derived from non-alcoholic beverages. More specifically, households with college and post-college education consume about 7mg of caffeine less than that of households with less than high school education.

Central, Southern and Western households consume 6, 7 and 2mg of caffeine respectively per person per day lesser than those in the East. Asians and Blacks consume significantly lower amount of caffeine relative to Whites. In particular, Black and Asian households respectively consume 22 and 14mg of caffeine lesser than that of White households.

Households with children consume about 38mg of caffeine per person per day lesser than those households without children. Especially, households with less than 12 year-olds consume 30mg of caffeine lesser than those without children and it is also lower by about 11mg of caffeine per person per day compared to those households with teens (13-17 year-olds). Households where the household food manager is a male consume 21mg of caffeine more than those households with food managers represented by both males and females. Former is also higher by about 12mg per person per day in comparison to those households that are managed exclusively by a female head.

Poverty households consume about 5mg of caffeine lesser per person per day than non-poverty households during the period 1998 through 2003. Hispanic origin of the household head was not a significant factor in driving the intake of caffeine from non-alcoholic beverages during the period 1998 through 2003.

Factors Affecting Calcium Intake: 1998 through 2003

In the following section, first we offer commentary on the factors affecting calcium intake derived from consumption of non-alcoholic beverages at home for each year from 1998 through 2003. Second, we offer an explanation for factors affecting caffeine intake for the entire sample 1998 through 2003.

Calcium Intake 1998

Regression results from factors affecting calcium intake derived from consumption of non-alcoholic beverages at home in 1998 is depicted in Appendix 6. Price, employment status of the household head, region, race, Hispanic origin, age and presence of children, and gender of household food manager are significant drivers of calcium intake.

The marginal effect of price on calcium intake is given as $49.04 - 20.58 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of non-alcoholic beverages associated with the maximum intake of calcium is $2.383 per gallon, all other factors invariant.

Full-time and part-time employed households consume 32 and 22mg of calcium per person per day respectively lesser than that of households where the household head is not employed for full pay. Households in the Central U.S. consume 22mg of calcium more that those in the Eastern United States.

Calcium intake by those who are classified as Black is 87mg per person per day lower than those of Whites. This result is probably consistent with lactose intolerance amongst Blacks and hence lower calcium intake derived from non-alcoholic beverages such as consumption of milk. Furthermore, Asians and those who are classified as Other also consume 67 and 28mg of calcium lesser compared to that of Whites.

Households with Hispanic origin intake 25mg of calcium lower than those by households with non-Hispanic origin. Households with children who are below 12 years consume 21mg of calcium per person per day lesser than those households without children.

Households where the household food manager is a male consume 46mg of calcium more than those households with both male and female food managers. Poverty status of the household is not a significant driver for calcium intake.

Calcium Intake 1999

Factors affecting calcium intake per person per day derived from consumption of non-alcoholic beverages at home in 1999 are shown in Appendix 6. Price, employment status of the household head, region, race, Hispanic origin, age and presence of children and gender of the household food manager are significant factors moving the calcium intake.

The marginal effect of price on calcium intake is given as $94.41 - 34.1 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of non-alcoholic beverages associated with the maximum intake of calcium is $2.76 per gallon, all other factors invariant.

Households where the household heads with full and part-time employment consume about 29mg of calcium per person per day less than those households where the household head is not employed for full pay.

Households located in the Central U.S. consume 20mg calcium more than those located in the Eastern United States. Those who are classified into Other, Asian and Black race categories consume 23, 63 and 92mg of calcium lesser respectively than those of Whites. Furthermore, Households with Hispanic origin consume 21mg of calcium less relative to those of households with non-Hispanic origin.

Households with children less than 12 years of age consume 25mg of calcium lower than those households without children. To add on to that, presence of teenagers (13-17 year-olds) further reduces the calcium intake by about another 25mg per person per day.

Households where the household food manager is primarily a male intake 29mg of calcium more than those managed by both male and a female.

Calcium Intake 2000

Factors affecting per capita intake of calcium per day derived from consumption of non-alcoholic beverages at home in year 2000 is explained in Appendix 6. Significant drivers of intake of calcium are, price, employment status and gender of household head, region, race, and age and presence of children.

The marginal effect of price on calcium intake is given as $65.97 - 24.92 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of

non-alcoholic beverages associated with the maximum intake of calcium is $2.65 per gallon, all other factors invariant.

Full-time employed households consume 22mg of calcium lesser in comparison to those of households that are not employed for full pay. Southern and Central households consume 13 and 32mg of calcium respectively more than that of Eastern households.

White is the predominant race category to consume a considerable amount of calcium in contrast to those of Black, Asians and others. The latter group consumes 25, 71 and 94mg of calcium respectively lesser than those consumed by Whites. Households with children who are below the age category of 12 years and younger, consume 30mg of calcium lower than those of households who do not have children.

Male household food manager contributes to intake 56mg of calcium more than that by households where the food managers are both male and a female.

Calcium Intake 2001

Factors affecting the per capita intake of calcium per day taken from consumption of non-alcoholic beverages at home during the calendar year 2001 are shown in Appendix 6. Price, employment status and gender of the household head, region, race, and age and presence of children are statistically important drivers of calcium intake.

The marginal effect of price on calcium intake is given as $65.99 - 21.58 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of

non-alcoholic beverages associated with the maximum intake of calcium is $3.06 per gallon, all other factors invariant.

Full-time and part-time employed households consume respectively, 36 and 31mg of calcium more relative to those of households that are not employed for full pay. Households that are located in Central and Southern parts of the United States consume more calcium than those households in the East. In particular, a household in the Central consume 35mg of calcium more than that of an Eastern household and it is also higher than by about 24mg of calcium than those households that are in Southern United States.

Intake of calcium is considerably lower for Black and Asian households than those of Whites. Out of which, lowest calcium intake is amongst Blacks, which is 78mg fewer than those for Whites. Asians consume 63mg of calcium lower than those for Whites. Presence of children who are under 12 years of age reduces calcium intake by 36mg than those households without children. Male household head contributes to increased intake of calcium derived from non-alcoholic beverages (62mg of calcium more) than those households with both male and female food managers.

Calcium Intake 2002

Factors affecting calcium intake drawn from consumption of non-alcoholic beverages at home in year 2002 is depicted in Appendix 6. Price, employment status and gender of the household head, region, race and age and presence of children are significant drivers of calcium intake.

The marginal effect of price on calcium intake is given as $20.65 - 7.62 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of

non-alcoholic beverages associated with the maximum intake of calcium is $2.71 per gallon, all other factors invariant.

Being employed either full or part-time for pay is an important driver of calcium intake from beverages such that households with full-time employed household heads consume about 24mg of calcium lesser than those households where household head is not employed for full pay. It is lower by about 22mg for part-time employed households.

Households located in the Central and Southern part of the United States intake32 and 17mg of calcium respectively more than those in the East. Blacks have the lowest amount of calcium intake derived from consumption of non-alcoholic beverags at home. They intake 77mg of calcium lower than those of Whites. Asians and Other race category consume 53 and 22mg of calcium respectively lesser than those of Whites.

Children who are lesser than 12 years of age consume the lowest amount of calcium derived from non-alcoholic beverages. It is 23mg of calcium lower than those of households without children. Male household food manager adds on 53mg of calcium more relative to a household managed by both males and females. Poverty status of the household is not a significant driver of calcium intake in 2002.

Calcium Intake 2003

Factors affecting calcium intake generated through consumption of non-alcoholic beverages at home in year 2003 are depicted in Appendix 6. Employment status and gender of the household head, region, race and age and presence of children are important determinants of calcium intake.

The marginal effect of price on calcium intake is given as $2.03 - 2.78 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is negative. The weighted average price of non-alcoholic beverages associated with the maximum intake of calcium is $0.73 per gallon, all other factors invariant. However, Coefficient associated with price with respect to calcium intake in year 2003 is not significant.

Intake of calcium is less for those households where the household head is employed full or part-time. More specifically, it is lower by about 24 and 16mg of calcium for those households where the household head is full-time and part-time employed respectively.

Central and Southern households consume considerably higher amounts of calcium compared to those of Eastern households. In particular, households in the Central United States consume 28mg of calcium more than those in the East and that is 9mg higher than that of those households in the South.

Those who are classified as Blacks and Asians consume 70 and 58mg of calcium less respectively than Whites. Households with children below the age of 12 have the lowest significant intake of calcium compared to those who do not have children.

Households where the food manager is exclusively a male consume 56mg of calcium low than that of those households where the food managers are both males and females.

Calcium Intake 1998 through 2003

Factors affecting the intake of calcium derived from consumption of non-alcoholic beverages at home for the entire sample of observations from 1998 through 2003 is shown in Appendix 6. Price, gender and employment status of the household head, region, race, Hispanic origin, and age and presence of children are significant drivers of intake of calcium.

The marginal effect of price on calcium intake is given as $32.72 - 12.36 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the period 1998 to 2003, this marginal impact is positive. The weighted average price of non-alcoholic beverages associated with the maximum intake of calcium is $2.65 per gallon, all other factors invariant.

Households where the household head is employed full-time or part-time have a lower intake of calcium from beverages compared to those of households where the household head is not employed for full pay. Full-time employed households consume 28mg of calcium more than those of households with household head not employed for full pay and it is also higher by about 6mg than part-time employed households.

Households that are in the Western, Southern and Central parts of the United States consume respectively 6, 12 and 28mg of calcium more than those households in the East. Blacks consume the lowest amount of calcium per person per day derived from beverages followed by Asians and Other category. In particular, Blacks' intake of calcium is 82mg lower than that for Whites. Asians and Other category consume 62 and 21mg of calcium respectively more than that of Whites.

Households with Hispanic origin consume 15mg of calcium lower relative to those of non-Hispanics. Presence of children in a household significantly reduces the calcium intake from beverages. Households with children below the age of 12 consume about 25mg of calcium lesser that those without children and it is lesser by another 6mg for those households with teenagers in them.

A household lead by a male food manager has 51mg of calcium per person per day more than those households where the food managers are both males and females. Poverty status of the household is not a significant factor determining the calcium intake generated through the consumption of non-alcoholic beverages at home in the period 1998 through 2003.

Factors Affecting Vitamin C Intake: 1998 through 2003

In the following section we discuss the factors affecting vitamin C intake obtained from consumption of non-alcoholic beverages at home for each year from 1998 through 2003. Factors affecting the vitamin C intake considering the entire sample or observations from 1998 through 2003 are provided next.

Vitamin C Intake 1998

Factors affecting per capita vitamin C intake per day derived from consumption of non-alcoholic beverages at home by US households in the year 1998 are shown in Appendix 6. Significant factors driving the vitamin C intake in 1998 are age, employment and education status and gender of household head, region, race, and age and presence of children.

The marginal effect of price on vitamin C intake is given as $4.62 - 4.52 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the 1998 to 2003 period, this marginal impact is negative. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is $1.02 per gallon. However, the coefficient associated with price is not significant at 0.05 level.

Older household heads have the highest vitamin C intake out of all the age categories and more specifically it is 15mg of vitamin C more than that of households with household head below 25 years. Full-time employed households consume 8mg of vitamin C lower than that of households where the household head is not employed for pay.

More educated the household head is, the more the vitamin C consumed. Households with household head educated at post-college level consume 11mg more vitamin C in comparison to those households where the household head is educated only up to high school level.

Households in the Central United States consume the smallest amount of vitamin C compared those in the East. Western, Southern and Central households do intake about 13, 5 and 7mg of vitamin C per person per day respectively lower than those in the East. Those who are classified as Blacks intake 19mg more vitamin C in contrast to Whites.

Households with children blow 6 years and teenagers (13 to 17 year-olds) show the lowest amount of vitamin C intake, which is 15mg lesser than those without children. The second lowest vitamin C intake is with households that have less than 12 year-olds which is 10mg less per person per day compared to those do not have children.

Male household food manager help intake about 17mg of vitamin C more than that of the households with both male and female heads.

Vitamin C Intake 1999

Factors affecting the per capita intake of vitamin C derived from consumption of non-alcoholic beverages at home in year 1999 is listed in Appendix 6. Price, age, gender, employment and education status of the household head, region, race, age and presence of children and poverty status of the household are significant factors affecting the vitamin C intake.

The marginal effect of price on vitamin C intake is given as $11.88 - 2.76 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive, just as in the case of calories and calcium. From this result, the price of non-alcoholic beverages associated with the maximum intake of vitamin C is $4.30 per gallon.

Higher the age of the household head, the higher the amount of vitamin C intake. Households where household head is above 64 years of age consume 14mg of vitamin C more than those of household heads who are below 25 years. Full-time employed households consume 7mg of vitamin C lesser compared to households where the household head is not employed for full pay.

More educated the household head is, the more the vitamin C consumed. Households where household head is educated up to high school, college or post-college level consume respectively 8, 9, and 11mg of vitamin C more than those who are educated below high school level. Households in the Eastern United States consume more vitamin C than those of other regions. More specifically, Southern, Central and Western households, respectively consume 5, 7 and 14mg of vitamin C lesser than those consumed in the East.

Blacks consume 20mg vitamin C more than that of Whites. It is also higher by about 13mg of vitamin C per person per day relative to Asian households. Presence of children in the household who are less than 12 years of age consume 10mg of vitamin C lesser than those households without children.

Households where male household head is the food manager consume 10mg of vitamin C more than those households where food managers are both female and male. Poverty households consume 4mg of vitamin C lesser than those of non-poverty households.

Vitamin C Intake 2000

Factors affecting per capita intake of vitamin C per day derived from consumption of non-alcoholic beverages at home in year 2000 are shown in Appendix 6. Employment status and gender of the household head, region, race, age and presence of children in the household and poverty status of the household are significant factors affecting vitamin C intake.

The marginal effect of price on vitamin C intake is given as $18.50 - 0.96 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is $19.27 per gallon. This optimum price associated with optimum vitamin C intake is preposterously high. It may be due to the fact that price squared term in the regression is not significant at 5 percent level.

Full-time employed household heads consume about 7mg of vitamin C lesser relative to those of household heads that are not employed for full pay. Most of the vitamin C from non-alcoholic beverages is consumed in the Eastern households of the United States. Households in the West intake 13mg of vitamin C less compared to those in the East and it is as twice as high relative to those in Central and South.

Those who are classified as Blacks and others consume respectively 20 and 10mg of vitamin C more compared to those of Whites. Presence of children in the household lowers the intake of vitamin C compared to those of households without children. Households with children, who are less than 12 years, consume 8mg of vitamin C lower than those households without children. Having teenagers (13-17 year-olds) in the household lowers vitamin C intake by only 3mg per person per day indicating that they consume more vitamin C from non-alcoholic beverages.

Male household head contributes to 18mg of vitamin C higher than those managed by both male and female household heads.

Vitamin C Intake 2001

Factors affecting the per capita intake of vitamin C per day come from consumption of non-alcoholic beverages at home in calendar year 2001 are shown in Appendix 6. According to that, statistically significant factors that affect the intake of vitamin C are price, gender, employment and education status of the household head, region, race, age and presence of children and poverty status of the household.

The marginal effect of price on vitamin C intake is given as $23.02 - 3.36 * price$. Given that the average price paid for non-alcoholic beverages is \$2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive, just as in the case of calories and calcium. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is \$6.85 per gallon.

Households where the household head is employed full-time or part-time consume respectively about 10 and 5mg of vitamin C lesser than those households where the household head is not employed for full pay.

More educated the household head is, the higher the intake of vitamin C per person per day. Post-college educated household heads consume 8mg of vitamin C relative to those household heads who have less than high school education. College level educated household heads intake just 2mg of vitamin C lesser than post-college educated household heads.

Central, Southern and Western households in the United States intake significantly lower amount of vitamin C compared to that of east. Households that are located in South and Central parts of the United States consume about 6mg of vitamin C lower than those in the East and it is twice as lower for those households in the West.

Those households who are classified as Black and other intake 23 and 7mg of vitamin C more than those of Whites. Having children who are below the age of 12 years would reduce the vitamin C intake by about 9mg per person per day in comparison to those who do not have children in the household. However, if there are teenagers in the household (13-17 year-olds), it is found that the intake of vitamin C is higher by about 3mg, compared to those who do not have teenagers.

Households where the food and nutrition decision maker is a male have 20mg of vitamin C intake higher than those households where the decision makers are both male and female. Poverty households consume about 3mg of vitamin C lower than that of non-poverty households.

Vitamin C Intake 2002

Factors that are affecting the per capita per day intake of vitamin C derived from consumption of non-alcoholic beverages at home in 2002 are depicted in Appendix 6.

Price, gender and employment status of the household head, region, race and age and presence of children are statistically significant factors driving the intake of vitamin C.

The marginal effect of price on vitamin C intake is given as $21.85 - 2.96 * price$. Given that the average price paid for non-alcoholic beverages is \$2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive, just as in the case of calories and calcium. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is \$7.38 per gallon. This optimum price appears to be too high for a gallon of non-alcoholic beverages.

Full-time employed household heads intake 5mg of vitamin C lesser than those household heads who are not employed for full pay. Households located in the Southern, Central and Western parts of United States consume, respectively 6, 7 and 15mg of vitamin C lesser than those in the East.

Blacks consume 17mg of vitamin C more than those consumed by Whites and it is about 3 times as high as vitamin C consumed by those who are classified as other. Households with children who are below 12 years of age consume about 9mg of vitamin C lower than those households without children.

Households where food and nutrition decision is primarily taken by a male household head consume 20mg of vitamin C more than those households where the decision makers are both male and a female. Poverty status of the households is not a significant factor contributing to intake of vitamin C in year 2002.

Vitamin C Intake 2003

Factors affecting the per capita intake of vitamin C per day, derived from consumption of non-alcoholic beverages at home in year 2003 are shown in Appendix 6.

Price, gender and employment status of the household head, region, race, age and presence of children and poverty status of household head are significant factors driving the intake of vitamin C in year 2003.

The marginal effect of price on vitamin C intake is given as $24.36 - 4.58 * price$. Given that the average price paid for non-alcoholic beverages is \$2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive, just as in the case of calories and calcium. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is \$5.32 per gallon.

Households where household head is full-time employed intake 5mg of vitamin C less compared to those who are not employed for full pay. Central, Southern and Western households consume respectively, 7, 8, and 14mg of vitamin C lesser than those in the East.

Those who are classified as Asians consume 6mg of vitamin C more than that of Whites. Blacks consume three times as much vitamin C as those consumed by household who are classified as Other.

Households with children who are below 6 years of age consume about 8mg of vitamin C lower than those who are without children. However, presence of a child who is in between the age of 6 and 12 consume about 2mg of vitamin C more than a household with a child below 6 years of age.

Intake of vitamin C is higher by about 23mg for those households where the household food/nutrition manager is a male, in comparison to those households where both male and female food/nutrition managers are present. Per capita vitamin C intake of poverty households is 3mg per day lesser than those who are categorized as non-poverty

Vitamin C Intake 1998 through 2003

We illustrate the factors affecting per capita intake of vitamin C per day taken in from consumption of non-alcoholic beverages at home taking the entire sample of observations running from 1998 through 2003 in the Appendix 6. Significant factors that are affecting the intake of vitamin C are as follows; price, gender, age, employment and education status of the household head, region, race, age and presence of children and poverty status.

The marginal effect of price on vitamin C intake is given as $19.53 - 1.78 * price$. Given that the average price paid for non-alcoholic beverages is $2.38 per gallon over the 1998 to 2003 period, this marginal impact is positive, just as in the case of calories and calcium. The weighted average price of non-alcoholic beverages associated with the maximum intake of vitamin C is $10.98 per gallon. However the calculated vitamin C optimizing price is too high.

We find that, older the household head is, the more the vitamin C consumed. The highest vitamin C intake is amongst the household heads who are over 64 years, which is about 8mg more compared to those who are below 25 years. Full-time employed household heads consume 7mg of vitamin C less in comparison to those who are not employed for full pay and it is also lower by about 5mg relative to half-time employed household heads.

Households where the household head are educated at high school, college and post college level respectively consume 3,4, and 6mg of vitamin C more than those households where household heads are educated below high school level.

Highest vitamin C intake is amongst the households in the Eastern parts of United States. More specifically, it is higher by about 14mg compared to that of households in the West and about 6mg relative to those in the central and South US.

Households having children (below 17 years) consume about 7mg of vitamin C lesser that those not having children. In particular, households with teenagers (13-17 year-olds) consume more vitamin C rich beverages (about 6mg more) compared to households with children below the age of 12. Households with children below the age of 6 years intake 6mg of vitamin C lesser than those households without children.

Households where the household head for food and nutrition purposes is exclusively a male, consume 19mg of vitamin C more compared to those households where food managers are both male and female. Poverty households receive about 3mg of vitamin C less compared to those who are categorized as non-poor.

Seemingly Unrelated Regression (SUR) of Calorie and Nutrient Intake

Seemingly unrelated regressions (SUR) were run for calories, calcium, vitamin C and caffeine intake derived from the consumption of non-alcoholic beverages at home from 1998 through 2003. This was done primarily to find out any efficiency improvements (through lower standard errors) over single equation ordinary least squares estimates for caloric, caffeine, vitamin C and calcium intake.

In doing the SUR analysis, we have considered each nutrient category and calories in a system of six equations representing six years from 1998 through 2003. As such we have four systems of equations for each nutrient category and calories. Results from the SUR for caloric intake from 1998 through 2003 are shown in Appendix 6. Comparing estimated coefficients and standard errors with single equation estimates for each year, we find no efficiency improvement in SUR. The SUR estimated coefficients for caffeine, vitamin C and calories intake also are shown in the Appendix 6. Again, we do not see any efficiency improvements over single equation models for caffeine, vitamin C and calories.

Calorie and Nutrient Intake with Yearly Dummies

In the following sections we discuss the impact of USDA year 2000 dietary guideline for Americans on sensible choice of beverages.

Caloric Intake and Yearly Dummies: 1998-2003

According to regression results shown in the Appendix 6we find that, per capita caloric intake per day derived from consumption of non-alcoholic beverages at home is significantly lower in years 2001 through 2003 compared to that of year 1998. In the year 2001, caloric intake dropped by 8 kilo calories per person per day in comparison year 2000. Caloric intake is about 37 kilo calories per person per day lower in years 2002 and 2003 compared to that of the reference period, 1998 through 2000. This result sheds light on the effectiveness of the USDA year 2000 Dietary Guidelines designed in part to reduce the intake of beverages to moderate the intake of sugars, and hence, extra calories. Moreover, the drop in per capita consumption of regular soft drinks (carbonated soft drinks) and fruit drinks respectively, is prominent after year 2001, further strengthens our finding of drop in per capita caloric intake after year 2001, because carbonated soft drinks and fruit drinks are major contributors for extra calories consumed derived from non-alcoholic beverages.

Caffeine Intake and Yearly Dummies: 1998-2003

As shown in the Appendix 6, per capita caffeine intake per day derived from consumption of non-alcoholic beverages at home is significantly lower in years 2002 through 2003 compared to that of in years 1998, 1999 and 2000.

This finding is on par with the expectations of the USDA year 2000 Dietary Guidelines and food guide pyramid, where it is advised to curtail the intake of caffeinated beverages and concentrate more on decaffeinated diet soft drinks (with low added sugar content) as beverages choices. Additionally, there is a rapid decreasing trend in per capita consumption of regular soft drinks (carbonated soft drinks), tea and coffee respectively, that provide caffeine to the diet, it supports the evidence of decreasing trend in intake of caffeine *vis-à-vis* non-alcoholic beverages, because regular soft drinks, tea and coffee are major suppliers of caffeine to the diet.

Calcium Intake and Yearly Dummies: 1998-2003

As shown in the Appendix 6, per capita intake in calcium derived from consumption of non-alcoholic beverages at home drops by 10, 33 and 34mg in years 2001, 2002 and 2003 respectively in contrast to that of in years 1998, 1999 and 2000. The USDA 2000 Dietary Guidelines for Americans recognize the importance of calcium intake either from food/beverages sources or from supplements. However, there may be reasons for the decline in calcium intake derived through consumption of non-alcoholic beverages at home. First, there is a possibility that while consumers are trying to reduce the intake of calories and caffeine by cutting back on the consumption of non-alcoholic beverages, intake of calcium drops as a consequence. Second, consumers may be substituting away from non-alcoholic beverages to other non-beverage choices for calcium intake. According to the USDA 2000 Dietary Guidelines, some of the other alternative calcium sources are yogurt, cheese, soy-based products with added calcium, tofu made with calcium sulfate, breakfast cereal with added calcium, canned fish with soft bones such as salmon and sardines, and dark green vegetables (collards, turnip greens). Third, some consumers may satisfy their daily calcium intake through supplements and simultaneously move away from non-alcoholic beverages. Finally, our study captures only at home consumption of non-alcoholic beverages and ignores the consumption of non-alcoholic beverages away from home.

Vitamin C Intake and Yearly Dummies: 1998-2003

As depicted the Appendix 6, intake of vitamin C is lower by 2, 9 and 10mg respectively, for years 2001, 2002 and 2003 compared to that of years 1998, 1999 and 2000. Possible reasons for the decline in the intake of vitamin C may be the following. First, decreased consumption of fruit juices and drinks (powdered soft drinks like fruit ades and fruit punch) occurred to reduce the intake of added sugars, thus extra calories. Second, just as in the case with calcium, consumers may be substituting away from non-alcoholic beverage choices. Even though the USDA 2000 Dietary Guidelines advocate the intake of citrus juices as a means of vitamin C intake, they also place a greater weight on one obtaining vitamin C through consumption of a wide variety of fresh fruits and vegetables, such as citrus fruits, kiwi fruit, strawberries, cantaloupe, broccoli, tomatoes and leafy greens like spinach. Third, some consumers may opt for supplements rather than depending on non-alcoholic beverages. Finally, again, our study revolves only around at home consumption, ignoring away-from-home consumption of NAB.

CHAPTER VIII

CONCLUSIONS, POLICY IMPLICATIONS, LIMITATIONS AND FUTURE WORK

In this section, we offer a narrative on the principal findings of our work and potential natural extensions for future work. First, we briefly recollect some key points pertaining to background information, problem statements and justification. Second, we place emphasis on major objectives of this dissertation. Third, important wrinkles with respect to data we used in our work are discussed. Fourth, we summarize key findings of our work, particularly concentrating on four major sections of this dissertation, namely, *Demographic Study, Probability Evaluation Study, Demand Systems Study,* and *Nutrition Study.* Fifth, we draw conclusions and discuss implications pertaining to each study. Finally, to bring this chapter to a close, we shed some light on limitations of our work and potential new frontiers we are in a position to explore.

Summary of Background Information

There are many different types of non-alcoholic beverages available today compared to a decade ago. It is clear that need states have evolved over the years centering attention on functionality and health dimensions desired by beverage consumers. More specifically, non-alcoholic beverages provide consumers not only with a basic refreshment function, but also beverages are available today for mood enhancement, for the satisfaction of sweet indulgences, for specific social occasions and for the nutrient fortification.

Over the period 1980-2007, there is a phenomenal growth in the consumption of bottled water. Consumption of diet soft drinks has grown, while regular soft drink consumption has declined. There is a noteworthy drop in coffee consumption, while low-fat and fat-free milk consumption has grown. Whole milk consumption dropped noticeably from 1970s through 2007. However, fruit juice and tea consumption has been more or less stable over the past 20 years. Potential contributing factors associated with these trends may be economic factors changes in consumer tastes and preferences, changes in the availability of a wide variety of new beverages in the market and changes in the dietary guidelines put forward by USDA.

Several studies involving non-alcoholic beverages have been conducted in the past, but most of these have centered attention on limited number of beverage items. Most of past work has been concentrated on milk consumption in the United States. There were few studies that concentrated on demand interrelationships among beverages in a system-wide framework.

In our work, we developed and employed a unique cross-sectional and time-series data set based on Nielsen HomseScan scanner panels for household purchases of non-alcoholic beverages from 1998 through 2003. Using these data along with a rich delineation of non-alcoholic beverage categories, we modeled economic and demographic drivers associated with the decision to purchase. As well, once the purchase decision was made, we modeled the quantity levels purchased of a given non-alcoholic beverage. We used both the Heckman two-step procedure as well as a demand systems approach. This study generated important information not only for government policy makers but also for beverage manufacturers, marketers, advertisers/promoters and managers in grocery stores.

Qualitative choice models have widely been used in economic modeling when the dependent variable corresponds to discrete outcomes. Among a wide range of qualitative choice models available to model different situations, dichotomous probit and logit models are important to model choices where the dependent variable is set up as a zero-one (0-1) dummy variable. For example, the dependent variable is set equal to 1 for those households who buy a non-alcoholic beverage, and equal to 0 for those who not buy. Once appropriately modeled, qualitative choice models determine the probability of the choice decision. Additionally, with an appropriate decision rule, these models provide predictions of various choices. A key question relates to the accuracy of these predictions.

Accuracy of predictions was measured using several methods. Traditional metrics such as expectation-prediction success tables were used, where the percentage of correct (incorrect) predictions were calculated in comparison to the total number of predictions based on a predetermined cut-off probability level as a reference point. On the other hand, other techniques such as calibration, resolution, the Brier score and Yates decomposition of Brier score were used to assess accuracy of predictions.

In our study we developed binary probit and logit models to center attention on the decision made by a sample of U.S. households to purchase various non-alcoholic beverages. The source of the data for this analysis was the Nielsen HomeScan data for calendar year 2003. We evaluated the probabilities generated through qualitative choice models both within sample and more importantly, out-of-sample.

Obesity among all walks of life is one of the most urgent and widely emphasized nutrition-related health problems in America today. In addition to environmental and genetic factors, the selection of food and beverages potentially may have contributed to the condition of obesity. The role of beverages in the American diet increased in attention recently with the publication of the 2000 and 2005 USDA Dietary Guidelines for Americans. There is a very wide variation in beverages in terms of their energy (caloric) content and nutrient composition, ranging from zero-calorie bottled water to low-calorie diet soft drinks to heavily-caloric coffee drinks. As a result, excessive consumption of beverages is not necessarily a good dietary choice due to extra calories they can contribute toward the daily recommended calorie requirement. Therefore, the beverage choice that individuals make has a potentially important influence on the quality of the diet, and more importantly on the risk of being obese and overweight.

Consumption of non-alcoholic beverages not only contributes extra calories, but also various kinds of nutrients to the diet. Two of them are calcium and vitamin C. Caffeine is another ingredient found in most carbonated soft drinks, coffee, and tea. Even though beverage manufacturers have responded positively to the changing needs and interests of consumers by introducing many low-calorie, zero-calorie, calcium fortified, and decaffeinated beverage choices, the problem of extra consumption of calories and hence obesity still persists.

Many U.S government programs targeting nutritional enhancement of households are in need of more current information pertaining to non-alcoholic beverage consumption. Profiling of households is important to identify demographic populations potentially at risk in the consumption of non-alcoholic beverages.

Summary of Objectives

Given this backdrop, next we briefly discuss the objectives we stated to achieve in this dissertation. A thorough and a complete analysis of non-alcoholic beverages was necessary because of changes in potential drivers of consumption over time. These objectives were achieved in four separate types of analyses. We used a cross-sectional data set (Nielsen HomeScan scanner data for calendar year 2003) to study factors affecting the probability of purchase as well as economic and demographic drivers of purchase volume. A unique time-series data set was generated based on Nielsen HomeScan scanner panels from 1998 through 2003 to model demand for non-alcoholic beverages using a systemwide approach. Based on the demand systems approach, expenditure and price elasticities (own-price and cross-price) were estimated for ten non-alcoholic beverage categories. Further, we investigated the dominance of inventory behavior or habit persistence in non-alcoholic beverage consumption.

The probability forecast evaluation study was performed to evaluate forecast probabilities generated through probit and logit models for the decision to purchase non-alcoholic beverages. Metrics used to evaluate probabilities were expectation/prediction success tables, calibration and calibration graphs, resolution and resolution graphs, the Brier score and the Yates-partition of the Brier Score.

The nutrition study was performed to achieve two objectives. First, it was done to ascertain the factors affecting calcium, caffeine, vitamin C and caloric intake from the consumption of non-alcoholic beverages. Second, we were in a position to determine the impact of the 2000 USDA Dietary Guidelines for Americans on the intake of calcium, caffeine, vitamin C and calories from non-alcoholic beverages consumed.

Summary of Data

We used Nielsen HomeScan scanner data for household purchases of non-alcoholic beverages along with demographic information for calendar years 1998 through 2003. Household level data were extracted from 53 rural and city markets from four regions (South, East, West, and Midwest) covering 48 contiguous states of the United States. We gathered information about total expenditures, volumes, and demographics of households making a non-alcoholic beverage purchase for all twelve months of a given calendar year from 1998 through 2003.

Ten types of non-alcoholic beverages considered in this study were: isotonics (sports drinks); regular soft drinks; diet soft drinks; high-fat milk (whole milk and 2% milk); low-fat milk (1% milk and skim milk); fruit drinks; fruit juices; bottled water; coffee; and tea. Demographic categories that we used in our analysis were as follows: age; employment status and education status of household head; region; race; presence of a Hispanic household; age and presence of children; household head male only; female only or both; poverty status based on 185% poverty level.

For the demographic study we used only Nielsen HomeScan scanner data for calendar year 2003. We had 7642 households which had purchases of non-alcoholic beverages for 12 months of year 2003. For those households, we aggregated non-alcoholic beverage total expenditure and quantity data for all ten non-alcoholic beverages concerned across 12 months to generate per household per year dollar and a volume value respectively. Total expenditure was calculated in dollars and the volume was in gallons.

However, it was obvious that some households may have not purchased a given non-alcoholic beverage during 2003, resulting in a zero for quantity and hence total expenditure for that beverage for that household during 2003. This afrementioned non-purchase had a direct consequence in calculating price for that particular beverage, because price or unit value is calculated taking the ratio of total expenditure to quantity. Furthermore, this zero observation phenomenon is called *"a censoring problem in data"*. Therefore, a special two-stage budgeting procedure was employed to circumvent above problem associated with such zero observations. As previously discussed, demographic information was brought in to generate the complete dataset ready for analysis.

For the probability study, we used the same data set we created above for the *"Demographic Study"* with few alterations. We split the sample of 7642 observations into two random samples, sample A and sample B. We used the same demographic information used for *Demographic Study*. The dependent variable was a zero-one dummy variable capturing purchase or non-purchase behavior of a given non-alcoholic beverage category. First we modeled a probit and a logit model for sample A, and within sample forecast probabilities were generated. Second, we used the data from Sample B and out-of-sample forecasts were generated. Next, we evaluated forecast probabilities using a host of metrics. The metrics used were as follows: expectation/prediction success tables; probability calibration and calibration graphs; resolution and resolution graphs; the Brier score; the Yates partition of the Brier score.

For the *"nutrition study"*, we used a similar data set we created for the *"demographic study"*, however it spanned across all calendar years considered, 1998 though 2003. Our demographic and price information were the same as what we had for the demographic study. Nevertheless, we had to create a new dependent variable that measured the nutrient and caloric intake derived from consumption of non-alcoholic beverages. Such information was not available with Nielsen HomeScan scanner panels. We extracted nutrient conversions for non-alcoholic beverages from information obtained from USDA. Finally, calories, caffeine and nutrients derived (calcium, vitamin C) from consumption of non-alcoholic beverages per person per day was calculated. We also stacked/pooled data from all six years to come up with a large sample of 41,071 households. Such pooling of data from 1998 through 2003 allowed us to investigate possible structural influences of USDA Dietary Guidelines on intake of calories, calcium, vitamin C and caffeine.

For the demand systems study, we created a unique time-series data set by aggregating monthly expenditure and volume information for each beverage across households (a total of 72 monthly observations for each beverage). We converted per household expenditure and volume information into *per capita* expenditure and per capita volume. Also, we adjusted the per capita expenditure information into *real* per capita expenditure using consumer price index information. Next, taking the ratio of per capita real expenditure to per capita volume, we created real price per gallon per month variable that was subsequently used in estimation of demand systems. Comparison of our time-series data with USDA-ERS disappearance data for similar non-alcoholic beverage categories confirmed strong correlations of our Nielsen data with USDA-ERS data.

In our demographic analysis we modeled the factors affecting the choice to consume through a probit model. A zero-one dummy variable that represented the purchase or non-purchase behavior was regressed on the demographic variables and a weighted average price of non-alcoholic beverages. Factors affecting the level of consumption were modeled through cross tabulations and regression analysis. The Heckman two-step procedure was employed in regressing volume of consumption of non-alcoholic beverages on price and demographic variables. A log-log functional form was employed in the regression analysis. Appropriate marginal effects in the second stage were obtained taking the calculated inverse mills ratio into account, which took care of the censoring problem in the sample.

Key Findings of Demographic Study

Older household heads; Black households, post-college educated household heads, and full time employed household heads are less likely to purchase isotonics. Western and Southern households, Hispanic households, and households with children are more likely to purchase isotonics.

Household heads that are employed full-time and post-college educated are less likely to purchase regular soft drinks, whereas Blacks and teenagers have a high chance to consume more regular soft drinks. Post-college educated households and households located in the Midwest have a high probability of purchasing diet soft drinks. Low probability of purchase of diet soft drinks is associated with Blacks, Asians, and households that are in poverty.

The more educated the household head, the lower the probability of purchase of high-fat milk and the higher the chance of purchasing low-fat milk. Households with children below twelve years of age are more likely to purchase high-fat milk. Southern and Western households, households that are in poverty and Black households are less likely to purchase low-fat milk. Households with older household heads are less likely to consume fruit drinks. Male headed households, Black households and households with children are more likely to consume fruit drinks. Households located in the South and West, Whites, and poverty households are less likely to buy fruit juices. Households with children are more likely to purchase fruit juices.

Black and Hispanic households are more prone to purchase bottled water. Poverty households are less likely to purchase bottled water. Older household heads, and Hispanic household heads are more likely to purchase coffee. Black household heads and household heads that are in poverty are less likely to purchase coffee. Midwestern, Western and Southern households are less likely to purchase tea.

We now summarize the key findings of the Heckman two-step volume analysis. Households with older household heads consumed less isotonics and regular soft drinks. Southern households purchased lowest amount of isotonics. Hispanics and households with adolescent children consumed more isotonics. College educated household heads, Asian households, and households located in the East purchased less regular soft drinks. Having a child in the household increased the consumption of regular soft drinks. Poverty households consumed more regular soft drinks. Households located in the Midwest, South, and West as well as White households purchased more diet soft drinks.

Southern and Western households, households with children below six years of age, and poverty households consumed more high-fat milk. More educated households purchased more low-fat milk. Midwestern, Southern and Western households consumed less low-fat milk. Households with White household heads and those with adolescent children consumed more low-fat milk.

Households located in the West, Black households, and households with children consumed more fruit drinks. Households with younger household heads purchased the highest amount of fruit juices. Households with children and Black households purchased more fruit juices. Fulltime employed household heads, Black households, and those with adolescent children purchased more bottled water. Midwestern and Southern households, households that are in poverty consumed less bottled water.

Post-college educated household heads, Midwestern and Southern households, Hispanic households and households with children consumed less coffee, while Western households consumed more. Middle aged household heads consumed more coffee and tea. Midwestern, Southern and Western households, and Black households and Asian households, and Hispanic households consumed less tea. Households with only adolescent children consumed more tea.

Conclusions of Demographic Study

Race, region, age and presence of children and gender of household head are the most important factors affecting the decision to purchase most non-alcoholic beverages. Age of the household head, region, race, age and presence of children in the household, poverty status of the household, and gender of the household food manager are significant drivers of level of consumption of most of the non-alcoholic beverages.

Policy Implications of Demographic Study

Product positioning and target marketing of non-alcoholic beverages based on identified demographic characteristics are two key areas where manufacturers and retailer of non-alcoholic beverages may pay close attention. For example, regular soft drinks, isotonics and fruit drinks can be marketed to households with younger household heads. Moreover, diet soft drinks can be positioned more into the Midwest and into the South. More isotonics could be marketed to Hispanics households and households with White household heads could be positioned with more low-fat milk. More bottled water and low-fat milk could be marketed to households with adolescent children.

Our findings reveal that poverty households (these are considered nutritionally at-risk populations by the U.S government) consume more high-calorie regular soft drinks. This finding could be used to appropriately design elements of government's Supplemental Nutrition Assistance Program (formally the Food Stamp Program). This finding also could act as a motivating factor for beverage manufacturers to introduce healthy non-alcoholic beverage alternatives in lieu of so-called unhealthy non-alcoholic beverages.

Key Findings of Probability Study

In using expectation-prediction success tables and a desired cut-off probability level to correctly classify probabilities, we paid attention to sensitivity and specificity values and their summation. Summation of sensitivity and specificity consistently were higher for within-sample generated probabilities compared to that of out-of-sample generated probabilities. This result is indicative of better performance in predicting within sample probabilities. However, they did not perform poorly out-of sample.

Also, high values of sensitivity and specificity were recorded for probabilities classified using the market penetration cut-off probability value compared to the naïve 0.50 cut-off probability value for all non-alcoholic beverages. Use of a naïve 0.50 cutoff probability to classify probabilities resulted in over or under estimated sensitivity and specificity values.

Next we used calibration and calibration graphs to evaluate probabilities generated through probit and logit models. Graphical analysis on calibration was focused on over or under-calibration looking at the deviation of the calibration plot away from a 45-degree perfect calibration line. Statistical analysis was performed focusing on the statistical significance of the calculated X^2 statistic, distributed as *chi*-squared with degrees of freedom $J-1$.

We did not find large differences between probit and logit model generated probabilities. However, there were noticeable differences between issued probability forecasts within-sample versus out-of-sample among the respective non-alcoholic beverages. Probit and logit models generated within and out-of-sample probabilities that were well calibrated for most of the non-alcoholic beverages (high-fat milk, low-fat milk, fruit drinks, fruit juices, and tea). For bottled water, isotonics and coffee, out-of-sample generated probabilities were not well calibrated for both probit and logit models.

Next, we used resolution graphs and resolution regressions (covariance regressions) to evaluate probabilities generated through probit and logit models. In our resolution regression, we were expecting intercept terms that were statistically not different from zero and slope coefficients that were not statistically different from one. This finding was required for perfect resolution (or sorting of probabilities). Any deviation of slope from one and intercept from zero was characterized by not-so-good resolved probabilities. We also plotted resolution graphs where forecast probabilities were plotted on the *y*-axis and outcome index on the *x*-axis. Goodness of sorting of probabilities were explained using the mean values of those forecast probabilities associated with outcome index zero and one.

There were not any differences between the results from probit and logit models. However, there were differences in probability forecasts generated within-sample and out-of-sample. We found that for all non-alcoholic beverages, the intercept coefficient was statistically different from zero and the slope parameter was statistically different from one. The estimated slope parameters were as low as 0.04 for fruit juice and as high as 0.16 for coffee for within-sample forecasts. For out-of-sample forecasts, it was as low as 0.04 for regular soft drinks, high-fat milk, fruit juices and tea, and as high as 0.14 for coffee. Calculated slope parameters indicated almost flat resolution graphs. Intercept coefficients were high (except for isotonics) indicating sub-optimal sorting of probabilities associated with events that did not occur.

All resolution graphs were almost flat against a 45-degreee perfect resolution graph. This finding is due to the high mean values of probabilities associates with events that did not occur. This latter result is indicative of sub-optimal sorting power.

Finally, we investigated the forecast probabilities generated through probit and logit models using the Brier score and the Yates partition of the Brier score. We expected to have a low Brier score for well issued forecast probabilities. In the Yates partition of the Brier score, we expected to have a smaller scatter and a bias with a minimally allowed minimum variance. More importantly, we expected to have a high Covariance associated with forecast probabilities and outcome index.

Calculated Brier score and the Yates partition of the Brier score were very similar between probit and logit models. The Brier score was lowest for fruit juices and the highest for low-fat milk. The lowest Brier score was 0.0614 for within sample forecasts of fruit drinks, and the highest score was 0.2235 for within sample forecasts for low-fat milk. Similar trend were evident with out-of-sample forecasts. According to the calculated Brier score, probability forecasts for fruit juices outperformed other non-alcoholic beverages.

Although the Brier score gave an overall indication of the ability of a model to forecast accurately, the components of the covariance decomposition of the Brier score provided a clearer and broader indication of the ability of the model to forecast. Covariance decomposition of the Brier score included the following: variance of the outcome index; minimum variance; scatter; bias; covariance of forecast probabilities and outcome indexes. Variance of outcome index cannot be controlled by the researcher or the model, but by the behavior of the agent. Highest variance of the outcome index was associated with low-fat milk was and low-fat milk also had the highest Brier score. This inflated Brier score was primarily due to the large variance of the outcome index which has a direct relationship with the market penetration value for a given beverage. Bias was almost negligible for all forecast probabilities associated with all non-alcoholic beverages. Scatter and minimum variance directly contributed to the variance of the forecast probabilities. The lowest scatter was associated with fruit juices for all scenarios, hence the lowest spread of forecast probabilities. The highest scatter was associated with coffee, hence the largest spread of forecast probabilities. The highest minimum variance was recorded with coffee; consequently the highest slope of the resolution graph. Highest covariance of outcome index and forecast probabilities were observed for coffee. Therefore, in terms of the Yates partition of the Brier score, coffee outperforms all other beverages in issuing forecast probabilities.

Conclusions of Probability Study

We did not find a major discrepancy between probabilities that are generated through probit and logit models. However, there were differences between within-sample generated probability forecasts versus out-of-sample generated probability forecasts. The choice of cut-off probability level in classifying probabilities was important for all non-alcoholic beverages. The market penetration probability level as a cut-off probability value to correctly classify probabilities outperformed the naïve 0.50 cut-off probability level. Therefore, it is recommended to use market penetration cut-off probability level to classify probabilities. This recommendation is consistent with the works by Park and Capps (1997) for example.

Most calibration graphs with respect to purchase decision of non-alcoholic beverages revealed that almost always there was a certain degree of over calibration and under-calibration with respect to probabilities generated.

Resolution regression analysis revealed that forecast probabilities generated for the decision to purchase all non-alcoholic beverages were not perfectly resolved (or perfectly sorted). All resolution graphs were upward sloping, indicating some degree of sorting power with respect to probit and logit models.

Yates decomposition of the Brier score was the best measure in evaluating the probabilities generated through probit and logit models. The covariance of the probabilities generated through the probit and logit models and the outcome index outperformed all other measures of probability evaluation in terms of correctly classifying probabilities.

Policy Implications of Probability Study

In the event where researchers are confronted with alternative models that issue probability forecasts, the accuracy of probability forecasts can be measured through a host of metrics. Even though traditional measures such as expectation-prediction success tables and calibration are still used, resolution, the Brier score and the Yates partition of the Brier score to evaluate probabilities generated through alternative models are highly recommended.

Key Findings of Demand Systems Study

In the *demand systems study,* we modeled interrelationships, dynamics and habits in determining demand for non-alcoholic beverages using a unique data set developed employing Nielsen HomeScan scanner data of household purchases of non-alcoholic beverages. We used 72 monthly observations of expenditure shares, real prices and real per capita expenditure of ten unique categories of non-alcoholic beverages in three demand systems. We used a linear approximated QUAIDS model, the Barten synthetic model, and Houthakker and Taylor State Adjustment model in achieving our objectives.

In comparison to similar studies done in the past literature, our study used a rich delineation of non-alcoholic beverage categories. Statistical significance of parameter estimates of LA/QUAIDS, Barten Synthetic and SAM model confirmed the presence of seasonality. Moreover, we found that LA/QUAIDS model superseded the AIDS model, hence support for non-linear flexible Engel curves in the logarithm of total expenditure.

First let us summarize elasticity estimates from LA/QUAIDS model. Calculated expenditure elasticities revealed that isotonics, regular soft drinks, diet soft drinks and fruit drinks were expenditure elastic. Regular soft drinks were the most expenditure elastic category. On the other hand, coffee was the most expenditure inelastic beverage category having an expenditure elasticity of 0.46. High-fat milk, low-fat milk, fruit juices, bottled water and tea also were expenditure inelastic.

All uncompensated and compensated own-price elasticities of demand were negative, consistent with theory and expectation. Isotonics was the most price sensitive beverage category. The compensated own-price elasticity of demand for regular soft drinks, diet soft drinks, fruit juices, and coffee were -1.97, -1.10, -1.03, and -1.61 respectively, indicating elastic nature of the demand. Fruit drinks had the most inelastic own-price elasticity of demand, which is -0.59. High-fat milk was more inelastic than low-fat milk. Bottled water and tea also were inelastic in demand.

Sixty percent of compensated cross-price elasticities were net substitutes. Diet soft drinks and fruit juices were net substitutes for isotonics while fruit drinks were a net complement. High-fat milk, low-fat milk, fruit juices, coffee and tea were net substitutes for regular soft drinks. Diet soft drinks were found to be a net complement for regular soft drinks.

Regular soft drinks, diet soft drinks, and low-fat milk were net substitutes for high-fat milk. On the other hand, fruit drinks, fruit juices and tea were net complements for high-fat milk. Diet soft drinks and coffee acted as net substitutes for fruit drinks. Consumers substituted isotonics and regular soft drinks for fruit juices. High-fat milk and low-fat milk were net complements for fruit juice. Diet soft drinks and tea were found to be net substitutes for bottled water. We find that high-fat milk is a strong net complement for tea.

According to diversion ratio calculations, the strongest substitute for isotonics was coffee, whereas the strongest complement was fruit drinks. The strongest substitute for regular soft drinks was coffee, while the strongest complement was diet soft drinks. The strongest substitute for diet soft drinks was bottled water. Diet soft drinks and regular soft drinks were found to be the strongest substitutes for high-fat milk and low-fat milk respectively.

Diversion ratio calculations could be used for evaluating impacts on one category of non-alcoholic beverages when a policy shock is implemented on a second non-alcoholic beverage. We demonstrated such policy effects based on a hypothetical sugar tax on beverages that contribute extra sugar (calories) to the diet. Emphasis was placed on direct effects and more importantly on the indirect effects of such policy shocks.

Concerning the Barten Synthetic model, the data supported the Central Bureau of Statistics (CBS) version of the general differential demand system over the Rotterdam, AIDS, and NBS versions. Isotonics were found to be the most expenditure elastic non-alcoholic beverage. Other expenditure elastic non-alcoholic beverages were regular soft drinks (1.21), diet soft drinks (1.29), fruit drinks (1.44), bottled water (1.12), and tea (1.11). Responsiveness of high-fat milk, low-fat milk, fruit juices and coffee were inelastic for changes in total expenditure. They were, 0.83, 0.86, 0.67, and 0.54 respectively.

All uncompensated and compensated own-price elasticity estimates had negative sign. Compensated own-price elasticity of demand for Isotonics was -4.70, which was the highest. Regular soft drinks and coffee too were price elastic (-1.52 and -1.55 respectively). All others were inelastic in demand. The most price inelastic non-alcoholic beverage was high-fat milk where the estimated own-price elasticity of demand was -0.53. Compensated own-price elasticity of demand for diet soft drinks, low-fat milk, fruit drinks, fruit juices, and tea was respectively -0.81, -0.84, -0.66, -0.89, and -0.65.

Sixty percent of compensated cross-price elasticities were net substitutes. Regular soft drinks and coffee were net substitutes for isotonics, while fruit drink was a net complement. Isotonics, high-fat milk, low-fat milk, fruit juices, and bottled water were net substitutes for regular soft drinks. Diet soft drinks were found to be a net complement to regular soft drinks. Net substitutes for diet soft drinks were high-fat milk, fruit drinks, and bottled water, while regular soft drinks were a net complement. Regular soft drinks and diet soft drinks were found to be net substitutes for high-fat milk. Fruit drinks and tea were net complements for high-fat milk. Regular soft drinks and coffee were found to be net substitutes for low-fat milk.

Diet soft drinks and coffee were net substitutes for fruit drinks. Results also showed that regular soft drinks were a net substitute for fruit juices. Net substitutes for coffee were found to be isotonics, low-fat milk, fruit drinks and tea. Coffee was the only net substitute for tea. High-fat milk was found to be a net complement for tea.

Next we estimated the reduced form version of the State Adjustment Model and recovered the structural form equation parameters. Estimated structural form parameters were used to calculate compensated and uncompensated own- and cross-price elasticities both short-run and long-run. They were also used to determine the dominance of inventory behavior or habit persistence in demand for non-alcoholic beverages. We also were able to show the direct relationship of the magnitude of short-run and long-run elasticities with the beverage being dominated by inventory behavior or habits.

Summary of estimated short-run elasticities are as follows. Bottled water was highly expenditure inelastic (0.17). Other non-alcoholic beverages showed following expenditure elasticities: isotonics 0.86; high-fat milk 0.84; low-fat milk 0.92; fruit drinks 0.91; fruit juices 0.98; coffee 0.81; tea 0.89. Isotonics, regular soft drinks, coffee and tea exhibited elastic own-price elasticities of demand. Regular soft drinks were the most elastic non-alcoholic beverage category, having own-price elasticity of demand of -1.70. Bottled water was the most price inelastic non-alcoholic beverage category, where the calculated own-price elasticity of demand was -0.28.

Fruit drinks were a net complements for both isotonics and regular soft drinks. Fruit juice and coffee were net substitutes for isotonics. Net substitutes associated with regular soft drinks were fruit juices, coffee and tea. Isotonics, regular soft drinks and low-fat milk were net complements for diet soft drinks, while high-fat milk, coffee and tea were net substitutes.

Isotonics, regular soft drinks and fruit drinks were net substitutes for high-fat milk, whereas fruit juices, coffee and tea acted as net complements. Net substitutes associated with low-fat milk were regular soft drinks and fruit drinks. Again, fruit juices, coffee and tea acted as net complements for low-fat milk. Isotonics and low fat milk act as net complements for fruit drinks, while tea, coffee and diet soft drinks were net substitutes. Net complements associated with fruit juices were isotonics, high-fat milk, coffee, and tea. Regular soft drinks, low-fat milk and fruit drinks were net substitutes for fruit juices. Fruit drinks and low-fat milk were net complements for bottled water, whereas high-fat milk and tea were net substitutes.

Net substitutes for coffee were isotonics, low-fat milk and fruit drinks. Regular soft drinks, high-fat milk, bottled water and tea act as net complements for coffee. Regular soft drinks, bottled water, high-fat milk, and fruit juices were net substitute for tea. Net complements for tea were diet soft drinks, low-fat milk, fruit drinks, and coffee.

A summary of estimated long-run elasticities of SAM is as follows. Isotonics, regular soft drinks, fruit drinks and fruit juices showed elastic expenditure elasticities (2.59, 1.26, 1.06 and 1.00 respectively). Bottled water was highly expenditure inelastic,0.49. Other non-alcoholic beverages showed following expenditure elasticities: diet soft drinks 0.90; high-fat milk 0.94; low-fat milk 0.90; coffee 0.79; tea 0.59.

Isotonics had the highest own-price elasticity of demand (-4.05). Also, regular soft drinks and coffee are elastic with respect to own-price elasticity of demand. Fruit juices were the highly inelastic non-alcoholic beverage category resulting in an own-price elasticity of demand of -0.46. Fruit drinks were the only significant net complement for isotonics, whereas fruit juices and coffee were net substitutes. Again, fruit drinks were the only net complement that is significantly affecting regular soft drinks, while fruit juices, coffee and tea were net substitutes. Net complements for diet soft drinks were isotonics, regular soft drinks and low-fat milk.

Isotonics, regular soft drinks and fruit drinks were net substitutes for high-fat milk, while fruit juices, coffee and tea were complements. Regular soft drinks, low-fat milk and fruit drinks were net substitutes for fruit juices. Net complements for fruit juices were found to be isotonics, high-fat milk, coffee and tea. High-fat milk and tea were net substitutes for bottled water, whereas low-fat milk and fruit drinks function as net complements. Net substitutes for coffee were identified to be isotonics, low-fat milk and fruit drinks. Regular soft drinks, high-fat milk, bottled water and tea were net complements to coffee. High-fat milk, regular soft drinks, fruit juices and bottled water were net substitutes for tea. Net complements for tea were identified to be diet soft drinks, low-fat milk, fruit drinks and coffee.

Habit persistence dominated with respect to isotonics, regular soft drinks, high-fat milk, fruit drinks, fruit juices and bottled water consumption. Diet soft drinks, low-fat milk, coffee and tea consumption exhibited adominance inventory behavior over habit persistence. Therefore, short-run elasticity estimates were larger compared to long-run counterparts for those non-alcoholic beverages dominated by inventories. Large long-run elasticity estimates in comparison to short-run estimates were evident for those non-alcoholic beverages where habit persistence dominated.

Conclusions of Demand Systems Study

Isotonics, regular soft drinks and coffee showed an elastic demand. On the other hand, inelastic demand was observed for high-fat milk, low-fat milk, fruit drinks and bottled water. Quarterly seasonality effects were significant across all models. Soft drinks are substitutes for most of non-alcoholic beverages while fruit juices and fruit drinks are mostly complements for other non-alcoholic beverages. Habits dominate inventory behavior for most non-alcoholic beverages, possibly due to monthly timeframe used in our analysis. Diversion ratio calculations were helpful in identifying movement of non-alcoholic beverages volume-wise, in the event where reduction of some non-alcoholic beverages was observed due to government policy actions.

Policy Implications of Demand Systems Study

Direct effects and indirect effects of government policy actions placed on non-alcoholic beverages can be ascertained through findings of this study. For example, we have investigated the effects of currently debated Federal excise tax or sales tax on sugar-sweetened beverages using own-price elasticities, cross-price elasticities and Diversion Ratios calculated in our study.

Not only government policy makers, but beverage manufactures and retailers could use interrelationships among non-alcoholic beverages revealed from our study to design and execute appropriate pricing strategies.

Key Findings of Nutrition Study

We found that at-home consumption of non-alcoholic beverages on average accounted for 220 kilo calories of caloric intake, 190 milligrams of calcium, 34 milligrams of vitamin C and 83 milligrams of caffeine per head per day. In other words, one derives 11% of calories, 19% of calcium, 34% of vitamin C and 41% of caffeine (daily recommended values are; 2000 kilo calories of energy, 1000 milligrams of calcium, 155 milligrams of vitamin C and 200 milligrams of caffeine) just by consuming non-alcoholic beverages at home. However, intakes of calories, calcium, vitamin C and caffeine experienced a significant drop after year 2001.

Price, gender, employment status and education status of the household head, region, race, poverty status, age and the presence of children were statistically important in the determination of daily caloric intake from the consumption of non-alcoholic beverages. Statistically significant factors in determining the daily calcium intake derived from non-alcoholic beverages for the same time period were price, employment status and gender of the household head, region, race, Hispanic origin, age and presence of children. Employment status, gender and education level of the household head, race, and region, presence of children and poverty status of the household head were the key drivers associated with daily availability of vitamin C. Age, employment and education status and gender of the head of the household head, region, race, presence of children and household poverty status were primary determinants of daily caffeine intake per person.

When yearly dummies were used to ascertain the impact of year 2000 USDA Dietary Guidelines, we found that there were significant drops in caloric, calcium, vitamin C and caffeine in year 2001, 2002 and 2003 compared to that of 1998, 1999 and 2000, our reference years. That is to say, the 2000 USDA Dietary Guidelines have been successful in reducing caloric and caffeine intake derived from non-alcoholic beverage consumption at home. The reduction in calcium intake may be due to the decline in milk consumption, substituting away from non-alcoholic beverages to food products such as cheese and yogurt, and the use of supplements. The drop in vitamin C intake derived from non-alcoholic beverage consumption probably is due to the fact that USDA Dietary Guidelines emphasized eating fresh fruits and vegetables compared to drinking non-alcoholic beverages to acquire daily vitamin C requirement. Also consumers may obtain vitamin C from supplements.

Conclusions of Nutrition Study

Significant demographic factors affecting caloric and nutrient intake from consumption of non-alcoholic beverages are employment status of household head, region, race, presence of children in the household and gender of the household food manager. Intervention program exercised by USDA through the year-2000 Dietary Guideline for Americans was found to be successful in reducing caloric and caffeine intake from the consumption of non-alcoholic beverages.

Policy Implications of Nutrition Study

In terms of designing nutrition policy pertaining to intake of calories and nutrients through the consumption of non-alcoholic beverages, policy makers are encouraged to pay attention to demographic characteristics such as region, race, presence of children, poverty status and employment status of the household. For example, poverty households derive more calories from the consumption of non-alcoholic beverages compared to non-poverty households. Nutrition policies could be defined such that poverty households intake low calories from consumption of non-alcoholic beverages through introduction of healthy low-calorie alternatives.

The methodologies used in our analysis to ascertain the impact of USDA Dietary Guidelines of consumption of non-alcoholic beverages could be used to assess future intervention programs. Beverage manufactures could use this information to design and market new non-alcoholic beverage alternatives to satisfy need of different demographic groups.

Limitations of Our Work

Limitations exist to each of our studies warranting attention. Our study concentrates on at-home consumption of non-alcoholic beverages and their interrelationships. The away-from-home intake of beverages is not accounted for in our analysis (The Nielsen HomeScan scanner panels pertain to at-home consumption only). More specifically with respect to our demand systems study, we used a unique set of time-series data. These data did allow a different way of capturing patterns of non-alcoholic beverage consumption through time, even though we had to forgo the demographic information in preparing the time-series data set. In this way, more refined categories of non-alcoholic beverages could be considered without the econometric issues associated with micro-level data.

Our nutrition analysis does not capture the substitution away from beverage choices to non-beverage choices such as consumption of fresh fruits and vegetables. As well, intakes from the use of dietary supplements are not captured.

Potential Future Frontiers

Our data series ends at calendar year 2003. With the availability of recent data, we are in a position to extend that to calendar year 2007. Doing so will give us more latitude in understanding influence of demographic and economic factors in determining demand for non-alcoholic beverage categories. We are in a position to develop a true data panel with household purchases of non-alcoholic beverages with 1700 households spanning over a 6 year period. This situation will allow us to perform panel econometrics in understanding fix effects and random effects. Now that we have used LA/QUAIDS model with time-series data, next step would be to perform a cross-sectional analysis using LA/QUAIDS or QUAIDS model thereby bringing in demographic information into the system. We also are in a position to incorporate advertising information to LA/QUAIDS model. With that, we are in a position to investigate responsiveness of non-alcoholic beverages to advertising expenditure and also to understand possible spillover effects of advertising.

Now that we have a time-series data set on non-alcoholic beverage we could test them for presence of unit roots, hence model it through an error correction model and discover short-run and long-run adjustments. Forecast probability evaluation analysis can be extended to include receiver operating characteristics (ROC) charts and cumulative accuracy profile (CAP) charts in evaluating forecast probabilities.

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APPENDIX 1

RESULTS FROM JOINT TESTS FOR DEMOGRAPHIC VARIABLE CATEGORIES IN THE PROBIT MODEL FOR EACH NON-ALCOHOLIC BEVERAGE CATEGORY

The joint tests were done in SHAZAM Version 10 statistical package. Abbreviations used are as follows.

a2529	age of household head between 25-29 years
a3034	age of household head between 30-34 years
a3544	age of household head between 35-44 years
a4554	age of household head between 45-54 years
a5564	age of household head between 55-64 years
agt64	age of household head above 64 years
eft	Employemnt status of household head: full-time employed
ept	Employemnt status of household head: part-time employed
eduhs	education level of household head: high-school educated
edupc	education level of household head: post-college educated
eduu	education level of household head: undergraduate education
mw	Midwest
s	South
w	West
blk	Black household
asian	Asian household
other	Other category (non-black, non-asian, non-white)
hsp	Hispanic houseshold head
ac1	Age and presence of children: less than 6 years of age
ac2	Age and presence of children: 6 to 12 years of age
ac3	Age and presence of children: 13 to 17 years of age
ac4	Age and presence of children: less than 6 years and 6 to 12 years of age
ac5	Age and presence of children: less than 6 years and 13 to 17 years of age
ac6	Age and presence of children: 6 to 12 years and 13 to 17 years of age
ac7	Age and presence of children: less than 6 years, 6 to 12 years and 13 to 17 years of age
fh	female only headed household
mh	male only headed household
pov	below 185% poverty status

Isotonics

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   70.671034     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08490
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   6.1985630     WITH    2 D.F.  P-VALUE=
0.04508
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.32266
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   11.517539     WITH    3 D.F.  P-VALUE=
0.00923
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.26047
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   20.269313     WITH    3 D.F.  P-VALUE=
0.00015
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.14801
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   13.390456     WITH    3 D.F.  P-VALUE=
0.00386
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.22404
 |_test hsp=0
 TEST VALUE =  0.26488     STD. ERROR OF TEST VALUE  0.72598E-01
 ASYMPTOTIC NORMAL STATISTIC =   3.6486160      P-VALUE= 0.00026
 WALD CHI-SQUARE STATISTIC =   13.312398     WITH    1 D.F.  P-VALUE=
0.00026
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07512
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
```

```
 |_end
 WALD CHI-SQUARE STATISTIC =   66.566620     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10516
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   30.901782     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.06472
 |_test pov=0
 TEST VALUE = -0.85444E-01 STD. ERROR OF TEST VALUE  0.53925E-01
 ASYMPTOTIC NORMAL STATISTIC =  -1.5844776      P-VALUE= 0.11309
 WALD CHI-SQUARE STATISTIC =   2.5105694     WITH    1 D.F.  P-VALUE=
0.11309
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.39832
```

Regular Soft Drinks

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   49.876073     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.12030
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   6.8027546     WITH    2 D.F.  P-VALUE=
0.03333
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.29400
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   30.279573     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09908
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   4.2963372     WITH    3 D.F.  P-VALUE=
0.23119
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.69827
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   20.580014     WITH    3 D.F.  P-VALUE=
0.00013
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.14577
 |_test hsp=0
 TEST VALUE =  0.20331     STD. ERROR OF TEST VALUE  0.11779
 ASYMPTOTIC NORMAL STATISTIC =   1.7260402      P-VALUE= 0.08434
 WALD CHI-SQUARE STATISTIC =   2.9792149     WITH    1 D.F.  P-VALUE=
0.08434
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.33566
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   47.651839     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.14690
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   108.42440     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01845
 |_test pov=0
 TEST VALUE = -0.43621E-01 STD. ERROR OF TEST VALUE  0.68064E-01
 ASYMPTOTIC NORMAL STATISTIC = -0.64088113      P-VALUE= 0.52160
 WALD CHI-SQUARE STATISTIC =  0.41072862     WITH    1 D.F.  P-VALUE=
0.52160
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
```

Diet Soft Drinks

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   29.849054     WITH    6 D.F.  P-VALUE=
0.00004
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.20101
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   1.2998500     WITH    2 D.F.  P-VALUE=
0.52208
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   6.6976926     WITH    3 D.F.  P-VALUE=
0.08218
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.44792
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   6.9130912     WITH    3 D.F.  P-VALUE=
0.07472
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.43396
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   184.44879     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01626
 |_test hsp=0
 TEST VALUE = -0.63790E-01 STD. ERROR OF TEST VALUE  0.69507E-01
 ASYMPTOTIC NORMAL STATISTIC = -0.91775784      P-VALUE= 0.35875
 WALD CHI-SQUARE STATISTIC =  0.84227946     WITH    1 D.F.  P-VALUE=
0.35875
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   6.5136754     WITH    7 D.F.  P-VALUE=
0.48121
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   113.92998     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01755
 |_test pov=0
 TEST VALUE = -0.23903     STD. ERROR OF TEST VALUE  0.46830E-01
 ASYMPTOTIC NORMAL STATISTIC =  -5.1041512      P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   26.052359     WITH    1 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.03838
```

High-Fat Milk

```
_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   12.236347     WITH    6 D.F.  P-VALUE=
0.05690
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.49034
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =  0.55710817     WITH    2 D.F.  P-VALUE=
0.75688
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   51.377206     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.05839
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   19.491720     WITH    3 D.F.  P-VALUE=
0.00022
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.15391
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   10.733490     WITH    3 D.F.  P-VALUE=
0.01326
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.27950
 |_test hsp=0
 TEST VALUE =  0.16718     STD. ERROR OF TEST VALUE  0.87786E-01
 ASYMPTOTIC NORMAL STATISTIC =   1.9044056      P-VALUE= 0.05686
 WALD CHI-SQUARE STATISTIC =   3.6267607     WITH    1 D.F.  P-VALUE=
0.05686
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.27573
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   89.134320     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07853
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   40.588577     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04927
 |_test pov=0
 TEST VALUE =  0.71590E-01 STD. ERROR OF TEST VALUE  0.57540E-01
 ASYMPTOTIC NORMAL STATISTIC =   1.2441682      P-VALUE= 0.21344
 WALD CHI-SQUARE STATISTIC =   1.5479545     WITH    1 D.F.  P-VALUE=
0.21344
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.64601
```

Low-Fat Milk

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   4.2105864     WITH    6 D.F.  P-VALUE=
0.64820
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   9.4893692     WITH    2 D.F.  P-VALUE=
0.00870
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.21076
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   50.576284     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.05932
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   27.400584     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10949
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   150.49377     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01993
 |_test hsp=0
 TEST VALUE = -0.61276E-01 STD. ERROR OF TEST VALUE  0.68432E-01
 ASYMPTOTIC NORMAL STATISTIC = -0.89541953      P-VALUE= 0.37056
 WALD CHI-SQUARE STATISTIC =  0.80177613     WITH    1 D.F.  P-VALUE=
0.37056
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   4.9552590     WITH    7 D.F.  P-VALUE=
0.66542
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   51.744852     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.03865
 |_test pov=0
 TEST VALUE = -0.22749     STD. ERROR OF TEST VALUE  0.46656E-01
 ASYMPTOTIC NORMAL STATISTIC =  -4.8758829      P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   23.774234     WITH    1 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04206
```

Fruit Drinks

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   74.303081     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08075
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   3.0904088     WITH    2 D.F.  P-VALUE=
0.21327
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.64716
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   15.565936     WITH    3 D.F.  P-VALUE=
0.00139
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.19273
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   4.2860444     WITH    3 D.F.  P-VALUE=
0.23219
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.69995
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   105.04602     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02856
 |_test hsp=0
 TEST VALUE =  0.70331E-01 STD. ERROR OF TEST VALUE  0.85276E-01
 ASYMPTOTIC NORMAL STATISTIC =  0.82474683      P-VALUE= 0.40952
 WALD CHI-SQUARE STATISTIC =  0.68020734     WITH    1 D.F.  P-VALUE=
0.40952
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   198.79141     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.03521
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   82.475668     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02425
 |_test pov=0
 TEST VALUE = -0.13454E-01 STD. ERROR OF TEST VALUE  0.54019E-01
 ASYMPTOTIC NORMAL STATISTIC = -0.24905808      P-VALUE= 0.80332
 WALD CHI-SQUARE STATISTIC =  0.62029926E-01 WITH    1 D.F.  P-VALUE=
0.80332
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
```

Fruit Juices

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   5.6670131     WITH    6 D.F.  P-VALUE=
0.46151
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   5.1920604     WITH    2 D.F.  P-VALUE=
0.07457
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.38520
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   2.9375235     WITH    3 D.F.  P-VALUE=
0.40136
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   29.177956     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10282
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   28.914785     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10375
 |_test hsp=0
 TEST VALUE =  0.11383     STD. ERROR OF TEST VALUE  0.11845
 ASYMPTOTIC NORMAL STATISTIC =  0.96102611      P-VALUE= 0.33654
 WALD CHI-SQUARE STATISTIC =  0.92357119     WITH    1 D.F.  P-VALUE=
0.33654
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   25.547280     WITH    7 D.F.  P-VALUE=
0.00061
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.27400
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   85.098708     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02350
 |_test pov=0
 TEST VALUE = -0.24537     STD. ERROR OF TEST VALUE  0.68292E-01
 ASYMPTOTIC NORMAL STATISTIC =  -3.5928652      P-VALUE= 0.00033
 WALD CHI-SQUARE STATISTIC =   12.908680     WITH    1 D.F.  P-VALUE=
0.00033
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07747
```

Bottled Water

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   89.609524     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.06696
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   5.3750845     WITH    2 D.F.  P-VALUE=
0.06805
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.37209
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   3.9360825     WITH    3 D.F.  P-VALUE=
0.26845
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.76218
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   12.582258     WITH    3 D.F.  P-VALUE=
0.00563
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.23843
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   19.735273     WITH    3 D.F.  P-VALUE=
0.00019
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.15201
 |_test hsp=0
 TEST VALUE =  0.17045     STD. ERROR OF TEST VALUE  0.76936E-01
 ASYMPTOTIC NORMAL STATISTIC =   2.2154429      P-VALUE= 0.02673
 WALD CHI-SQUARE STATISTIC =   4.9081871     WITH    1 D.F.  P-VALUE=
0.02673
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.20374
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   9.2772214     WITH    7 D.F.  P-VALUE=
0.23336
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.75454
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   98.541075     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02030
 |_test pov=0
 TEST VALUE = -0.30311     STD. ERROR OF TEST VALUE  0.47857E-01
 ASYMPTOTIC NORMAL STATISTIC =  -6.3336555      P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   40.115192     WITH    1 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02493
```

Coffee

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   135.91562     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04415
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =  0.81611405     WITH    2 D.F.  P-VALUE=
0.66494
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   4.3349768     WITH    3 D.F.  P-VALUE=
0.22749
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.69205
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   44.056723     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.06809
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   73.927552     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04058
 |_test hsp=0
 TEST VALUE =  0.18373     STD. ERROR OF TEST VALUE  0.76600E-01
 ASYMPTOTIC NORMAL STATISTIC =   2.3985027      P-VALUE= 0.01646
 WALD CHI-SQUARE STATISTIC =   5.7528154     WITH    1 D.F.  P-VALUE=
0.01646
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.17383
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   7.0893553     WITH    7 D.F.  P-VALUE=
0.41964
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.98740
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   160.86926     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01243
 |_test pov=0
 TEST VALUE = -0.17675     STD. ERROR OF TEST VALUE  0.51102E-01
 ASYMPTOTIC NORMAL STATISTIC =  -3.4587107      P-VALUE= 0.00054
 WALD CHI-SQUARE STATISTIC =   11.962680     WITH    1 D.F.  P-VALUE=
0.00054
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08359
```

Tea

```
|_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 WALD CHI-SQUARE STATISTIC =   12.999290     WITH    6 D.F.  P-VALUE=
0.04305
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.46156
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 WALD CHI-SQUARE STATISTIC =   18.202500     WITH    2 D.F.  P-VALUE=
0.00011
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10988
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 WALD CHI-SQUARE STATISTIC =   4.5698849     WITH    3 D.F.  P-VALUE=
0.20614
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.65647
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 WALD CHI-SQUARE STATISTIC =   144.38518     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02078
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 WALD CHI-SQUARE STATISTIC =   6.6747262     WITH    3 D.F.  P-VALUE=
0.08302
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.44946
 |_test hsp=0
 TEST VALUE = -0.10699     STD. ERROR OF TEST VALUE  0.72065E-01
 ASYMPTOTIC NORMAL STATISTIC =  -1.4845983      P-VALUE= 0.13765
 WALD CHI-SQUARE STATISTIC =   2.2040321     WITH    1 D.F.  P-VALUE=
0.13765
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.45371
 |_test
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
```

```
 WALD CHI-SQUARE STATISTIC =   5.9747492     WITH    7 D.F.  P-VALUE=
0.54270
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 WALD CHI-SQUARE STATISTIC =   117.97087     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01695
 |_test pov=0
 TEST VALUE = -0.48912E-01 STD. ERROR OF TEST VALUE  0.49307E-01
 ASYMPTOTIC NORMAL STATISTIC = -0.99200307      P-VALUE= 0.32120
 WALD CHI-SQUARE STATISTIC =  0.98407008     WITH    1 D.F.  P-VALUE=
0.32120
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
```

APPENDIX 2

RESULTS FROM JOINT TESTS FOR DEMOGRAPHIC VARIABLE CATEGORIES IN THE HECKMAN MODEL FOR EACH NON-ALCOHOLIC BEVERAGE CATEGORY

The joint tests were done in SHAZAM Version 10 statistical package. Abbreviations used are as follows.

a2529	age of household head between 25-29 years
a3034	age of household head between 30-34 years
a3544	age of household head between 35-44 years
a4554	age of household head between 45-54 years
a5564	age of household head between 55-64 years
agt64	age of household head above 64 years
eft	Employemnt status of household head: full-time employed
ept	Employemnt status of household head: part-time employed
eduhs	education level of household head: high-school educated
edupc	education level of household head: post-college educated
eduu	education level of household head: undergraduate education
mw	Midwest
s	South
w	West
blk	Black household
asian	Asian household
other	Other category (non-black, non-asian, non-white)
hsp	Hispanic househsold head
ac1	Age and presence of children: less than 6 years of age
ac2	Age and presence of children: 6 to 12 years of age
ac3	Age and presence of children: 13 to 17 years of age
ac4	Age and presence of children: less than 6 years and 6 to 12 years of age
ac5	Age and presence of children: less than 6 years and 13 to 17 years of age
ac6	Age and presence of children: 6 to 12 years and 13 to 17 years of age
ac7	Age and presence of children: less than 6 years, 6 to 12 years and 13 to 17 years of age
fh	female only headed household
mh	male only headed household
pov	below 185% poverty status

Isotonics

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   5.3178539     WITH    6 AND 1578 D.F.  P-VALUE= 0.00002
 WALD CHI-SQUARE STATISTIC =   31.907123     WITH    6 D.F.  P-VALUE=
0.00002
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.18805
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   7.1139976     WITH    2 AND 1578 D.F.  P-VALUE= 0.00084
 WALD CHI-SQUARE STATISTIC =   14.227995     WITH    2 D.F.  P-VALUE=
0.00081
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.14057
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   1.8514024     WITH    3 AND 1578 D.F.  P-VALUE= 0.13590
 WALD CHI-SQUARE STATISTIC =   5.5542073     WITH    3 D.F.  P-VALUE=
0.13543
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.54013
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   10.334816     WITH    3 AND 1578 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   31.004447     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09676
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   2.8559891     WITH    3 AND 1578 D.F.  P-VALUE= 0.03595
 WALD CHI-SQUARE STATISTIC =   8.5679673     WITH    3 D.F.  P-VALUE=
0.03562
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.35014
 |_test hsp=0
 TEST VALUE = -0.50990     STD. ERROR OF TEST VALUE  0.14369
 T STATISTIC =  -3.5486116     WITH 1578 D.F.    P-VALUE= 0.00040
 F STATISTIC =   12.592644     WITH    1 AND 1578 D.F.  P-VALUE= 0.00040
 WALD CHI-SQUARE STATISTIC =   12.592644     WITH    1 D.F.  P-VALUE=
0.00039
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07941
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   3.5540290     WITH    7 AND 1578 D.F.  P-VALUE= 0.00085
 WALD CHI-SQUARE STATISTIC =   24.878203     WITH    7 D.F.  P-VALUE=
0.00080
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.28137
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   10.678574     WITH    2 AND 1578 D.F.  P-VALUE= 0.00002
 WALD CHI-SQUARE STATISTIC =   21.357148     WITH    2 D.F.  P-VALUE=
0.00002
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09365
 |_test pov=0
 TEST VALUE =  0.97676E-01 STD. ERROR OF TEST VALUE  0.98635E-01
 T STATISTIC =  0.99027935     WITH 1578 D.F.    P-VALUE= 0.32219
 F STATISTIC =  0.98065318     WITH    1 AND 1578 D.F.  P-VALUE= 0.32219
 WALD CHI-SQUARE STATISTIC =  0.98065318     WITH    1 D.F.  P-VALUE=
0.32204
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
```

Regular Soft Drinks

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   8.9532690     WITH    6 AND 6890 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   53.719614     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.11169
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   1.6898121     WITH    2 AND 6890 D.F.  P-VALUE= 0.18463
 WALD CHI-SQUARE STATISTIC =   3.3796241     WITH    2 D.F.  P-VALUE=
0.18455
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.59178
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   29.134488     WITH    3 AND 6890 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   87.403464     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.03432
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   9.3173439     WITH    3 AND 6890 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   27.952032     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10733
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   6.6253194     WITH    3 AND 6890 D.F.  P-VALUE= 0.00018
 WALD CHI-SQUARE STATISTIC =   19.875958     WITH    3 D.F.  P-VALUE=
0.00018
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.15094
 |_test hsp=0
 TEST VALUE = -0.10330     STD. ERROR OF TEST VALUE  0.74463E-01
 T STATISTIC =  -1.3872915     WITH 6890 D.F.    P-VALUE= 0.16540
 F STATISTIC =   1.9245777     WITH    1 AND 6890 D.F.  P-VALUE= 0.16540
 WALD CHI-SQUARE STATISTIC =   1.9245777     WITH    1 D.F.  P-VALUE=
0.16535
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.51959
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   11.567186     WITH    7 AND 6890 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   80.970304     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08645
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   11.746667     WITH    2 AND 6890 D.F.  P-VALUE= 0.00001
 WALD CHI-SQUARE STATISTIC =   23.493334     WITH    2 D.F.  P-VALUE=
0.00001
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08513
 |_test pov=0
 TEST VALUE =  0.14379     STD. ERROR OF TEST VALUE  0.51103E-01
 T STATISTIC =   2.8138163     WITH 6890 D.F.    P-VALUE= 0.00491
 F STATISTIC =   7.9175620     WITH    1 AND 6890 D.F.  P-VALUE= 0.00491
 WALD CHI-SQUARE STATISTIC =   7.9175620     WITH    1 D.F.  P-VALUE=
0.00490
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.12630
```

Diet Soft Drinks

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   7.4545865     WITH    6 AND 4962 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   44.727519     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.13415
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =  0.34040735     WITH    2 AND 4962 D.F.  P-VALUE= 0.71150
 WALD CHI-SQUARE STATISTIC =  0.68081469     WITH    2 D.F.  P-VALUE=
0.71148
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =  0.66551979     WITH    3 AND 4962 D.F.  P-VALUE= 0.57316
 WALD CHI-SQUARE STATISTIC =   1.9965594     WITH    3 D.F.  P-VALUE=
0.57312
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   6.1877723     WITH    3 AND 4962 D.F.  P-VALUE= 0.00034
 WALD CHI-SQUARE STATISTIC =   18.563317     WITH    3 D.F.  P-VALUE=
0.00034
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.16161
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   4.3441369     WITH    3 AND 4962 D.F.  P-VALUE= 0.00460
 WALD CHI-SQUARE STATISTIC =   13.032411     WITH    3 D.F.  P-VALUE=
0.00457
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.23020
 |_test hsp=0
 TEST VALUE = -0.40086E-01 STD. ERROR OF TEST VALUE  0.10805
 T STATISTIC = -0.37100384     WITH 4962 D.F.    P-VALUE= 0.71065
 F STATISTIC =  0.13764385     WITH    1 AND 4962 D.F.  P-VALUE= 0.71065
 WALD CHI-SQUARE STATISTIC =  0.13764385     WITH    1 D.F.  P-VALUE=
0.71063
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   1.3311288     WITH    7 AND 4962 D.F.  P-VALUE= 0.23090
 WALD CHI-SQUARE STATISTIC =   9.3179013     WITH    7 D.F.  P-VALUE=
0.23063
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.75124
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   10.401287     WITH    2 AND 4962 D.F.  P-VALUE= 0.00003
 WALD CHI-SQUARE STATISTIC =   20.802574     WITH    2 D.F.  P-VALUE=
0.00003
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09614
 |_test pov=0
 TEST VALUE = -0.17400     STD. ERROR OF TEST VALUE  0.10573
 T STATISTIC =  -1.6457806     WITH 4962 D.F.    P-VALUE= 0.09987
 F STATISTIC =   2.7085939     WITH    1 AND 4962 D.F.  P-VALUE= 0.09987
 WALD CHI-SQUARE STATISTIC =   2.7085939     WITH    1 D.F.  P-VALUE=
0.09981
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.36920
```

High-Fat Milk

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   2.0149430     WITH    6 AND 6251 D.F.  P-VALUE= 0.06017
 WALD CHI-SQUARE STATISTIC =   12.089658     WITH    6 D.F.  P-VALUE=
0.06000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.49629
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =  0.46871068     WITH    2 AND 6251 D.F.  P-VALUE= 0.62583
 WALD CHI-SQUARE STATISTIC =  0.93742135     WITH    2 D.F.  P-VALUE=
0.62581
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   11.866979     WITH    3 AND 6251 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   35.600937     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08427
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   49.788383     WITH    3 AND 6251 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   149.36515     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.02009
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   1.7520320     WITH    3 AND 6251 D.F.  P-VALUE= 0.15409
 WALD CHI-SQUARE STATISTIC =   5.2560959     WITH    3 D.F.  P-VALUE=
0.15398
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.57077
 |_test hsp=0
 TEST VALUE =  0.70349E-01 STD. ERROR OF TEST VALUE  0.80545E-01
 T STATISTIC =  0.87341489     WITH 6251 D.F.    P-VALUE= 0.38247
 F STATISTIC =  0.76285358     WITH    1 AND 6251 D.F.  P-VALUE= 0.38247
 WALD CHI-SQUARE STATISTIC =  0.76285358     WITH    1 D.F.  P-VALUE=
0.38244
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   12.874801     WITH    7 AND 6251 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   90.123605     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07767
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   24.592972     WITH    2 AND 6251 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   49.185944     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04066
 |_test pov=0
 TEST VALUE =  0.20603     STD. ERROR OF TEST VALUE  0.54041E-01
 T STATISTIC =   3.8125154     WITH 6251 D.F.    P-VALUE= 0.00014
 F STATISTIC =   14.535274     WITH    1 AND 6251 D.F.  P-VALUE= 0.00014
 WALD CHI-SQUARE STATISTIC =   14.535274     WITH    1 D.F.  P-VALUE=
0.00014
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.06880
```

Low-Fat Milk

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   1.3872154     WITH    6 AND 4741 D.F.  P-VALUE= 0.21562
 WALD CHI-SQUARE STATISTIC =   8.3232926     WITH    6 D.F.  P-VALUE=
0.21536
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.72087
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   1.5589722     WITH    2 AND 4741 D.F.  P-VALUE= 0.21046
 WALD CHI-SQUARE STATISTIC =   3.1179445     WITH    2 D.F.  P-VALUE=
0.21035
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.64145
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   2.7506338     WITH    3 AND 4741 D.F.  P-VALUE= 0.04120
 WALD CHI-SQUARE STATISTIC =   8.2519014     WITH    3 D.F.  P-VALUE=
0.04108
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.36355
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   14.262667     WITH    3 AND 4741 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   42.788000     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07011
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   2.5536830     WITH    3 AND 4741 D.F.  P-VALUE= 0.05369
 WALD CHI-SQUARE STATISTIC =   7.6610489     WITH    3 D.F.  P-VALUE=
0.05356
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.39159
 |_test hsp=0
 TEST VALUE =  0.81355E-01 STD. ERROR OF TEST VALUE  0.96493E-01
 T STATISTIC =  0.84312226     WITH 4741 D.F.    P-VALUE= 0.39920
 F STATISTIC =  0.71085514     WITH    1 AND 4741 D.F.  P-VALUE= 0.39920
 WALD CHI-SQUARE STATISTIC =  0.71085514     WITH    1 D.F.  P-VALUE=
0.39916
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
```

```
|_test ac1=0
|_test ac2=0
|_test ac3=0
|_test ac4=0
|_test ac5=0
|_test ac6=0
|_test ac7=0
|_end
F STATISTIC =   3.0783952     WITH    7 AND 4741 D.F.  P-VALUE= 0.00308
WALD CHI-SQUARE STATISTIC =   21.548766     WITH    7 D.F.  P-VALUE=
0.00304
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.32484
|_test
|_test fh=0
|_test mh=0
|_end
F STATISTIC =   10.403079     WITH    2 AND 4741 D.F.  P-VALUE= 0.00003
WALD CHI-SQUARE STATISTIC =   20.806158     WITH    2 D.F.  P-VALUE=
0.00003
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09613
|_test pov=0
TEST VALUE =  0.11134     STD. ERROR OF TEST VALUE  0.78817E-01
T STATISTIC =   1.4125753     WITH 4741 D.F.    P-VALUE= 0.15785
F STATISTIC =   1.9953690     WITH    1 AND 4741 D.F.  P-VALUE= 0.15785
WALD CHI-SQUARE STATISTIC =   1.9953690     WITH    1 D.F.  P-VALUE=
0.15778
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.50116
```

Fruit Drinks

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   1.3607788     WITH    6 AND 5758 D.F.  P-VALUE= 0.22649
 WALD CHI-SQUARE STATISTIC =   8.1646726     WITH    6 D.F.  P-VALUE=
0.22629
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.73487
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =  0.39515267     WITH    2 AND 5758 D.F.  P-VALUE= 0.67360
 WALD CHI-SQUARE STATISTIC =  0.79030534     WITH    2 D.F.  P-VALUE=
0.67358
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   1.0958615     WITH    3 AND 5758 D.F.  P-VALUE= 0.34947
 WALD CHI-SQUARE STATISTIC =   3.2875846     WITH    3 D.F.  P-VALUE=
0.34937
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.91252
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   13.498111     WITH    3 AND 5758 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   40.494332     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07408
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   2.4664271     WITH    3 AND 5758 D.F.  P-VALUE= 0.06031
 WALD CHI-SQUARE STATISTIC =   7.3992813     WITH    3 D.F.  P-VALUE=
0.06020
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.40544
 |_test hsp=0
 TEST VALUE =  0.78360E-01 STD. ERROR OF TEST VALUE  0.69416E-01
 T STATISTIC =   1.1288461     WITH 5758 D.F.    P-VALUE= 0.25901
 F STATISTIC =   1.2742936     WITH    1 AND 5758 D.F.  P-VALUE= 0.25901
 WALD CHI-SQUARE STATISTIC =   1.2742936     WITH    1 D.F.  P-VALUE=
0.25896
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.78475
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   7.3159859     WITH    7 AND 5758 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   51.211902     WITH    7 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.13669
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   9.5560546     WITH    2 AND 5758 D.F.  P-VALUE= 0.00007
 WALD CHI-SQUARE STATISTIC =   19.112109     WITH    2 D.F.  P-VALUE=
0.00007
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10465
 |_test pov=0
 TEST VALUE = -0.76878E-01 STD. ERROR OF TEST VALUE  0.49386E-01
 T STATISTIC =  -1.5566818     WITH 5758 D.F.    P-VALUE= 0.11960
 F STATISTIC =   2.4232581     WITH    1 AND 5758 D.F.  P-VALUE= 0.11960
 WALD CHI-SQUARE STATISTIC =   2.4232581     WITH    1 D.F.  P-VALUE=
0.11955
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.41267
```

Fruit Juices

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   6.4471473     WITH    6 AND 7108 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   38.682884     WITH    6 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.15511
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   2.8417873     WITH    2 AND 7108 D.F.  P-VALUE= 0.05839
 WALD CHI-SQUARE STATISTIC =   5.6835745     WITH    2 D.F.  P-VALUE=
0.05832
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.35189
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   2.2704143     WITH    3 AND 7108 D.F.  P-VALUE= 0.07826
 WALD CHI-SQUARE STATISTIC =   6.8112428     WITH    3 D.F.  P-VALUE=
0.07816
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.44045
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   19.084275     WITH    3 AND 7108 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   57.252826     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.05240
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   5.0016648     WITH    3 AND 7108 D.F.  P-VALUE= 0.00183
 WALD CHI-SQUARE STATISTIC =   15.004994     WITH    3 D.F.  P-VALUE=
0.00181
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.19993
 |_test hsp=0
 TEST VALUE = -0.84672E-01 STD. ERROR OF TEST VALUE  0.62413E-01
 T STATISTIC =  -1.3566448     WITH 7108 D.F.    P-VALUE= 0.17494
 F STATISTIC =   1.8404852     WITH    1 AND 7108 D.F.  P-VALUE= 0.17494
 WALD CHI-SQUARE STATISTIC =   1.8404852     WITH    1 D.F.  P-VALUE=
0.17489
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.54333
 |_test
```

```
|_test ac1=0
|_test ac2=0
|_test ac3=0
|_test ac4=0
|_test ac5=0
|_test ac6=0
|_test ac7=0
|_end
F STATISTIC =   2.6961151     WITH    7 AND 7108 D.F.  P-VALUE= 0.00866
WALD CHI-SQUARE STATISTIC =   18.872806     WITH    7 D.F.  P-VALUE=
0.00860
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.37090
|_test
|_test fh=0
|_test mh=0
|_end
F STATISTIC =   94.240236     WITH    2 AND 7108 D.F.  P-VALUE= 0.00000
WALD CHI-SQUARE STATISTIC =   188.48047     WITH    2 D.F.  P-VALUE=
0.00000
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.01061
|_test pov=0
TEST VALUE =  0.10616     STD. ERROR OF TEST VALUE  0.46288E-01
T STATISTIC =   2.2934869     WITH 7108 D.F.    P-VALUE= 0.02185
F STATISTIC =   5.2600821     WITH    1 AND 7108 D.F.  P-VALUE= 0.02185
WALD CHI-SQUARE STATISTIC =   5.2600821     WITH    1 D.F.  P-VALUE=
0.02182
UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.19011
```

Bottled Water

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   3.4700011     WITH    6 AND 5343 D.F.  P-VALUE= 0.00200
 WALD CHI-SQUARE STATISTIC =   20.820007     WITH    6 D.F.  P-VALUE=
0.00198
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.28818
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   4.3485429     WITH    2 AND 5343 D.F.  P-VALUE= 0.01297
 WALD CHI-SQUARE STATISTIC =   8.6970859     WITH    2 D.F.  P-VALUE=
0.01293
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.22996
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =  0.84647306     WITH    3 AND 5343 D.F.  P-VALUE= 0.46827
 WALD CHI-SQUARE STATISTIC =   2.5394192     WITH    3 D.F.  P-VALUE=
0.46821
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   10.296794     WITH    3 AND 5343 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   30.890381     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.09712
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   4.1555341     WITH    3 AND 5343 D.F.  P-VALUE= 0.00598
 WALD CHI-SQUARE STATISTIC =   12.466602     WITH    3 D.F.  P-VALUE=
0.00594
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.24064
 |_test hsp=0
 TEST VALUE = -0.11610     STD. ERROR OF TEST VALUE  0.91091E-01
 T STATISTIC =  -1.2745422     WITH 5343 D.F.    P-VALUE= 0.20253
 F STATISTIC =   1.6244577     WITH    1 AND 5343 D.F.  P-VALUE= 0.20253
 WALD CHI-SQUARE STATISTIC =   1.6244577     WITH    1 D.F.  P-VALUE=
0.20247
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.61559
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   1.6956167     WITH    7 AND 5343 D.F.  P-VALUE= 0.10520
 WALD CHI-SQUARE STATISTIC =   11.869317     WITH    7 D.F.  P-VALUE=
0.10494
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.58976
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   6.9518395     WITH    2 AND 5343 D.F.  P-VALUE= 0.00097
 WALD CHI-SQUARE STATISTIC =   13.903679     WITH    2 D.F.  P-VALUE=
0.00096
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.14385
 |_test pov=0
 TEST VALUE = -0.23774     STD. ERROR OF TEST VALUE  0.10583
 T STATISTIC =  -2.2464231     WITH 5343 D.F.    P-VALUE= 0.02472
 F STATISTIC =   5.0464168     WITH    1 AND 5343 D.F.  P-VALUE= 0.02472
 WALD CHI-SQUARE STATISTIC =   5.0464168     WITH    1 D.F.  P-VALUE=
0.02468
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.19816
```

Coffee

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   3.3910035     WITH    6 AND 5527 D.F.  P-VALUE= 0.00243
 WALD CHI-SQUARE STATISTIC =   20.346021     WITH    6 D.F.  P-VALUE=
0.00240
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.29490
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =  0.78569426     WITH    2 AND 5527 D.F.  P-VALUE= 0.45585
 WALD CHI-SQUARE STATISTIC =   1.5713885     WITH    2 D.F.  P-VALUE=
0.45580
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =   1.5101045     WITH    3 AND 5527 D.F.  P-VALUE= 0.20973
 WALD CHI-SQUARE STATISTIC =   4.5303136     WITH    3 D.F.  P-VALUE=
0.20960
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.66221
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   20.332302     WITH    3 AND 5527 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   60.996905     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.04918
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =  0.61059692     WITH    3 AND 5527 D.F.  P-VALUE= 0.60807
 WALD CHI-SQUARE STATISTIC =   1.8317908     WITH    3 D.F.  P-VALUE=
0.60804
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test hsp=0
 TEST VALUE = -0.25534     STD. ERROR OF TEST VALUE  0.62593E-01
 T STATISTIC =  -4.0793396     WITH 5527 D.F.    P-VALUE= 0.00005
 F STATISTIC =   16.641012     WITH    1 AND 5527 D.F.  P-VALUE= 0.00005
 WALD CHI-SQUARE STATISTIC =   16.641012     WITH    1 D.F.  P-VALUE=
0.00005
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.06009
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   1.3250983     WITH    7 AND 5527 D.F.  P-VALUE= 0.23371
 WALD CHI-SQUARE STATISTIC =   9.2756880     WITH    7 D.F.  P-VALUE=
0.23346
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.75466
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   13.125475     WITH    2 AND 5527 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   26.250950     WITH    2 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07619
 |_test pov=0
 TEST VALUE =  0.14871E-01 STD. ERROR OF TEST VALUE  0.44571E-01
 T STATISTIC =  0.33365354     WITH 5527 D.F.    P-VALUE= 0.73865
 F STATISTIC =  0.11132469     WITH    1 AND 5527 D.F.  P-VALUE= 0.73865
 WALD CHI-SQUARE STATISTIC =  0.11132469     WITH    1 D.F.  P-VALUE=
0.73864
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
```

Tea

```
|_**joint f-tests for demographic variables to see if they are
significantly affecting the dependent variable
 |_test
 |_test a2529=0
 |_test a3034=0
 |_test a3544=0
 |_test a4554=0
 |_test a5564=0
 |_test agt64=0
 |_end
 F STATISTIC =   2.8712918     WITH    6 AND 5507 D.F.  P-VALUE= 0.00855
 WALD CHI-SQUARE STATISTIC =   17.227751     WITH    6 D.F.  P-VALUE=
0.00848
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.34828
 |_test
 |_test eft=0
 |_test ept=0
 |_end
 F STATISTIC =   3.1206997     WITH    2 AND 5507 D.F.  P-VALUE= 0.04420
 WALD CHI-SQUARE STATISTIC =   6.2413994     WITH    2 D.F.  P-VALUE=
0.04413
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.32044
 |_test
 |_test eduhs=0
 |_test edupc=0
 |_test eduu=0
 |_end
 F STATISTIC =  0.32232685     WITH    3 AND 5507 D.F.  P-VALUE= 0.80924
 WALD CHI-SQUARE STATISTIC =  0.96698055     WITH    3 D.F.  P-VALUE=
0.80924
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 1.00000
 |_test
 |_test mw=0
 |_test s=0
 |_test w=0
 |_end
 F STATISTIC =   25.947947     WITH    3 AND 5507 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   77.843840     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.03854
 |_test
 |_test blk=0
 |_test asian=0
 |_test other=0
 |_end
 F STATISTIC =   9.2934140     WITH    3 AND 5507 D.F.  P-VALUE= 0.00000
 WALD CHI-SQUARE STATISTIC =   27.880242     WITH    3 D.F.  P-VALUE=
0.00000
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.10760
 |_test hsp=0
 TEST VALUE = -0.34972     STD. ERROR OF TEST VALUE  0.94170E-01
 T STATISTIC =  -3.7136954     WITH 5507 D.F.    P-VALUE= 0.00021
 F STATISTIC =   13.791533     WITH    1 AND 5507 D.F.  P-VALUE= 0.00021
 WALD CHI-SQUARE STATISTIC =   13.791533     WITH    1 D.F.  P-VALUE=
0.00020
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.07251
 |_test
```

```
 |_test ac1=0
 |_test ac2=0
 |_test ac3=0
 |_test ac4=0
 |_test ac5=0
 |_test ac6=0
 |_test ac7=0
 |_end
 F STATISTIC =   3.1813145     WITH    7 AND 5507 D.F.  P-VALUE= 0.00231
 WALD CHI-SQUARE STATISTIC =   22.269201     WITH    7 D.F.  P-VALUE=
0.00228
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.31434
 |_test
 |_test fh=0
 |_test mh=0
 |_end
 F STATISTIC =   11.138072     WITH    2 AND 5507 D.F.  P-VALUE= 0.00001
 WALD CHI-SQUARE STATISTIC =   22.276145     WITH    2 D.F.  P-VALUE=
0.00001
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.08978
 |_test pov=0
 TEST VALUE = -0.10242     STD. ERROR OF TEST VALUE  0.56793E-01
 T STATISTIC =  -1.8033388     WITH 5507 D.F.    P-VALUE= 0.07139
 F STATISTIC =   3.2520308     WITH    1 AND 5507 D.F.  P-VALUE= 0.07139
 WALD CHI-SQUARE STATISTIC =   3.2520308     WITH    1 D.F.  P-VALUE=
0.07134
 UPPER BOUND ON P-VALUE BY CHEBYCHEV INEQUALITY = 0.30750
```

APPENDIX 3

PROBIT AND HECKMAN MODEL REGRESSION RESULTS

The Abbreviations used are as follows:

a2529	age of household head between 25-29 years
a3034	age of household head between 30-34 years
a3544	age of household head between 35-44 years
a4554	age of household head between 45-54 years
a5564	age of household head between 55-64 years
agt64	age of household head above 64 years
eft	Employemnt status of household head: full-time employed
ept	Employemnt status of household head: part-time employed
eduhs	education level of household head: high-school educated
edupc	education level of household head: post-college educated
eduu	education level of household head: undergraduate education
mw	Midwest
s	South
w	West
blk	Black household
asian	Asian household
other	Other category (non-black, non-asian, non-white)
hsp	Hispanic houseshold head
ac1	Age and presence of children: less than 6 years of age
ac2	Age and presence of children: 6 to 12 years of age
ac3	Age and presence of children: 13 to 17 years of age
ac4	Age and presence of children: less than 6 years and 6 to 12 years of age
ac5	Age and presence of children: less than 6 years and 13 to 17 years of age
ac6	Age and presence of children: 6 to 12 years and 13 to 17 years of age
ac7	Age and presence of children: less than 6 years, 6 to 12 years and 13 to 17 years of age
fh	female only headed household
mh	male only headed household
pov	below 185% poverty status
p	price
p2	price squared

α	Estimated coefficient associated with inverse mills ratio
Z_bar	Predicted value of indicator variable at the sample means
f(Z_bar)	Calculated probability density *(pdf)* at sample means
F(Z_bar)	Calculated cumulative density *(cdf)* at sample means
λ_bar	Mean of inverse mills ratio evaluated at sample means
EST COF	estimated coefficient
ADJ COF	adjusted coefficient

Probit Estimation Results for Isotonics and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.336	0.067	5.027	0.093
P2	-0.037	0.010	-3.681	-0.010
A2529	-0.309	0.286	-1.081	-0.085
A3034	-0.425	0.277	-1.533	-0.117
A3544	-0.317	0.272	-1.164	-0.088
A4554	-0.471	0.272	-1.732	-0.130
A5564	-0.674	0.273	-2.470	-0.186
AGT64	-0.806	0.275	-2.933	-0.223
EFT	-0.104	0.044	-2.359	-0.029
EPT	-0.022	0.051	-0.426	-0.006
EDUHS	-0.054	0.095	-0.568	-0.015
EDUPC	-0.250	0.105	-2.376	-0.069
EDUU	-0.141	0.092	-1.531	-0.039
MW	0.106	0.055	1.935	0.029
S	0.204	0.046	4.451	0.056
W	0.131	0.053	2.453	0.036
BLK	-0.152	0.053	-2.871	-0.042
ASIAN	-0.174	0.101	-1.719	-0.048
OTHER	-0.169	0.084	-2.013	-0.047
HSP	0.265	0.073	3.649	0.073
AC1	0.272	0.089	3.058	0.075
AC2	0.347	0.069	5.025	0.096
AC3	0.384	0.063	6.122	0.106
AC4	0.313	0.097	3.235	0.086
AC5	0.537	0.203	2.643	0.148
AC6	0.338	0.080	4.229	0.093
AC7	0.398	0.158	2.516	0.110
FH	-0.224	0.043	-5.197	-0.062
MH	-0.198	0.062	-3.215	-0.055
POV	-0.085	0.054	-1.585	-0.024
CONSTANT	-0.818	0.303	-2.701	

LOG-LIKELIHOOD FUNCTION = -3680.5
LOG-LIKELIHOOD(0) = -3932.5
LIKELIHOOD RATIO TEST = 503.898 WITH 30 D.F. P-VALUE= 0.00000

ESTRELLA R-SQUARE 0.65900E-01
MADDALA R-SQUARE 0.63835E-01
CRAGG-UHLER R-SQUARE 0.99302E-01
MCFADDEN R-SQUARE 0.64069E-01

Probit Estimation Results for Regular Soft Drinks and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.018	0.050	0.358	0.002
P2	-0.014	0.006	-2.406	-0.002
A2529	0.584	0.433	1.350	0.075
A3034	0.579	0.405	1.429	0.075
A3544	0.278	0.393	0.708	0.036
A4554	0.131	0.391	0.335	0.017
A5564	0.080	0.391	0.204	0.010
AGT64	-0.179	0.393	-0.455	-0.023
EFT	-0.142	0.060	-2.386	-0.018
EPT	-0.009	0.070	-0.132	-0.001
EDUHS	0.001	0.130	0.010	0.000
EDUPC	-0.400	0.136	-2.943	-0.052
EDUU	-0.142	0.126	-1.128	-0.018
MW	0.102	0.067	1.520	0.013
S	0.113	0.057	1.978	0.015
W	0.063	0.064	0.976	0.008
BLK	0.308	0.071	4.325	0.040
ASIAN	-0.140	0.130	-1.075	-0.018
OTHER	0.069	0.120	0.579	0.009
HSP	0.203	0.118	1.726	0.026
AC1	0.096	0.148	0.647	0.012
AC2	0.416	0.130	3.205	0.054
AC3	0.801	0.144	5.550	0.104
AC4	0.271	0.201	1.351	0.035
AC5	5.138	1.9E+03	0.003	0.664
AC6	0.613	0.188	3.267	0.079
AC7	0.133	0.316	0.422	0.017
FH	-0.462	0.049	-9.354	-0.060
MH	-0.506	0.064	-7.866	-0.065
POV	-0.044	0.068	-0.641	-0.006
CONSTANT	1.522	0.416	3.663	

```
LOG-LIKELIHOOD FUNCTION =  -2133.5
 LOG-LIKELIHOOD(0)  =   -2380.9
 LIKELIHOOD RATIO TEST  =    494.757    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.66099E-01
 MADDALA R-SQUARE            0.62714E-01
 CRAGG-UHLER R-SQUARE        0.13520
 MCFADDEN R-SQUARE           0.10390
```

Probit Estimation Results for Diet Soft Drinks and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.052	0.040	1.286	0.019
P2	-0.015	0.005	-2.910	-0.005
A2529	0.032	0.287	0.110	0.012
A3034	0.163	0.278	0.585	0.060
A3544	0.377	0.274	1.372	0.138
A4554	0.277	0.274	1.012	0.102
A5564	0.386	0.274	1.407	0.141
AGT64	0.234	0.275	0.850	0.086
EFT	0.032	0.040	0.784	0.012
EPT	-0.017	0.047	-0.373	-0.006
EDUHS	0.073	0.084	0.871	0.027
EDUPC	0.193	0.093	2.070	0.071
EDUU	0.130	0.082	1.584	0.048
MW	0.097	0.049	1.999	0.036
S	-0.010	0.041	-0.245	-0.004
W	-0.009	0.047	-0.191	-0.003
BLK	-0.570	0.045	-12.686	-0.209
ASIAN	-0.510	0.090	-5.656	-0.187
OTHER	-0.184	0.076	-2.426	-0.068
HSP	-0.064	0.070	-0.918	-0.023
AC1	0.073	0.089	0.821	0.027
AC2	0.107	0.069	1.555	0.039
AC3	0.079	0.063	1.266	0.029
AC4	0.069	0.098	0.701	0.025
AC5	0.010	0.205	0.486	0.004
AC6	-0.072	0.080	-0.902	-0.026
AC7	0.156	0.165	0.948	0.057
FH	-0.207	0.037	-5.608	-0.076
MH	-0.533	0.052	-10.337	-0.196
POV	-0.239	0.047	-5.104	-0.088
CONSTANT	0.176	0.292	0.603	

```
LOG-LIKELIHOOD FUNCTION =  -4698.6
 LOG-LIKELIHOOD(0)  =   -4928.5
 LIKELIHOOD RATIO TEST  =    459.758    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.59773E-01
 MADDALA R-SQUARE            0.58410E-01
 CRAGG-UHLER R-SQUARE        0.80585E-01
 MCFADDEN R-SQUARE           0.46643E-01
```

Probit Estimation Results for High-Fat Milk and Associated Marginal Effects

VARIABLE	ESTIMATED	STANDARD	T- RATIO	
NAME	COEFFICIENT	ERROR		
P	-0.092	0.047	-1.968	-0.022
P2	0.003	0.006	0.535	0.001
A2529	-0.166	0.381	-0.435	-0.041
A3034	0.172	0.372	0.461	0.042
A3544	0.015	0.366	0.041	0.004
A4554	0.082	0.365	0.225	0.020
A5564	0.109	0.365	0.299	0.027
AGT64	-0.014	0.366	-0.038	-0.003
EFT	0.022	0.047	0.456	0.005
EPT	-0.017	0.055	-0.306	-0.004
EDUHS	-0.027	0.108	-0.250	-0.007
EDUPC	-0.457	0.114	-4.016	-0.112
EDUU	-0.235	0.105	-2.246	-0.058
MW	0.061	0.055	1.110	0.015
S	0.150	0.047	3.197	0.037
W	-0.042	0.053	-0.802	-0.010
BLK	0.151	0.055	2.749	0.037
ASIAN	-0.109	0.103	-1.064	-0.027
OTHER	0.130	0.095	1.365	0.032
HSP	0.167	0.088	1.904	0.041
AC1	1.090	0.168	6.475	0.267
AC2	0.436	0.088	4.928	0.107
AC3	0.358	0.078	4.591	0.088
AC4	0.592	0.139	4.242	0.145
AC5	0.374	0.277	1.347	0.092
AC6	0.326	0.101	3.241	0.080
AC7	0.479	0.235	2.039	0.117
FH	-0.217	0.042	-5.205	-0.053
MH	-0.289	0.056	-5.168	-0.071
POV	0.072	0.058	1.244	0.018
CONSTANT	1.181	0.387	3.055	

```
LOG-LIKELIHOOD FUNCTION =  -3374.1
 LOG-LIKELIHOOD(0)  =   -3573.5
 LIKELIHOOD RATIO TEST  =    398.908    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.52316E-01
 MADDALA R-SQUARE            0.50880E-01
 CRAGG-UHLER R-SQUARE        0.83732E-01
 MCFADDEN R-SQUARE           0.55815E-01
```

Probit Estimation Results for Low-Fat Milk and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.417	0.050	8.372	0.157
P2	-0.043	0.007	-6.087	-0.016
A2529	-0.044	0.291	-0.150	-0.017
A3034	-0.019	0.282	-0.066	-0.007
A3544	-0.046	0.278	-0.164	-0.017
A4554	-0.030	0.277	-0.108	-0.011
A5564	-0.003	0.278	-0.012	-0.001
AGT64	0.064	0.279	0.229	0.024
EFT	-0.118	0.040	-2.952	-0.044
EPT	-0.028	0.046	-0.593	-0.010
EDUHS	0.274	0.084	3.275	0.104
EDUPC	0.577	0.093	6.206	0.218
EDUU	0.403	0.081	4.953	0.152
MW	-0.078	0.048	-1.620	-0.029
S	-0.165	0.041	-4.042	-0.062
W	-0.224	0.047	-4.740	-0.085
BLK	-0.536	0.045	-11.897	-0.202
ASIAN	-0.211	0.091	-2.319	-0.080
OTHER	-0.278	0.075	-3.704	-0.105
HSP	-0.061	0.068	-0.895	-0.023
AC1	0.097	0.089	1.084	0.036
AC2	0.034	0.067	0.511	0.013
AC3	0.022	0.061	0.360	0.008
AC4	0.146	0.099	1.472	0.055
AC5	-0.034	0.202	-0.169	-0.013
AC6	0.113	0.080	1.425	0.043
AC7	-0.071	0.156	-0.457	-0.027
FH	-0.166	0.037	-4.514	-0.063
MH	-0.345	0.052	-6.674	-0.130
POV	-0.227	0.047	-4.876	-0.086
CONSTANT	-0.385	0.298	-1.293	

```
LOG-LIKELIHOOD FUNCTION =  -4812.6
 LOG-LIKELIHOOD(0)  =   -5054.9
 LIKELIHOOD RATIO TEST  =    484.592    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE            0.62939E-01
 MADDALA R-SQUARE             0.61466E-01
 CRAGG-UHLER R-SQUARE         0.83766E-01
 MCFADDEN R-SQUARE            0.47933E-01
```

Probit Estimation Results for Fruit Drinks and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.157	0.044	3.589	0.044
P2	-0.014	0.005	-2.563	-0.004
A2529	-0.407	0.422	-0.964	-0.115
A3034	-0.409	0.412	-0.993	-0.116
A3544	-0.393	0.406	-0.968	-0.111
A4554	-0.462	0.405	-1.140	-0.131
A5564	-0.632	0.405	-1.559	-0.179
AGT64	-0.876	0.406	-2.157	-0.248
EFT	-0.025	0.046	-0.540	-0.007
EPT	0.067	0.053	1.261	0.019
EDUHS	0.026	0.096	0.275	0.007
EDUPC	-0.201	0.104	-1.937	-0.057
EDUU	-0.094	0.093	-1.012	-0.027
MW	0.089	0.053	1.680	0.025
S	0.052	0.045	1.138	0.015
W	-0.004	0.052	-0.696	-0.001
BLK	0.587	0.059	9.965	0.166
ASIAN	0.158	0.111	1.430	0.045
OTHER	0.267	0.094	2.844	0.076
HSP	0.070	0.085	0.825	0.020
AC1	0.469	0.114	4.128	0.133
AC2	0.881	0.107	8.263	0.250
AC3	0.708	0.086	8.256	0.201
AC4	1.131	0.193	5.858	0.321
AC5	1.094	0.434	2.522	0.310
AC6	0.946	0.134	7.079	0.268
AC7	1.025	0.307	3.337	0.291
FH	-0.238	0.040	-5.986	-0.067
MH	-0.448	0.054	-8.380	-0.127
POV	-0.013	0.054	-0.249	-0.004
CONSTANT	0.935	0.420	2.226	

LOG-LIKELIHOOD FUNCTION = -3735.8
LOG-LIKELIHOOD(0) = -4228.8
LIKELIHOOD RATIO TEST = 986.022 WITH 30 D.F. P-VALUE= 0.00000

ESTRELLA R-SQUARE 0.12824
MADDALA R-SQUARE 0.12109
CRAGG-UHLER R-SQUARE 0.18087
MCFADDEN R-SQUARE 0.11658

Probit Estimation Results for Fruit Juices and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	**0.470**	**0.057**	**8.250**	0.044
P2	-0.032	0.007	-4.843	-0.003
A2529	-5.527	4.E+03	-0.001	-0.518
A3034	-5.441	4.E+03	-0.001	-0.510
A3544	-5.486	4.E+03	-0.001	-0.515
A4554	-5.427	4.E+03	-0.001	-0.509
A5564	-5.381	4.E+03	-0.001	-0.505
AGT64	-5.283	4.E+03	-0.001	-0.496
EFT	-0.075	0.064	-1.171	-0.007
EPT	0.096	0.077	1.239	0.009
EDUHS	0.041	0.126	0.322	0.004
EDUPC	0.133	0.141	0.943	0.012
EDUU	0.125	0.123	1.017	0.012
MW	-0.123	0.078	-1.576	-0.012
S	-0.147	0.068	-2.149	-0.014
W	-0.384	0.075	-5.137	-0.036
BLK	0.474	0.089	5.351	0.044
ASIAN	0.065	0.153	0.423	0.006
OTHER	-0.022	0.121	-0.178	-0.002
HSP	0.114	0.118	0.961	0.011
AC1	1.089	0.345	3.153	0.102
AC2	0.215	0.118	1.821	0.020
AC3	0.270	0.109	2.487	0.025
AC4	0.606	0.242	2.508	0.057
AC5	5.411	4.E+03	0.002	0.508
AC6	0.287	0.142	2.021	0.027
AC7	0.694	0.412	1.684	0.065
FH	-0.366	0.056	-6.515	-0.034
MH	-0.605	0.071	-8.555	-0.057
POV	-0.245	0.068	-3.593	-0.023
CONSTANT	6.227	4.E+03	0.001	

```
LOG-LIKELIHOOD FUNCTION =  -1672.3
 LOG-LIKELIHOOD(0)  =   -1846.5
 LIKELIHOOD RATIO TEST  =    348.442    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.46782E-01
 MADDALA R-SQUARE            0.44589E-01
 CRAGG-UHLER R-SQUARE        0.11632
 MCFADDEN R-SQUARE           0.94353E-01
```

Probit Estimation Results for Bottled Water and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.174	0.042	4.197	0.059
P2	-0.018	0.005	-3.507	-0.006
A2529	-0.095	3.E-01	-0.295	-0.032
A3034	0.065	3.E-01	0.210	0.022
A3544	-0.046	3.E-01	-0.150	-0.016
A4554	-0.148	3.E-01	-0.482	-0.050
A5564	-0.258	3.E-01	-0.843	-0.088
AGT64	-0.551	3.E-01	-1.794	-0.187
EFT	0.082	0.042	1.968	0.028
EPT	0.095	0.048	1.977	0.032
EDUHS	-0.099	0.088	-1.125	-0.034
EDUPC	-0.176	0.097	-1.823	-0.060
EDUU	-0.098	0.086	-1.139	-0.033
MW	-0.084	0.049	-1.721	-0.029
S	-0.056	0.042	-1.321	-0.019
W	0.076	0.049	1.540	0.026
BLK	0.194	0.049	3.958	0.066
ASIAN	0.061	0.100	0.609	0.021
OTHER	0.194	0.085	2.287	0.066
HSP	0.170	0.077	2.215	0.058
AC1	0.019	0.094	0.202	0.006
AC2	0.113	0.074	1.526	0.038
AC3	0.098	0.066	1.488	0.033
AC4	0.075	0.106	0.710	0.026
AC5	0.219	2.E-01	0.923	0.075
AC6	0.165	0.088	1.878	0.056
AC7	0.360	0.189	1.901	0.122
FH	-0.026	0.038	-0.674	-0.009
MH	-0.504	0.052	-9.666	-0.171
POV	-0.303	0.048	-6.334	-0.103
CONSTANT	0.567	3.E-01	1.758	

LOG-LIKELIHOOD FUNCTION = -4385.2
LOG-LIKELIHOOD(0) = -4643.5
LIKELIHOOD RATIO TEST = 516.661 WITH 30 D.F. P-VALUE= 0.00000

ESTRELLA R-SQUARE 0.67223E-01
MADDALA R-SQUARE 0.65398E-01
CRAGG-UHLER R-SQUARE 0.92960E-01
MCFADDEN R-SQUARE 0.55632E-01

Probit Estimation Results for Coffee and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	-0.571	0.049	-11.560	-0.180
P2	0.029	7.E-03	4.405	0.009
A2529	0.071	3.E-01	0.237	0.023
A3034	-0.051	3.E-01	-0.174	-0.016
A3544	0.313	3.E-01	1.086	0.099
A4554	0.448	3.E-01	1.558	0.141
A5564	0.637	3.E-01	2.214	0.201
AGT64	0.821	0.290	2.834	0.260
EFT	-0.031	0.044	-0.698	-0.010
EPT	-0.043	0.051	-0.841	-0.013
EDUHS	-0.132	0.101	-1.302	-0.042
EDUPC	-0.200	0.109	-1.844	-0.063
EDUU	-0.175	0.099	-1.776	-0.055
MW	-0.247	0.052	-4.732	-0.078
S	-0.002	0.045	-0.046	-0.001
W	-0.201	0.051	-3.947	-0.063
BLK	-0.401	0.047	-8.558	-0.127
ASIAN	-0.095	0.096	-0.990	-0.030
OTHER	-0.124	0.082	-1.504	-0.039
HSP	0.184	0.077	2.399	0.058
AC1	-0.024	0.090	-0.271	-0.008
AC2	0.023	0.071	0.321	0.007
AC3	-0.072	0.064	-1.121	-0.023
AC4	0.055	1.E-01	0.549	0.017
AC5	-0.109	0.212	-0.515	-0.035
AC6	-0.163	0.081	-2.008	-0.052
AC7	0.122	0.172	0.710	0.039
FH	-0.355	0.040	-8.899	-0.112
MH	-0.618	0.054	-11.423	-0.195
POV	-0.177	5.E-02	-3.459	-0.056
CONSTANT	1.902	0.312	6.094	

```
LOG-LIKELIHOOD FUNCTION =  -3921.5
 LOG-LIKELIHOOD(0)  =   -4473.8
 LIKELIHOOD RATIO TEST  =    1104.45    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.14300
 MADDALA R-SQUARE            0.13461
 CRAGG-UHLER R-SQUARE        0.19508
 MCFADDEN R-SQUARE           0.12344
```

Probit Estimation Results for Tea and Associated Marginal Effects

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO	MARGINAL EFFECT
P	0.035	0.044	0.795	0.012
P2	-0.005	0.006	-0.874	-0.002
A2529	0.235	0.294	0.799	0.077
A3034	0.279	0.284	0.981	0.092
A3544	0.380	0.280	1.357	0.125
A4554	0.421	0.279	1.507	0.138
A5564	0.335	0.280	1.199	0.110
AGT64	0.270	0.281	0.962	0.089
EFT	-0.163	0.042	-3.874	-0.054
EPT	-0.011	0.049	-0.231	-0.004
EDUHS	0.125	0.088	1.425	0.041
EDUPC	0.147	0.096	1.531	0.048
EDUU	0.168	0.085	1.976	0.055
MW	-0.525	0.050	-10.419	-0.173
S	-0.221	0.045	-4.952	-0.073
W	-0.468	0.050	-9.381	-0.154
BLK	0.041	0.048	0.856	0.014
ASIAN	-0.177	0.092	-1.914	-0.058
OTHER	0.105	0.080	1.312	0.035
HSP	-0.107	0.072	-1.485	-0.035
AC1	0.082	0.093	0.873	0.027
AC2	-0.032	0.070	-0.458	-0.011
AC3	0.077	0.066	1.169	0.025
AC4	-0.103	0.101	-1.026	-0.034
AC5	0.176	0.235	0.752	0.058
AC6	0.017	0.084	0.204	0.006
AC7	0.219	0.184	1.194	0.072
FH	-0.157	0.038	-4.090	-0.052
MH	-0.563	0.052	-10.833	-0.185
POV	-0.049	0.049	-0.992	-0.016
CONSTANT	0.533	0.300	1.778	

```
LOG-LIKELIHOOD FUNCTION =  -4317.8
 LOG-LIKELIHOOD(0)  =   -4493.3
 LIKELIHOOD RATIO TEST  =    351.070    WITH    30  D.F.   P-VALUE=
0.00000

 ESTRELLA R-SQUARE           0.45797E-01
 MADDALA R-SQUARE            0.44917E-01
 CRAGG-UHLER R-SQUARE        0.64946E-01
 MCFADDEN R-SQUARE           0.39066E-01
```

Heckman Two-Step Regression Results for Isotonics

```
R-SQUARE =   0.0716     R-SQUARE ADJUSTED =   0.0540
VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.3403
STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.1577
SUM OF SQUARED ERRORS-SSE=   2114.9
MEAN OF DEPENDENT VARIABLE =  0.34174
LOG OF THE LIKELIHOOD FUNCTION = -2503.03

SCHWARZ (1978) CRITERION - SC =                  1.5154
AKAIKE (1974) INFORMATION CRITERION - AIC =       1.3661

DURBIN-WATSON = 1.9075    VON NEUMANN RATIO = 1.9087    RHO =  0.04623
RESIDUAL SUM = -0.21388E-10  RESIDUAL VARIANCE =   1.3403
SUM OF ABSOLUTE ERRORS=   1493.9
```

VARIABLE NAME	**ESTIMATED COEFFICIENT**	**STANDARD ERROR**	**T-RATIO**	**P-VALUE**
LP_ISO[48]	-0.52701	0.1261	-4.179	0.000
A2529	0.26220	0.4254	0.6164	0.538
A3034	0.52465	0.4202	1.249	0.212
A3544	0.43384	0.4041	1.073	0.283
A4554	0.80517	0.4168	1.932	0.054
A5564	1.2231	0.4460	2.742	0.006
AGT64	1.3324	0.4685	2.844	0.005
EFT	0.28764	0.7932E-01	3.626	0.000
EPT	0.67142E-01	0.8626E-01	0.7784	0.436
EDUHS	0.43216E-01	0.1632	0.2648	0.791
EDUPC	0.32373	0.1921	1.685	0.092
EDUU	0.14409	0.1613	0.8932	0.372
MW	-0.31927	0.1002	-3.185	0.001
S	-0.55323	0.1002	-5.522	0.000
W	-0.33193	0.1041	-3.188	0.001
BLK	0.89549E-01	0.1061	0.8441	0.399
ASIAN	0.42602	0.1811	2.352	0.019
OTHER	0.32644	0.1527	2.138	0.033
HSP	-0.50990	0.1437	-3.549	0.000
AC1	-0.45887	0.1619	-2.835	0.005
AC2	-0.65636	0.1485	-4.420	0.000
AC3	-0.45891	0.1532	-2.996	0.003
AC4	-0.69818	0.1742	-4.008	0.000
AC5	-0.50144	0.3306	-1.517	0.130
AC6	-0.46792	0.1569	-2.983	0.003
AC7	-0.38124	0.2580	-1.478	0.140
FH	0.24330	0.1062	2.291	0.022
MH	0.58939	0.1281	4.603	0.000
POV	0.97676E-01	0.9863E-01	0.9903	0.322
IMR_ISO[49]	-2.6678	0.3928	-6.791	0.000
CONSTANT	3.9847	0.6059	6.576	0.000

[48] LP_ISO=log price of isotonics
[49] IMR_ISO=inverse mills ratio for isotonics

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Isotonics

Isotonics						
		Probit		**Volume**		
VARIABLE	**SAMPLE**	**EST**		**EST**	**ADJ**	
NAME	**MEANS**	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		β		
P	2.439	0.336	0.819			
P2	6.692	-0.037	-0.247			
A2529	0.024	-0.309	-0.007	0.262	-0.361	-30.3%
A3034	0.062	-0.425	-0.026	0.525	-0.331	-28.2%
A3544	0.212	-0.317	-0.067	0.434	-0.205	-18.6%
A4554	0.276	-0.471	-0.130	**0.805**	-0.145	**-13.5%**
A5564	0.232	-0.674	-0.157	**1.223**	-0.135	**-12.7%**
AGT64	0.191	-0.806	-0.154	**1.332**	-0.292	**-25.3%**
EFT	0.454	-0.104	-0.047	**0.288**	0.078	**8.1%**
EPT	0.164	-0.022	-0.004	0.067	0.023	2.4%
EDUHS	0.242	-0.054	-0.013	0.043	-0.065	-6.3%
EDUPC	0.110	-0.250	-0.027	0.324	-0.180	-16.4%
EDUU	0.613	-0.141	-0.086	0.144	-0.140	-13.1%
MW	0.186	0.106	0.020	**-0.319**	-0.106	**-10.1%**
S	0.389	0.204	0.079	**-0.553**	-0.141	**-13.2%**
W	0.212	0.131	0.028	**-0.332**	-0.068	**-6.5%**
BLK	0.130	-0.152	-0.020	0.090	-0.216	-19.4%
ASIAN	0.029	-0.174	-0.005	**0.426**	0.076	**7.9%**
OTHER	0.064	-0.169	-0.011	**0.326**	-0.014	**-1.4%**
HSP	0.080	0.265	0.021	**-0.510**	0.024	**2.4%**
AC1	0.035	0.272	0.010	**-0.459**	0.089	**9.3%**
AC2	0.061	0.347	0.021	**-0.656**	0.042	**4.3%**
AC3	0.072	0.384	0.028	**-0.459**	0.316	**37.2%**
AC4	0.029	0.313	0.009	**-0.698**	-0.067	**-6.5%**
AC5	0.005	0.537	0.003	-0.501	0.582	78.9%
AC6	0.044	0.338	0.015	**-0.468**	0.213	**23.8%**
AC7	0.009	0.398	0.004	-0.381	0.422	52.5%
FH	0.276	-0.224	-0.062	**0.243**	-0.209	**-18.9%**
MH	0.106	-0.198	-0.021	**0.589**	0.190	**20.9%**
POV	0.134	-0.085	-0.011	0.098	-0.075	-7.2%
CONSTANT		-0.818		**3.985**	2.336	
α	**-2.668**					
Z_bar	-0.857					
f(Z_bar)	0.276					
F(Z_bar)	0.198					
λ_bar	1.398					

Heckman Two-Step Regression Results for Regular Soft Drinks

```
R-SQUARE =   0.1606     R-SQUARE ADJUSTED =   0.1569
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.7874
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.3369
 SUM OF SQUARED ERRORS-SSE=   12315.
 MEAN OF DEPENDENT VARIABLE =   2.4664
 LOG OF THE LIKELIHOOD FUNCTION = -11814.7

  SCHWARZ (1978) CRITERION - SC =                     1.8513
  AKAIKE (1974) INFORMATION CRITERION - AIC =         1.7954

DURBIN-WATSON = 2.0059    VON NEUMANN RATIO = 2.0062    RHO = -0.00307
 RESIDUAL SUM =  0.11814E-09  RESIDUAL VARIANCE =   1.7874
 SUM OF ABSOLUTE ERRORS=   7414.2
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 6890 DF	P-VALUE
LP_RSD[50]	-0.83976	0.5017E-01	-16.74	0.000
A2529	-0.71148	0.3190	-2.230	0.026
A3034	-0.52459	0.3098	-1.693	0.090
A3544	-0.53978	0.3038	-1.777	0.076
A4554	-0.50390	0.3026	-1.665	0.096
A5564	-0.66217	0.3028	-2.187	0.029
AGT64	-0.94682	0.3048	-3.106	0.002
EFT	0.72757E-01	0.4404E-01	1.652	0.099
EPT	0.72813E-01	0.4944E-01	1.473	0.141
EDUHS	-0.12854	0.9143E-01	-1.406	0.160
EDUPC	-0.67201	0.1102	-6.100	0.000
EDUU	-0.45721	0.9006E-01	-5.076	0.000
MW	0.23070	0.5219E-01	4.421	0.000
S	0.20939	0.4489E-01	4.665	0.000
W	0.10418	0.5132E-01	2.030	0.042
BLK	0.96288E-01	0.5671E-01	1.698	0.090
ASIAN	-0.26992	0.1004	-2.688	0.007
OTHER	0.24774	0.8139E-01	3.044	0.002
HSP	-0.10330	0.7446E-01	-1.387	0.165
AC1	0.19957	0.9212E-01	2.166	0.030
AC2	0.27912	0.7569E-01	3.688	0.000
AC3	0.57245	0.7939E-01	7.211	0.000
AC4	0.33699	0.1010	3.335	0.001
AC5	0.39335	0.2168	1.814	0.070
AC6	0.58499	0.8848E-01	6.611	0.000
AC7	0.66778	0.1670	3.998	0.000
FH	-0.30035	0.6346E-01	-4.733	0.000
MH	-0.20124	0.8434E-01	-2.386	0.017
POV	0.14379	0.5110E-01	2.814	0.005
IMR_RSD[51]	-0.71657	0.3905	-1.835	0.067
CONSTANT	4.1232	0.3208	12.85	0.000

[50] LP_RSD=log price of regular soft drinks
[51] IMR_RSD=inverse mills ratio for regular soft drinks

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Regular Soft Drinks

Regular Soft Drinks						
		Probit		Volume		
VARIABLE	**SAMPLE**	**EST**	**MEANS*γ**	**EST**	**ADJ**	
NAME	**MEANS**	**COEF**		**COEF**	**COEF**	**% CHANGE**
		γ		β		
P	2.439	0.018	0.044			
P2	6.692	-0.014	-0.094			
A2529	0.024	0.584	0.014	**-0.711**	-0.616	**-50.9%**
A3034	0.062	0.579	0.036	-0.525	-0.430	-40.8%
A3544	0.212	0.278	0.059	-0.540	-0.495	-41.7%
A4554	0.276	0.131	0.036	-0.504	-0.483	-39.6%
A5564	0.232	0.080	0.019	**-0.662**	-0.649	**-48.4%**
AGT64	0.191	-0.179	-0.034	**-0.947**	-0.976	**-61.2%**
EFT	0.454	-0.142	-0.065	0.073	0.050	7.5%
EPT	0.164	-0.009	-0.002	0.073	0.071	7.6%
EDUHS	0.242	0.001	0.000	-0.129	-0.128	-12.1%
EDUPC	0.110	-0.400	-0.044	**-0.672**	-0.737	**-48.9%**
EDUU	0.613	-0.142	-0.087	**-0.457**	-0.480	**-36.7%**
MW	0.186	0.102	0.019	**0.231**	0.247	**25.9%**
S	0.389	0.113	0.044	**0.209**	0.228	**23.3%**
W	0.212	0.063	0.013	**0.104**	0.114	**11.0%**
BLK	0.130	0.308	0.040	0.096	0.146	10.1%
ASIAN	0.029	-0.140	-0.004	**-0.270**	-0.293	**-23.7%**
OTHER	0.064	0.069	0.004	**0.248**	0.259	**28.1%**
HSP	0.080	0.203	0.016	-0.103	-0.070	-9.8%
AC1	0.035	0.096	0.003	**0.200**	0.215	**22.1%**
AC2	0.061	0.416	0.025	**0.279**	0.347	**32.2%**
AC3	0.072	0.801	0.057	**0.572**	0.703	**77.3%**
AC4	0.029	0.271	0.008	**0.337**	0.381	**40.1%**
AC5	0.005	5.138	0.028	0.393	1.230	48.2%
AC6	0.044	0.613	0.027	**0.585**	0.685	**79.5%**
AC7	0.009	0.133	0.001	**0.668**	0.689	**95.0%**
FH	0.276	-0.462	-0.127	**-0.300**	-0.375	**-25.9%**
MH	0.106	-0.506	-0.054	**-0.201**	-0.284	**-18.2%**
POV	0.134	-0.044	-0.006	**0.144**	0.137	**15.5%**
CONSTANT		1.522		**4.123**		
α	-0.717	**(NS)**				
Z_bar	1.501					
f(Z_bar)	0.129					
F(Z_bar)	0.933					
λ_bar	0.139					

Heckman Two-Step Regression Results for Diet Soft Drinks

```
R-SQUARE =   0.0751     R-SQUARE ADJUSTED =   0.0695
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   2.5256
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.5892
 SUM OF SQUARED ERRORS-SSE=   12532.
 MEAN OF DEPENDENT VARIABLE =   2.2229
 LOG OF THE LIKELIHOOD FUNCTION = -9382.20

  SCHWARZ (1978) CRITERION - SC =                   2.6462
  AKAIKE (1974) INFORMATION CRITERION - AIC =       2.5413

DURBIN-WATSON = 1.9694    VON NEUMANN RATIO = 1.9698    RHO =  0.01507
 RESIDUAL SUM =  0.15185E-10  RESIDUAL VARIANCE =   2.5256
 SUM OF ABSOLUTE ERRORS=   6595.6
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 4962 DF	P-VALUE
LP_DSD[52]	-0.76248	0.6670E-01	-11.43	0.000
A2529	-0.68203E-01	0.4859	-0.1404	0.888
A3034	0.54984	0.4727	1.163	0.245
A3544	0.56524	0.4765	1.186	0.236
A4554	0.56695	0.4708	1.204	0.229
A5564	0.66369	0.4772	1.391	0.164
AGT64	0.17023	0.4708	0.3616	0.718
EFT	-0.23188E-01	0.6115E-01	-0.3792	0.705
EPT	-0.57637E-01	0.6985E-01	-0.8251	0.409
EDUHS	0.29079E-01	0.1380	0.2108	0.833
EDUPC	-0.91420E-01	0.1565	-0.5841	0.559
EDUU	0.56619E-02	0.1376	0.4115E-01	0.967
MW	0.26430	0.7593E-01	3.481	0.001
S	0.22448	0.6114E-01	3.672	0.000
W	0.23971	0.7185E-01	3.336	0.001
BLK	-0.64898	0.1944	-3.339	0.001
ASIAN	-0.54076	0.2205	-2.453	0.014
OTHER	-0.33310	0.1305	-2.552	0.011
HSP	-0.40086E-01	0.1080	-0.3710	0.711
AC1	0.20868E-01	0.1325	0.1576	0.875
AC2	-0.15609	0.1042	-1.498	0.134
AC3	-0.16689	0.9346E-01	-1.786	0.074
AC4	-0.80580E-01	0.1453	-0.5544	0.579
AC5	-0.22368	0.3169	-0.7059	0.480
AC6	-0.26378	0.1208	-2.183	0.029
AC7	-0.28815	0.2374	-1.214	0.225
FH	-0.28532	0.8187E-01	-3.485	0.000
MH	-0.82248E-01	0.1874	-0.4388	0.661
POV	-0.17400	0.1057	-1.646	0.100
IMR_DSD[53]	-0.17620	0.5421	-0.3250	0.745
CONSTANT	2.5816	0.5964	4.329	0.000

[52] LP_DSD=log price of diet soft drinks
[53] IMR_DSD=inverse mills ratio for diet soft drinks

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Diet Soft Drinks

Diet Soft Drinks						
		Probit		**Volume**		
VARIABLE	**SAMPLE**	**EST**		**EST**	**ADJ**	
NAME	**MEANS**	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		β		
P	2.439	0.052	0.126			
P2	6.692	-0.015	-0.099			
A2529	0.024	0.032	0.001	-0.068	-0.063	-6.6%
A3034	0.062	0.163	0.010	0.550	0.576	73.3%
A3544	0.212	0.377	0.080	0.565	0.627	76.0%
A4554	0.276	0.277	0.076	0.567	0.612	76.3%
A5564	0.232	0.386	0.090	0.664	0.726	94.2%
AGT64	0.191	0.234	0.045	0.170	0.208	18.6%
EFT	0.454	0.032	0.014	-0.023	-0.018	-2.3%
EPT	0.164	-0.017	-0.003	-0.058	-0.060	-5.6%
EDUHS	0.242	0.073	0.018	0.029	0.041	3.0%
EDUPC	0.110	0.193	0.021	-0.091	-0.060	-8.7%
EDUU	0.613	0.130	0.080	0.006	0.027	0.6%
MW	0.186	0.097	0.018	**0.264**	0.280	**30.3%**
S	0.389	-0.010	-0.004	**0.224**	0.223	**25.2%**
W	0.212	-0.009	-0.002	**0.240**	0.238	**27.1%**
BLK	0.130	-0.570	-0.074	**-0.649**	-0.742	**-47.7%**
ASIAN	0.029	-0.510	-0.015	**-0.541**	-0.624	**-41.8%**
OTHER	0.064	-0.184	-0.012	**-0.333**	-0.363	**-28.3%**
HSP	0.080	-0.064	-0.005	-0.040	-0.050	-3.9%
AC1	0.035	0.073	0.003	0.021	0.033	2.1%
AC2	0.061	0.107	0.007	-0.156	-0.139	-14.5%
AC3	0.072	0.079	0.006	-0.167	-0.154	-15.4%
AC4	0.029	0.069	0.002	-0.081	-0.069	-7.7%
AC5	0.005	0.010	0.000	-0.224	-0.222	-20.0%
AC6	0.044	-0.072	-0.003	**-0.264**	-0.275	**-23.2%**
AC7	0.009	0.156	0.001	-0.288	-0.263	-25.0%
FH	0.276	-0.207	-0.057	**-0.285**	-0.319	**-24.8%**
MH	0.106	-0.533	-0.056	-0.082	-0.169	-7.9%
POV	0.134	-0.239	-0.032	-0.174	-0.213	-16.0%
CONSTANT		0.176		2.582		
α	-0.176	**(NS)**				
Z_bar	0.411					
f(Z_bar)	0.367					
F(Z_bar)	0.659					
λ_bar	0.556					

Heckman Two-Step Regression Results for High-Fat Milk

```
R-SQUARE =   0.3094     R-SQUARE ADJUSTED =   0.3061
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.7132
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.3089
 SUM OF SQUARED ERRORS-SSE=   10709.
 MEAN OF DEPENDENT VARIABLE =   1.9692
 LOG OF THE LIKELIHOOD FUNCTION = -10589.3


  SCHWARZ (1978) CRITERION - SC =                     1.7799
  AKAIKE (1974) INFORMATION CRITERION - AIC =         1.7217

 DURBIN-WATSON = 1.9804    VON NEUMANN RATIO = 1.9807    RHO =  0.00969
 RESIDUAL SUM =  0.46102E-10  RESIDUAL VARIANCE =   1.7132
 SUM OF ABSOLUTE ERRORS=   6664.0
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 6251 DF	P-VALUE
LP_HFM[54]	-2.1899	0.5559E-01	-39.40	0.000
A2529	-0.17117	0.3208	-0.5335	0.594
A3034	0.12646	0.3101	0.4078	0.683
A3544	-0.30221E-01	0.3048	-0.9915E-01	0.921
A4554	0.33792E-01	0.3049	0.1108	0.912
A5564	-0.67593E-01	0.3058	-0.2210	0.825
AGT64	-0.10777	0.3061	-0.3520	0.725
EFT	-0.42366E-01	0.4381E-01	-0.9671	0.334
EPT	-0.24474E-01	0.5102E-01	-0.4797	0.631
EDUHS	-0.13040	0.9212E-01	-1.416	0.157
EDUPC	-0.79608	0.1460	-5.452	0.000
EDUU	-0.41596	0.1013	-4.106	0.000
MW	0.66278E-01	0.5503E-01	1.204	0.228
S	0.54682	0.5439E-01	10.05	0.000
W	0.30308	0.5492E-01	5.518	0.000
BLK	0.37929E-02	0.5991E-01	0.6331E-01	0.950
ASIAN	-0.12245	0.1080	-1.134	0.257
OTHER	0.16530	0.8583E-01	1.926	0.054
HSP	0.70349E-01	0.8054E-01	0.8734	0.382
AC1	1.1104	0.1778	6.245	0.000
AC2	0.56025	0.1092	5.128	0.000
AC3	0.66469	0.9523E-01	6.980	0.000
AC4	0.90712	0.1419	6.394	0.000
AC5	1.1500	0.2299	5.001	0.000
AC6	0.78345	0.1059	7.398	0.000
AC7	1.2117	0.1859	6.516	0.000
FH	-0.44806	0.6445E-01	-6.952	0.000
MH	-0.40452	0.9636E-01	-4.198	0.000
POV	0.20603	0.5404E-01	3.813	0.000
IMR_HFM[55]	1.5371	0.5711	2.692	0.007
CONSTANT	4.0684	0.3560	11.43	0.000

[54] LP_HFM=log price of high-fat milk
[55] IMR_HFM=inverse mills ratio for high-fat milk

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: High-Fat Milk

High Fat Milk						
		Probit		**Volume**		
VARIABLE	**SAMPLE**	**EST**		**EST**	**ADJ**	
NAME	**MEANS**	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		β		
P	2.439	-0.092	-0.224			
P2	6.692	0.003	0.021			
A2529	0.024	-0.166	-0.004	-0.171	-0.076	-7.3%
A3034	0.062	0.172	0.011	0.126	0.027	2.8%
A3544	0.212	0.015	0.003	-0.030	-0.039	-3.8%
A4554	0.276	0.082	0.023	0.034	-0.013	-1.3%
A5564	0.232	0.109	0.025	-0.068	-0.130	-12.2%
AGT64	0.191	-0.014	-0.003	-0.108	-0.100	-9.5%
EFT	0.454	0.022	0.010	-0.042	-0.055	-5.3%
EPT	0.164	-0.017	-0.003	-0.024	-0.015	-1.5%
EDUHS	0.242	-0.027	-0.007	-0.130	-0.115	-10.9%
EDUPC	0.110	-0.457	-0.050	**-0.796**	-0.533	**-41.3%**
EDUU	0.613	-0.235	-0.144	**-0.416**	-0.281	**-24.5%**
MW	0.186	0.061	0.011	0.066	0.031	3.2%
S	0.389	0.150	0.058	**0.547**	0.460	**58.4%**
W	0.212	-0.042	-0.009	**0.303**	0.327	**38.7%**
BLK	0.130	0.151	0.020	0.004	-0.083	-8.0%
ASIAN	0.029	-0.109	-0.003	-0.122	-0.059	-5.8%
OTHER	0.064	0.130	0.008	0.165	0.090	9.5%
HSP	0.080	0.167	0.013	0.070	-0.026	-2.6%
AC1	0.035	1.090	0.039	**1.110**	0.482	**62.0%**
AC2	0.061	0.436	0.027	**0.560**	0.309	**36.2%**
AC3	0.072	0.358	0.026	**0.665**	0.458	**58.1%**
AC4	0.029	0.592	0.017	**0.907**	0.566	**76.2%**
AC5	0.005	0.374	0.002	**1.150**	0.935	**154.6%**
AC6	0.044	0.326	0.014	**0.783**	0.596	**81.4%**
AC7	0.009	0.479	0.005	**1.212**	0.935	**154.8%**
FH	0.276	-0.217	-0.060	**-0.448**	-0.323	**-27.6%**
MH	0.106	-0.289	-0.031	**-0.405**	-0.238	**-21.2%**
POV	0.134	0.072	0.010	**0.206**	0.165	**17.9%**
CONSTANT		1.181				
α	1.537					
Z_bar	0.988					
f(Z_bar)	0.245					
F(Z_bar)	0.837					
λ_bar	0.293					

Heckman Two-Step Regression Results for Low-Fat Milk

```
R-SQUARE =   0.2666     R-SQUARE ADJUSTED =   0.2620
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.9178
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.3849
 SUM OF SQUARED ERRORS-SSE=   9092.5
 MEAN OF DEPENDENT VARIABLE =   1.7691
 LOG OF THE LIKELIHOOD FUNCTION = -8309.38

  SCHWARZ (1978) CRITERION - SC =                    2.0132
  AKAIKE (1974) INFORMATION CRITERION - AIC =        1.9303

DURBIN-WATSON = 2.0102    VON NEUMANN RATIO = 2.0106    RHO = -0.00543
 RESIDUAL SUM = -0.43310E-12  RESIDUAL VARIANCE =   1.9178
 SUM OF ABSOLUTE ERRORS=   5452.2
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 4741 DF	P-VALUE
LP_LFM[56]	-2.1756	0.6234E-01	-34.90	0.000
A2529	-0.44080	0.3930	-1.122	0.262
A3034	-0.58664	0.3805	-1.542	0.123
A3544	-0.48482	0.3746	-1.294	0.196
A4554	-0.57590	0.3731	-1.543	0.123
A5564	-0.50479	0.3732	-1.352	0.176
AGT64	-0.42494	0.3750	-1.133	0.257
EFT	0.92100E-01	0.5580E-01	1.650	0.099
EPT	0.13767E-01	0.6191E-01	0.2224	0.824
EDUHS	-0.26696	0.1403	-1.903	0.057
EDUPC	-0.46111	0.1701	-2.710	0.007
EDUU	-0.35320	0.1467	-2.408	0.016
MW	-0.20298	0.6451E-01	-3.147	0.002
S	0.16139	0.5865E-01	2.752	0.006
W	0.16936	0.6768E-01	2.502	0.012
BLK	0.19044	0.1096	1.737	0.082
ASIAN	0.19597	0.1293	1.516	0.130
OTHER	0.27824	0.1182	2.355	0.019
HSP	0.81355E-01	0.9649E-01	0.8431	0.399
AC1	-0.67108E-01	0.1152	-0.5826	0.560
AC2	0.15516	0.9160E-01	1.694	0.090
AC3	0.26453	0.8344E-01	3.170	0.002
AC4	-0.29215	0.1273	-2.295	0.022
AC5	0.16775	0.2930	0.5724	0.567
AC6	0.44636E-01	0.1067	0.4184	0.676
AC7	0.19140	0.2230	0.8582	0.391
FH	-0.10582	0.5592E-01	-1.892	0.058
MH	0.25978	0.8716E-01	2.980	0.003
POV	0.11134	0.7882E-01	1.413	0.158
IMR_LFM[57]	-2.7146	0.2671	-10.16	0.000
CONSTANT	6.5244	0.4418	14.77	0.000

[56] LP_LFM=log of price of low-fat milk
[57] IMR_LFM=inverse mills ratio for low-fat milk

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Low-Fat Milk

Low Fat Milk						
		Probit		**Volume**		
VARIABLE	**SAMPLE**	**EST**		**EST**	**ADJ**	
NAME	**MEANS**	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	0.417	1.017			
P2	6.692	-0.043	-0.289			
A2529	0.024	-0.044	-0.001	-0.441	-0.507	-39.8%
A3034	0.062	-0.019	-0.001	-0.587	-0.615	-45.9%
A3544	0.212	-0.046	-0.010	-0.485	-0.554	-42.5%
A4554	0.276	-0.030	-0.008	-0.576	-0.621	-46.3%
A5564	0.232	-0.003	-0.001	-0.505	-0.510	-39.9%
AGT64	0.191	0.064	0.012	-0.425	-0.328	-28.0%
EFT	0.454	-0.118	-0.054	0.092	-0.087	-8.3%
EPT	0.164	-0.028	-0.005	0.014	-0.028	-2.8%
EDUHS	0.242	0.274	0.066	-0.267	0.149	16.1%
EDUPC	0.110	0.577	0.063	**-0.461**	0.414	**51.3%**
EDUU	0.613	0.403	0.247	**-0.353**	0.259	**29.6%**
MW	0.186	-0.078	-0.014	**-0.203**	-0.321	**-27.5%**
S	0.389	-0.165	-0.064	**0.161**	-0.088	**-8.5%**
W	0.212	-0.224	-0.047	**0.169**	-0.170	**-15.7%**
BLK	0.130	-0.536	-0.070	0.190	-0.623	-46.3%
ASIAN	0.029	-0.211	-0.006	0.196	-0.125	-11.7%
OTHER	0.064	-0.278	-0.018	**0.278**	-0.143	**-13.3%**
HSP	0.080	-0.061	-0.005	0.081	-0.012	-1.2%
AC1	0.035	0.097	0.003	-0.067	0.079	8.3%
AC2	0.061	0.034	0.002	0.155	0.207	23.1%
AC3	0.072	0.022	0.002	**0.265**	0.298	**34.7%**
AC4	0.029	0.146	0.004	**-0.292**	-0.071	**-6.9%**
AC5	0.005	-0.034	0.000	0.168	0.116	12.3%
AC6	0.044	0.113	0.005	0.045	0.217	24.2%
AC7	0.009	-0.071	-0.001	0.191	0.083	8.7%
FH	0.276	-0.166	-0.046	-0.106	-0.357	-30.0%
MH	0.106	-0.345	-0.036	**0.260**	-0.263	**-23.1%**
POV	0.134	-0.227	-0.030	0.111	-0.234	-20.8%
CONSTANT		-0.385				
α	-2.715					
Z_bar	0.331					
f(Z_bar)	0.378					
F(Z_bar)	0.629					
λ_bar	0.600					

Heckman Two-Step Regression Results for Fruit Drinks

```
R-SQUARE =   0.2805     R-SQUARE ADJUSTED =   0.2768
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.3975
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.1822
 SUM OF SQUARED ERRORS-SSE=   8046.8
 MEAN OF DEPENDENT VARIABLE =   1.3927
 LOG OF THE LIKELIHOOD FUNCTION = -9167.43

   SCHWARZ (1978) CRITERION - SC =                   1.4560
  AKAIKE (1974) INFORMATION CRITERION - AIC =       1.4050

DURBIN-WATSON = 2.0231    VON NEUMANN RATIO = 2.0235    RHO = -0.01163
 RESIDUAL SUM =  0.53135E-10  RESIDUAL VARIANCE =   1.3975
 SUM OF ABSOLUTE ERRORS=   5500.0
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 5758 DF	P-VALUE
LP_FD[58]	-0.92664	0.4029E-01	-23.00	0.000
A2529	-0.13729	0.2843	-0.4830	0.629
A3034	-0.17282	0.2754	-0.6275	0.530
A3544	-0.98201E-01	0.2715	-0.3617	0.718
A4554	-0.48396E-01	0.2722	-0.1778	0.859
A5564	-0.17898	0.2788	-0.6419	0.521
AGT64	-0.19322	0.2961	-0.6526	0.514
EFT	-0.32246E-01	0.4090E-01	-0.7885	0.430
EPT	0.12866E-03	0.4823E-01	0.2668E-02	0.998
EDUHS	-0.15056	0.8943E-01	-1.684	0.092
EDUPC	-0.17654	0.1024	-1.724	0.085
EDUU	-0.14885	0.8804E-01	-1.691	0.091
MW	-0.13337	0.5102E-01	-2.614	0.009
S	-0.15312	0.4281E-01	-3.577	0.000
W	0.10778	0.4938E-01	2.183	0.029
BLK	0.19150	0.8635E-01	2.218	0.027
ASIAN	-0.95495E-01	0.9544E-01	-1.001	0.317
OTHER	0.54303E-01	0.8288E-01	0.6552	0.512
HSP	0.78360E-01	0.6942E-01	1.129	0.259
AC1	0.47362E-01	0.1038	0.4563	0.648
AC2	0.48718	0.1112	4.381	0.000
AC3	0.39679	0.1011	3.925	0.000
AC4	0.53320	0.1334	3.998	0.000
AC5	0.46288	0.2118	2.185	0.029
AC6	0.71889	0.1181	6.085	0.000
AC7	0.67029	0.1759	3.811	0.000
FH	-0.46702E-01	0.5189E-01	-0.9001	0.368
MH	0.26059	0.9332E-01	2.793	0.005
POV	-0.76878E-01	0.4939E-01	-1.557	0.120
IMR_FD[59]	-1.7637	0.3431	-5.141	0.000
CONSTANT	3.3640	0.2986	11.26	0.000

[58] LP_FD=log price of fruit drinks
[59] IMR_FD=inverse mills ratio for fruit drinks

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Fruit Drinks

Fruit Drinks						
VARIABLE		**Probit**		**Volume**		
NAME	**SAMPLE**	**EST**		**EST**	**ADJ**	
	MEANS	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	0.157	0.383			
P2	6.692	-0.014	-0.094			
A2529	0.024	-0.407	-0.010	-0.137	-0.441	-35.6%
A3034	0.062	-0.409	-0.025	-0.173	-0.477	-38.0%
A3544	0.212	-0.393	-0.083	-0.098	-0.391	-32.4%
A4554	0.276	-0.462	-0.127	-0.048	-0.393	-32.5%
A5564	0.232	-0.632	-0.147	-0.179	-0.650	-47.8%
AGT64	0.191	-0.876	-0.167	-0.193	-0.846	-57.1%
EFT	0.454	-0.025	-0.011	-0.032	-0.051	-4.9%
EPT	0.164	0.067	0.011	0.000	0.050	5.2%
EDUHS	0.242	0.026	0.006	-0.151	-0.131	-12.3%
EDUPC	0.110	-0.201	-0.022	-0.177	-0.327	-27.9%
EDUU	0.613	-0.094	-0.058	-0.149	-0.219	-19.7%
MW	0.186	0.089	0.017	**-0.133**	-0.067	**-6.5%**
S	0.389	0.052	0.020	**-0.153**	-0.115	**-10.8%**
W	0.212	-0.004	-0.001	**0.108**	0.105	**11.1%**
BLK	0.130	0.587	0.076	**0.192**	0.629	**87.6%**
ASIAN	0.029	0.158	0.005	-0.095	0.022	2.3%
OTHER	0.064	0.267	0.017	0.054	0.253	28.8%
HSP	0.080	0.070	0.006	0.078	0.131	14.0%
AC1	0.035	0.469	0.017	0.047	0.397	48.7%
AC2	0.061	0.881	0.054	**0.487**	1.144	**213.9%**
AC3	0.072	0.708	0.051	**0.397**	0.925	**152.2%**
AC4	0.029	1.131	0.033	**0.533**	1.377	**296.1%**
AC5	0.005	1.094	0.006	**0.463**	1.278	**259.1%**
AC6	0.044	0.946	0.042	**0.719**	1.424	**315.5%**
AC7	0.009	1.025	0.010	**0.670**	1.434	**319.7%**
FH	0.276	-0.238	-0.066	-0.047	-0.224	-20.1%
MH	0.106	-0.448	-0.047	**0.261**	-0.074	**-7.1%**
POV	0.134	-0.013	-0.002	-0.077	-0.087	-8.3%
CONSTANT		0.935				
α	-1.764					
Z_bar	0.827					
f(Z_bar)	0.283					
F(Z_bar)	0.794					
λ_bar	0.357					

Heckman Two-Step Regression Results for Fruit Juices

```
R-SQUARE =   0.1689     R-SQUARE ADJUSTED =   0.1654
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.2846
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.1334
 SUM OF SQUARED ERRORS-SSE=   9130.8
 MEAN OF DEPENDENT VARIABLE =   1.9622
 LOG OF THE LIKELIHOOD FUNCTION = -11008.2


  SCHWARZ (1978) CRITERION - SC =                    1.3292
  AKAIKE (1974) INFORMATION CRITERION - AIC =        1.2902

 DURBIN-WATSON = 1.9833    VON NEUMANN RATIO = 1.9836    RHO =  0.00831
 RESIDUAL SUM = -0.11684E-10  RESIDUAL VARIANCE =   1.2846
 SUM OF ABSOLUTE ERRORS=   6442.1
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 7108 DF	P-VALUE
LP_FJ[60]	-0.73117	0.4809E-01	-15.21	0.000
A2529	0.64998	0.2585	2.514	0.012
A3034	0.52338	0.2501	2.092	0.036
A3544	0.70538	0.2469	2.857	0.004
A4554	0.73466	0.2461	2.986	0.003
A5564	0.82209	0.2462	3.340	0.001
AGT64	0.88378	0.2467	3.582	0.000
EFT	0.75621E-02	0.3605E-01	0.2098	0.834
EPT	-0.84275E-01	0.4176E-01	-2.018	0.044
EDUHS	0.37483E-01	0.7793E-01	0.4810	0.631
EDUPC	0.15752	0.8556E-01	1.841	0.066
EDUU	0.53837E-01	0.7621E-01	0.7065	0.480
MW	-0.19950	0.4327E-01	-4.610	0.000
S	-0.15920	0.3685E-01	-4.320	0.000
W	0.73835E-01	0.4604E-01	1.604	0.109
BLK	-0.11468	0.4665E-01	-2.458	0.014
ASIAN	0.14848	0.8305E-01	1.788	0.074
OTHER	0.15106	0.6926E-01	2.181	0.029
HSP	-0.84672E-01	0.6241E-01	-1.357	0.175
AC1	0.44326E-01	0.8153E-01	0.5437	0.587
AC2	0.49934E-01	0.6121E-01	0.8158	0.415
AC3	0.11215	0.5642E-01	1.988	0.047
AC4	0.18565	0.8753E-01	2.121	0.034
AC5	-0.26941	0.1832	-1.471	0.141
AC6	0.18604	0.7185E-01	2.589	0.010
AC7	0.34986	0.1432	2.443	0.015
FH	-0.16647	0.3862E-01	-4.311	0.000
MH	0.55765	0.5946E-01	9.379	0.000
POV	0.10616	0.4629E-01	2.293	0.022
IMR_FJ[61]	-5.4572	0.2635	-20.71	0.000
CONSTANT	2.9465	0.2633	11.19	0.000

[60] LP_FJ=log price of fruit juices
[61] IMR_FJ=inverse mills ratio for fruit juices

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Fruit Juices

Fruit Juices						
VARIABLE		**Probit**		**Volume**		
NAME	**SAMPLE**	**EST**		**EST**	**ADJ**	
	MEANS	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	0.470	1.147			
P2	6.692	-0.032	-0.216			
A2529	0.024	-5.527	-0.134	**0.650**	-1.072	**-65.8%**
A3034	0.062	-5.441	-0.335	**0.523**	-1.172	**-69.0%**
A3544	0.212	-5.486	-1.162	**0.705**	-1.004	**-63.4%**
A4554	0.276	-5.427	-1.497	**0.735**	-0.956	**-61.6%**
A5564	0.232	-5.381	-1.251	**0.822**	-0.855	**-57.5%**
AGT64	0.191	-5.283	-1.009	**0.884**	-0.763	**-53.4%**
EFT	0.454	-0.075	-0.034	0.008	-0.016	-1.6%
EPT	0.164	0.096	0.016	**-0.084**	-0.054	**-5.3%**
EDUHS	0.242	0.041	0.010	0.037	0.050	5.1%
EDUPC	0.110	0.133	0.015	0.158	0.199	22.0%
EDUU	0.613	0.125	0.076	0.054	0.093	9.7%
MW	0.186	-0.123	-0.023	**-0.200**	-0.238	**-21.2%**
S	0.389	-0.147	-0.057	**-0.159**	-0.205	**-18.5%**
W	0.212	-0.384	-0.081	0.074	-0.046	-4.5%
BLK	0.130	0.474	0.062	**-0.115**	0.033	**3.4%**
ASIAN	0.029	0.065	0.002	0.148	0.169	18.4%
OTHER	0.064	-0.022	-0.001	**0.151**	0.144	**15.5%**
HSP	0.080	0.114	0.009	-0.085	-0.049	-4.8%
AC1	0.035	1.089	0.039	0.044	0.384	46.8%
AC2	0.061	0.215	0.013	0.050	0.117	12.4%
AC3	0.072	0.270	0.019	**0.112**	0.196	**21.7%**
AC4	0.029	0.606	0.018	**0.186**	0.375	**45.4%**
AC5	0.005	5.411	0.029	-0.269	1.417	312.4%
AC6	0.044	0.287	0.013	**0.186**	0.276	**31.7%**
AC7	0.009	0.694	0.007	**0.350**	0.566	**76.1%**
FH	0.276	-0.366	-0.101	-0.166	-0.281	-24.5%
MH	0.106	-0.605	-0.064	0.558	0.369	44.6%
POV	0.134	-0.245	-0.033	0.106	0.030	3.0%
CONSTANT		6.227				
α	-1.764					
Z_bar	1.702					
f(Z_bar)	0.094					
F(Z_bar)	0.955					
λ_bar	0.098					

Heckman Two-Step Regression Results for Bottled Water

```
R-SQUARE =   0.2373     R-SQUARE ADJUSTED =   0.2330
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.9772
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.4061
 SUM OF SQUARED ERRORS-SSE=   10564.
 MEAN OF DEPENDENT VARIABLE =   1.8346
 LOG OF THE LIKELIHOOD FUNCTION = -9441.52

  SCHWARZ (1978) CRITERION - SC =                   2.0657
  AKAIKE (1974) INFORMATION CRITERION - AIC =       1.9886

DURBIN-WATSON = 2.0113    VON NEUMANN RATIO = 2.0117    RHO = -0.00574
 RESIDUAL SUM =  0.52474E-10  RESIDUAL VARIANCE =   1.9772
 SUM OF ABSOLUTE ERRORS=   6141.8
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 5343 DF	P-VALUE
LP_BW[62]	-1.1496	0.3127E-01	-36.76	0.000
A2529	0.27695	0.3630	0.7630	0.445
A3034	0.40275	0.3504	1.150	0.250
A3544	0.59228	0.3459	1.712	0.087
A4554	0.60995	0.3470	1.758	0.079
A5564	0.48148	0.3520	1.368	0.171
AGT64	0.34110	0.3796	0.8987	0.369
EFT	0.15730	0.5592E-01	2.813	0.005
EPT	0.56953E-01	0.6484E-01	0.8784	0.380
EDUHS	-0.72683E-01	0.1148	-0.6330	0.527
EDUPC	-0.73276E-02	0.1282	-0.5714E-01	0.954
EDUU	-0.96445E-01	0.1112	-0.8674	0.386
MW	-0.23534	0.6681E-01	-3.523	0.000
S	-0.21335	0.5396E-01	-3.954	0.000
W	0.97740E-01	0.6319E-01	1.547	0.122
BLK	0.25723	0.7408E-01	3.472	0.001
ASIAN	0.10692	0.1147	0.9322	0.351
OTHER	0.16611	0.1022	1.625	0.104
HSP	-0.11610	0.9109E-01	-1.275	0.203
AC1	-0.94795E-01	0.1071	-0.8850	0.376
AC2	0.86074E-01	0.8543E-01	1.008	0.314
AC3	0.18821	0.7881E-01	2.388	0.017
AC4	0.10075	0.1188	0.8484	0.396
AC5	-0.28891	0.2499	-1.156	0.248
AC6	-0.49815E-01	0.1018	-0.4895	0.624
AC7	-0.89614E-01	0.2047	-0.4378	0.662
FH	-0.17749	0.4795E-01	-3.702	0.000
MH	-0.18876	0.1551	-1.217	0.224
POV	-0.23774	0.1058	-2.246	0.025
IMR_BW[63]	-0.58049	0.5123	-1.133	0.257
CONSTANT	2.3866	0.4029	5.924	0.000

[62] LP_BW=log price of bottled water
[63] IMR_BW=inverse mills ratio for bottled water

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Bottled Water

Bottled Water						
VARIABLE		**Probit**		**Volume**		
NAME	**SAMPLE**	**EST**		**EST**	**ADJ**	
	MEANS	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	0.174	0.426			
P2	6.692	-0.018	-0.123			
A2529	0.024	-0.095	-0.002	0.277	0.250	31.9%
A3034	0.062	0.065	0.004	0.403	0.422	49.6%
A3544	0.212	-0.046	-0.010	0.592	0.579	80.8%
A4554	0.276	-0.148	-0.041	0.610	0.567	84.0%
A5564	0.232	-0.258	-0.060	0.481	0.407	61.8%
AGT64	0.191	-0.551	-0.105	0.341	0.182	40.6%
EFT	0.454	0.082	0.037	**0.157**	0.181	**17.0%**
EPT	0.164	0.095	0.016	0.057	0.084	5.9%
EDUHS	0.242	-0.099	-0.024	-0.073	-0.101	-7.0%
EDUPC	0.110	-0.176	-0.019	-0.007	-0.058	-0.7%
EDUU	0.613	-0.098	-0.060	-0.096	-0.125	-9.2%
MW	0.186	-0.084	-0.016	**-0.235**	-0.260	**-21.0%**
S	0.389	-0.056	-0.022	**-0.213**	-0.229	**-19.2%**
W	0.212	0.076	0.016	0.098	0.120	10.3%
BLK	0.130	0.194	0.025	**0.257**	0.313	**29.3%**
ASIAN	0.029	0.061	0.002	0.107	0.125	11.3%
OTHER	0.064	0.194	0.013	0.166	0.222	18.1%
HSP	0.080	0.170	0.014	-0.116	-0.067	-11.0%
AC1	0.035	0.019	0.001	-0.095	-0.089	-9.0%
AC2	0.061	0.113	0.007	0.086	0.119	9.0%
AC3	0.072	0.098	0.007	**0.188**	0.217	**20.7%**
AC4	0.029	0.075	0.002	0.101	0.123	10.6%
AC5	0.005	0.219	0.001	-0.289	-0.226	-25.1%
AC6	0.044	0.165	0.007	-0.050	-0.002	-4.9%
AC7	0.009	0.360	0.003	-0.090	0.014	-8.6%
FH	0.276	-0.026	-0.007	**-0.177**	-0.185	**-16.3%**
MH	0.106	-0.504	-0.053	-0.189	-0.334	-17.2%
POV	0.134	-0.303	-0.041	**-0.238**	-0.325	**-21.2%**
CONSTANT		0.567				
α	-0.580	**(NS)**				
Z_bar	0.565					
f(Z_bar)	0.340					
F(Z_bar)	0.712					
λ_bar	0.478					

Heckman Two-Step Regression Results for Coffee

```
R-SQUARE =   0.2730     R-SQUARE ADJUSTED =   0.2691
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.0467
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.0231
 SUM OF SQUARED ERRORS-SSE=   5785.0
 MEAN OF DEPENDENT VARIABLE =   2.9857
 LOG OF THE LIKELIHOOD FUNCTION = -7997.69

  SCHWARZ (1978) CRITERION - SC =                     1.0921
  AKAIKE (1974) INFORMATION CRITERION - AIC =         1.0525

DURBIN-WATSON = 2.0312    VON NEUMANN RATIO = 2.0316    RHO = -0.01580
 RESIDUAL SUM =  0.37781E-11  RESIDUAL VARIANCE =   1.0467
 SUM OF ABSOLUTE ERRORS=   4543.7
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 5527 DF	P-VALUE
LP_COF[64]	-0.72469	0.3182E-01	-22.77	0.000
A2529	0.39624	0.3011	1.316	0.188
A3034	0.58465	0.2924	1.999	0.046
A3544	0.39795	0.2876	1.384	0.167
A4554	0.36575	0.2875	1.272	0.203
A5564	0.29570	0.2884	1.025	0.305
AGT64	0.21289	0.2898	0.7345	0.463
EFT	-0.46676E-02	0.3651E-01	-0.1278	0.898
EPT	0.44637E-01	0.4214E-01	1.059	0.290
EDUHS	0.93507E-01	0.7428E-01	1.259	0.208
EDUPC	0.16847	0.8390E-01	2.008	0.045
EDUU	0.91461E-01	0.7262E-01	1.259	0.208
MW	0.13351	0.4440E-01	3.007	0.003
S	-0.74173E-01	0.3662E-01	-2.025	0.043
W	0.22316	0.4559E-01	4.895	0.000
BLK	0.65760E-01	0.5136E-01	1.280	0.201
ASIAN	-0.62935E-02	0.9100E-01	-0.6916E-01	0.945
OTHER	0.36819E-01	0.7095E-01	0.5190	0.604
HSP	-0.25534	0.6259E-01	-4.079	0.000
AC1	0.46007E-01	0.8406E-01	0.5473	0.584
AC2	0.47028E-01	0.6334E-01	0.7425	0.458
AC3	0.57015E-01	0.5736E-01	0.9941	0.320
AC4	-0.18740	0.9029E-01	-2.076	0.038
AC5	-0.25204	0.2000	-1.260	0.208
AC6	0.31512E-01	0.7534E-01	0.4182	0.676
AC7	-0.72073E-01	0.1446	-0.4984	0.618
FH	0.86508E-02	0.3785E-01	0.2286	0.819
MH	0.30194	0.6301E-01	4.792	0.000
POV	0.14871E-01	0.4457E-01	0.3337	0.739
IMR_COF[65]	-2.1346	0.1096	-19.48	0.000
CONSTANT	3.3729	0.2970	11.36	0.000

[64] LP_COF=log price of coffee
[65] IMR_COF=inverse mills ratio for coffee

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Coffee

Coffee						
VARIABLE		**Probit**		**Volume**		
NAME	**SAMPLE**	**EST**		**EST**	**ADJ**	
	MEANS	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	-0.571	-1.392			
P2	6.692	0.029	0.195			
A2529	0.024	0.071	0.002	0.396	0.467	59.5%
A3034	0.062	-0.051	-0.003	**0.585**	0.534	**70.6%**
A3544	0.212	0.313	0.066	0.398	0.707	102.9%
A4554	0.276	0.448	0.124	0.366	0.809	124.5%
A5564	0.232	0.637	0.148	0.296	0.927	152.6%
AGT64	0.191	0.821	0.157	0.213	1.026	178.9%
EFT	0.454	-0.031	-0.014	-0.005	-0.035	-3.4%
EPT	0.164	-0.043	-0.007	0.045	0.002	0.2%
EDUHS	0.242	-0.132	-0.032	0.094	-0.037	-3.7%
EDUPC	0.110	-0.200	-0.022	**0.168**	-0.030	**-2.9%**
EDUU	0.613	-0.175	-0.107	0.091	-0.082	-7.8%
MW	0.186	-0.247	-0.046	**0.134**	-0.111	**-10.5%**
S	0.389	-0.002	-0.001	**-0.074**	-0.076	**-7.3%**
W	0.212	-0.201	-0.042	**0.223**	0.024	**2.5%**
BLK	0.130	-0.401	-0.052	0.066	-0.331	-28.2%
ASIAN	0.029	-0.095	-0.003	-0.006	-0.101	-9.6%
OTHER	0.064	-0.124	-0.008	0.037	-0.086	-8.2%
HSP	0.080	0.184	0.015	**-0.255**	-0.073	**-7.1%**
AC1	0.035	-0.024	-0.001	0.046	0.022	2.2%
AC2	0.061	0.023	0.001	0.047	0.070	7.2%
AC3	0.072	-0.072	-0.005	0.057	-0.014	-1.4%
AC4	0.029	0.055	0.002	**-0.187**	-0.133	**-12.4%**
AC5	0.005	-0.109	-0.001	-0.252	-0.360	-30.2%
AC6	0.044	-0.163	-0.007	0.032	-0.130	-12.2%
AC7	0.009	0.122	0.001	-0.072	0.049	5.0%
FH	0.276	-0.355	-0.098	0.009	-0.343	-29.0%
MH	0.106	-0.618	-0.065	**0.302**	-0.310	**-26.7%**
POV	0.134	-0.177	-0.024	0.015	-0.160	-14.8%
CONSTANT		1.902		3.373		
α	-2.135					
Z_bar	0.683					
f(Z_bar)	0.316					
F(Z_bar)	0.752					
λ_bar	0.420					

Heckman Two-Step Regression Results for Tea

```
R-SQUARE =   0.2944     R-SQUARE ADJUSTED =   0.2905
 VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.3201
 STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.1489
 SUM OF SQUARED ERRORS-SSE=   7269.7
 MEAN OF DEPENDENT VARIABLE =   1.8486
 LOG OF THE LIKELIHOOD FUNCTION = -8611.47

  SCHWARZ (1978) CRITERION - SC =                    1.3776
  AKAIKE (1974) INFORMATION CRITERION - AIC =        1.3275

DURBIN-WATSON = 1.9658    VON NEUMANN RATIO = 1.9662    RHO =  0.01705
 RESIDUAL SUM =  0.29875E-10  RESIDUAL VARIANCE =   1.3201
 SUM OF ABSOLUTE ERRORS=   5166.5
```

VARIABLE NAME	ESTIMATED COEFFICIENT	STANDARD ERROR	T-RATIO 5507 DF	P-VALUE
LP_TEA[66]	-0.82746	0.1985E-01	-41.68	0.000
A2529	0.47541	0.3557	1.336	0.181
A3034	0.64215	0.3597	1.785	0.074
A3544	0.88156	0.3890	2.266	0.023
A4554	1.0089	0.4030	2.503	0.012
A5564	0.90249	0.3738	2.415	0.016
AGT64	0.75848	0.3561	2.130	0.033
EFT	-0.19469	0.1020	-1.908	0.056
EPT	0.46624E-01	0.4765E-01	0.9784	0.328
EDUHS	0.34859E-01	0.1174	0.2970	0.766
EDUPC	-0.32449E-02	0.1322	-0.2455E-01	0.980
EDUU	0.48286E-01	0.1336	0.3615	0.718
MW	-0.98851	0.3101	-3.188	0.001
S	-0.63633	0.1237	-5.146	0.000
W	-0.81029	0.2735	-2.963	0.003
BLK	-0.17058	0.5374E-01	-3.174	0.002
ASIAN	-0.36291	0.1507	-2.408	0.016
OTHER	0.20496	0.1008	2.034	0.042
HSP	-0.34972	0.9417E-01	-3.714	0.000
AC1	-0.23356	0.1004	-2.326	0.020
AC2	-0.61793E-01	0.7158E-01	-0.8632	0.388
AC3	0.21288	0.7509E-01	2.835	0.005
AC4	-0.14562	0.1149	-1.267	0.205
AC5	0.56322E-01	0.2207	0.2552	0.799
AC6	0.39208E-01	0.8033E-01	0.4881	0.626
AC7	0.16487	0.1905	0.8655	0.387
FH	-0.36135	0.9964E-01	-3.627	0.000
MH	-0.83385	0.3752	-2.222	0.026
POV	-0.10242	0.5679E-01	-1.803	0.071
IMR_TEA[67]	1.9235	1.247	1.543	0.123
CONSTANT	1.3533	0.6899	1.962	0.050

[66] LP_TEA=log price of tea
[67] IMR_TEA=inverse mills ratio for tea

Heckman Second Stage Adjusted Marginal Effects and Percentage Changes of Demographic Dummy Variables: Tea

Tea						
VARIABLE		**Probit**		**Volume**		
NAME	**SAMPLE**	**EST**		**EST**	**ADJ**	
	MEANS	**COEF**	**MEANS*γ**	**COEF**	**COEF**	**% CHANGE**
		γ		**β**		
P	2.439	0.035	0.085			
P2	6.692	-0.005	-0.033			
A2529	0.024	0.235	0.006	0.475	0.259	60.9%
A3034	0.062	0.279	0.017	0.642	0.384	90.1%
A3544	0.212	0.380	0.080	**0.882**	0.530	**141.5%**
A4554	0.276	0.421	0.116	**1.009**	0.620	**174.3%**
A5564	0.232	0.335	0.078	**0.902**	0.592	**146.6%**
AGT64	0.191	0.270	0.052	**0.758**	0.509	**113.5%**
EFT	0.454	-0.163	-0.074	-0.195	-0.044	-17.7%
EPT	0.164	-0.011	-0.002	0.047	0.057	4.8%
EDUHS	0.242	0.125	0.030	0.035	-0.081	3.5%
EDUPC	0.110	0.147	0.016	-0.003	-0.139	-0.3%
EDUU	0.613	0.168	0.103	0.048	-0.107	4.9%
MW	0.186	-0.525	-0.098	**-0.989**	-0.503	**-62.8%**
S	0.389	-0.221	-0.086	**-0.636**	-0.432	**-47.1%**
W	0.212	-0.468	-0.099	**-0.810**	-0.377	**-55.5%**
BLK	0.130	0.041	0.005	**-0.171**	-0.209	**-15.7%**
ASIAN	0.029	-0.177	-0.005	**-0.363**	-0.199	**-30.4%**
OTHER	0.064	0.105	0.007	**0.205**	0.108	**22.7%**
HSP	0.080	-0.107	-0.009	**-0.350**	-0.251	**-29.5%**
AC1	0.035	0.082	0.003	**-0.234**	-0.309	**-20.8%**
AC2	0.061	-0.032	-0.002	-0.062	-0.032	-6.0%
AC3	0.072	0.077	0.006	**0.213**	0.142	**23.7%**
AC4	0.029	-0.103	-0.003	-0.146	-0.050	-13.6%
AC5	0.005	0.176	0.001	0.056	-0.107	5.8%
AC6	0.044	0.017	0.001	0.039	0.023	4.0%
AC7	0.009	0.219	0.002	0.165	-0.038	17.9%
FH	0.276	-0.157	-0.043	**-0.361**	-0.216	**-30.3%**
MH	0.106	-0.563	-0.060	**-0.834**	-0.313	**-56.6%**
POV	0.134	-0.049	-0.007	-0.102	-0.057	-9.7%
CONSTANT		0.533		1.353		
α	1.924	**(NS)**				
Z_bar	0.621					
f(Z_bar)	0.329					
F(Z_bar)	0.732					
λ_bar	0.449					

APPENDIX 4

DERIVATION OF THE COVARIANCE DECOMPOSITION OF THE BRIER SCORE AND COVARIANCE REGRESSION RESULTS FOR PROBIT AND LOGIT MODELS

Derivation of the covariance decomposition of the Brier score is done. Also, regression results from covariance regressions (resolution regressions) are reported.

Derivation of the Covariance decomposition of the Brier score

Recall from basic statistics that variance of a random variable can be written as follows:

(A1) $$Var(x) = \frac{\sum (x_i - \bar{x})^2}{n} \equiv \frac{\sum x_i^2}{n} - (\frac{\sum x_i}{n})^2$$

We use the relationship A1 in deriving the Yate's partition to the mean probability score as follows.

Mean probability score $(P\bar{S})$ expressed the following way. Please note that we are leaving all subscripts out of the derivation to keep it from having a lot of clutter:

(A2) $$P\bar{S} = \frac{\sum (f - d)^2}{n}$$

We can expand the above A2 as follows using the definition given in A1:

(A3) $$P\bar{S} = \frac{\sum (f^2 - 2fd + d^2)}{n}$$

(A4) $$P\bar{S} = \frac{\sum f^2 - 2\sum fd + \sum d^2)}{n}$$

(A5) $$P\bar{S} = \frac{\sum f^2}{n} + \frac{\sum d^2}{n} - \frac{2\sum fd)}{n}$$

Now each expression of right hand side of above A5 can be interpreted as follows.

Variance of outcome index is expressed as:

(A6) $$Var(d) = \frac{\sum (d-\bar{d})^2}{n} \equiv \frac{\sum d^2}{n} - (\frac{\sum d}{n})^2$$

(A7) $$\frac{\sum d^2}{n} = Var(d) + (\frac{\sum d}{n})^2$$

Variance of forecast probabilities is expressed as:

(A8) $$Var(f) = \frac{\sum (f-\bar{f})^2}{n} \equiv \frac{\sum f^2}{n} - (\frac{\sum f}{n})^2$$

(A9) $$\frac{\sum f^2}{n} = Var(f) + (\frac{\sum f}{n})^2$$

Covariance of forecast probabilities and outcome index is expressed as:

(A10) $$Cov(f,d) = \frac{\sum (f-\bar{f})(d-\bar{d})}{n} \equiv \frac{\sum fd}{n} - \frac{\sum f \sum d}{n^2}$$

(A11) $$\frac{\sum fd}{n} = Cov(f,d) + \frac{\sum f \sum d}{n^2}$$

Substituting A7, A9 and A11 in A5 would give us the following:

(A12) $$P\bar{S} = [Var(d) + (\frac{\sum d}{n})^2] + [Var(f) + (\frac{\sum f}{n})^2] - 2[Cov(f,d) + \frac{\sum f \sum d}{n^2}]$$

Simplifying above A12 further gives us the following:

(A13) $$P\bar{S} = Var(f) + Var(d) - 2Cov(f,d) + (\frac{\sum f}{n})^2 + (\frac{\sum d}{n})^2 - \frac{2\sum f \sum d}{n^2}$$

(A14) $$P\bar{S} = Var(f) + Var(d) - 2Cov(f,d) + \bar{f}^2 + \bar{d}^2 - 2\,\overline{fd}$$

(A15) $$P\bar{S} = Var(f) + Var(d) - 2Cov(f,d) + (\bar{f} - \bar{d})^2$$

Above equation A15 gives us a familiar relationship where mean squared error (the mean probability score here) is partitioned into its variance and covariance components. This is the same expression Yates (1982) has on page 138.

Variance of forecast probabilities can be further partitioned into two parts that consist of means of forecast probabilities associated with outcome index zero and one. Such derivation is borrowed from Yates (1984).

Let $f_{1m}, m = 1 - N_1$, represent the values of f on the N_1 occasions when $d = 1$ and let f_{0n}, $n = 1 - N_0$ represent values of f on the N_0 occasions when $d = 0$. Now we can write the $Var(f)$ as follows:

(A16) $$Var(f) = \frac{1}{N}\sum_{k=1}^{N}(f_k - \bar{f})^2$$

(A17) $$Var(f) = \frac{1}{N}\sum_{m=1}^{N_1}[(f_{m1} - \bar{f}_1) + (\bar{f}_1 - \bar{f})]^2 + \frac{1}{N}\sum_{n=1}^{N_1}[(f_{n0} - \bar{f}_0) + (\bar{f}_0 - \bar{f})]^2$$

Simplifying above equation A17 would give us the following relationship:

(A18) $$\begin{aligned} Var(f) = &\{\frac{1}{N}\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + 2(\bar{f}_1 - \bar{f})\frac{1}{N}\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1) + \frac{1}{N}\sum_{m=1}^{N_1}(\bar{f}_1 - \bar{f})^2\} + \\ &\{\frac{1}{N}\sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2 + 2(\bar{f}_0 - \bar{f})\frac{1}{N}\sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0) + \frac{1}{N}\sum_{n=1}^{N_0}(\bar{f}_0 - \bar{f})^2\} \end{aligned}$$

We can simplify above A18 further as follows:

we know that:

(A19) $$\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1) = 0$$

and

(A20) $$\sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0) = 0$$

also recognizing that:

$$\bar{f} = \frac{[N_1 \bar{f}_1 + N_0 \bar{f}_0]}{N}$$

(A21) $$\bar{d} = \frac{N_1}{N}$$

$$(1 - \bar{d}) = \frac{N_0}{N}$$

above A18 can further be simplified as follows:

(A22) $$Var(f) = \frac{1}{N}\{\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + \sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2\} + (\bar{f}_1 - \bar{f}_0)^2 \bar{d}(1 - \bar{d})$$

In the above expression A22, $\{\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + \sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2\}$ must be non-negative.

Therefore the minimum variance that must be present in forecast probabilities is as follows:

(A23) $$MinVar(f) = (\bar{f}_1 - \bar{f}_0)^2 \bar{d}(1 - \bar{d})$$

and $\{\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + \sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2\}$ is the variability of forecast probabilities associated with outcome index one and zero, which Yates (1984) names Scatter:

(A24) $$Scatter = \frac{1}{N}\{\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + \sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2\}$$

After some simplification, we can represent Scatter in its more familiar form as follows:

$$Scatter = \frac{N_1}{N}\sum_{m=1}^{N_1}(f_{m1} - \bar{f}_1)^2 + \frac{N_0}{N}\sum_{n=1}^{N_0}(f_{n0} - \bar{f}_0)^2$$

(A25) $$Scatter = \frac{N_1}{N}Var(f_1) + \frac{N_0}{N}Var(f_0)$$

$$Scatter = \frac{1}{N}[N_1 Var(f_1) + N_0 Var(f_0)]$$

Therefore:

(A26) $$Var(f) = \frac{1}{N}[N_1 Var(f_1) + N_0 Var(f_0)] + (\bar{f}_1 - \bar{f}_0)^2 \bar{d}(1 - \bar{d})$$

The final version of the covariance decomposition of the mean probability score can be written as follows:

(A27) $$\overline{PS} = Var(d) + Scatter + MinVar(f) + (\bar{f} - \bar{d})^2 - 2Cov(f, d)$$

Covariance Regressions (Resolution Regressions) of Forecast Probabilities and Outcome Indexes

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Isotonics[68]

Dependent Variable: PROB_ISO
Method: Least Squares
Date: 10/14/09 Time: 13:10
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.202887	0.002109	96.21352	0.0000
DUM_ISOTONICS	0.083940	0.004481	18.73299	0.0000

R-squared	0.084176	Mean dependent var	0.221477
Adjusted R-squared	0.083936	S.D. dependent var	0.120150
S.E. of regression	0.114997	Akaike info criterion	-1.487290
Sum squared resid	50.49082	Schwarz criterion	-1.484019
Log likelihood	2842.724	F-statistic	350.9248
Durbin-Watson stat	1.850638	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-in-Sample for Isotonics

Dependent Variable: PROB_ISO
Method: Least Squares
Date: 10/14/09 Time: 13:28
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.208617	0.002143	97.33832	0.0000
DUM_ISOTONICS	0.065197	0.004795	13.59724	0.0000

R-squared	0.046199	Mean dependent var	0.221643
Adjusted R-squared	0.045950	S.D. dependent var	0.121299
S.E. of regression	0.118479	Akaike info criterion	-1.427631
Sum squared resid	53.58067	Schwarz criterion	-1.424359
Log likelihood	2728.062	F-statistic	184.8849
Durbin-Watson stat	1.885208	Prob(F-statistic)	0.000000

[68] PROB_ISO=probability isotonics (probit model generated)
DUM_ISOTONICS=dummy variable isotonics
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Isotonics[69]

Dependent Variable: LOGI_ISO
Method: Least Squares
Date: 10/14/09 Time: 13:41
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.202751	0.002118	95.71698	0.0000
DUM_ISOTONICS	0.084506	0.004501	18.77458	0.0000

R-squared	0.084519	Mean dependent var	0.221466
Adjusted R-squared	0.084279	S.D. dependent var	0.120715
S.E. of regression	0.115516	Akaike info criterion	-1.478285
Sum squared resid	50.94756	Schwarz criterion	-1.475014
Log likelihood	2825.524	F-statistic	352.4849
Durbin-Watson stat	1.854165	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Isotonics

Dependent Variable: LOGI_ISO
Method: Least Squares
Date: 10/14/09 Time: 14:28
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.208556	0.002152	96.92536	0.0000
DUM_ISOTONICS	0.065503	0.004814	13.60706	0.0000

R-squared	0.046263	Mean dependent var	0.221643
Adjusted R-squared	0.046013	S.D. dependent var	0.121784
S.E. of regression	0.118949	Akaike info criterion	-1.419714
Sum squared resid	54.00654	Schwarz criterion	-1.416442
Log likelihood	2712.945	F-statistic	185.1521
Durbin-Watson stat	1.887312	Prob(F-statistic)	0.000000

[69] LOGI_ISO=probability isotonics (logit model generated)
DUM_ISOTONICS=dummy variable isotonics
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Regular Soft Drinks[70]

Dependent Variable: PROB_RSD
Method: Least Squares
Date: 10/14/09 Time: 13:12
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.841659	0.003742	224.8946	0.0000
DUM_REGSOFTDNK	0.066372	0.003941	16.83954	0.0000

R-squared	0.069137	Mean dependent var	0.901499
Adjusted R-squared	0.068893	S.D. dependent var	0.075206
S.E. of regression	0.072569	Akaike info criterion	-2.408035
Sum squared resid	20.10658	Schwarz criterion	-2.404763
Log likelihood	4601.346	F-statistic	283.5701
Durbin-Watson stat	1.848246	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Regular Soft Drinks

Dependent Variable: PROB_RSD
Method: Least Squares
Date: 10/14/09 Time: 13:37
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.864727	0.003204	269.8520	0.0000
DUM_REGSOFTDNK	0.041557	0.003358	12.37425	0.0000

R-squared	0.038569	Mean dependent var	0.902562
Adjusted R-squared	0.038317	S.D. dependent var	0.060430
S.E. of regression	0.059261	Akaike info criterion	-2.813219
Sum squared resid	13.40463	Schwarz criterion	-2.809947
Log likelihood	5373.842	F-statistic	153.1220
Durbin-Watson stat	1.896404	Prob(F-statistic)	0.000000

[70] PROB_RSD=probability regular soft drinks (probit model generated)
DUM_REGSOFTDNK=dummy variable regular soft drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Regular Soft Drinks[71]

Dependent Variable: LOGI_RSD
Method: Least Squares
Date: 10/14/09 Time: 14:12
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.839161	0.003842	218.4350	0.0000
DUM_REGSOFTDNK	0.069223	0.004046	17.10917	0.0000

R-squared	0.071210	Mean dependent var	0.901571
Adjusted R-squared	0.070966	S.D. dependent var	0.077286
S.E. of regression	0.074493	Akaike info criterion	-2.355692
Sum squared resid	21.18703	Schwarz criterion	-2.352421
Log likelihood	4501.372	F-statistic	292.7236
Durbin-Watson stat	1.855574	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Regular Soft Drinks

Dependent Variable: LOGI_RSD
Method: Least Squares
Date: 10/14/09 Time: 14:25
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.863862	0.003292	262.3928	0.0000
DUM_REGSOFTDNK	0.042541	0.003450	12.32939	0.0000

R-squared	0.038300	Mean dependent var	0.902593
Adjusted R-squared	0.038048	S.D. dependent var	0.062077
S.E. of regression	0.060884	Akaike info criterion	-2.759159
Sum squared resid	14.14924	Schwarz criterion	-2.755887
Log likelihood	5270.613	F-statistic	152.0139
Durbin-Watson stat	1.897315	Prob(F-statistic)	0.000000

[71] LOGI_RSD=probability regular soft drinks (logit model generated)
DUM_REGSOFTDNK=dummy variable regular soft drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Diet Soft Drinks[72]

Dependent Variable: PROB_DSD
Method: Least Squares
Date: 10/14/09 Time: 13:13
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.607561	0.003315	183.3004	0.0000
DUM_DIETSOFTDNK	0.069684	0.004102	16.98713	0.0000

R-squared	0.070269	Mean dependent var	0.653056
Adjusted R-squared	0.070025	S.D. dependent var	0.125159
S.E. of regression	0.120698	Akaike info criterion	-1.390534
Sum squared resid	55.62023	Schwarz criterion	-1.387263
Log likelihood	2657.921	F-statistic	288.5625
Durbin-Watson stat	1.791491	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Diet Soft Drinks

Dependent Variable: PROB_DSD
Method: Least Squares
Date: 10/14/09 Time: 13:35
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.614625	0.003247	189.2746	0.0000
DUM_DIETSOFTDNK	0.052483	0.004014	13.07396	0.0000

R-squared	0.042861	Mean dependent var	0.648968
Adjusted R-squared	0.042611	S.D. dependent var	0.120576
S.E. of regression	0.117979	Akaike info criterion	-1.436095
Sum squared resid	53.12910	Schwarz criterion	-1.432823
Log likelihood	2744.223	F-statistic	170.9285
Durbin-Watson stat	1.802162	Prob(F-statistic)	0.000000

[72] PROB_DSD=probability diet soft drinks (probit model generated)
DUM_DIETSOFTDNK=dummy variable diet soft drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Diet Soft Drinks[73]

Dependent Variable: LOGI_DSD
Method: Least Squares
Date: 10/14/09 Time: 14:13
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.606253	0.003340	181.5297	0.0000
DUM_DIETSOFTDNK	0.071417	0.004133	17.27877	0.0000

R-squared	0.072526	Mean dependent var	0.652880
Adjusted R-squared	0.072283	S.D. dependent var	0.126261
S.E. of regression	0.121612	Akaike info criterion	-1.375432
Sum squared resid	56.46660	Schwarz criterion	-1.372161
Log likelihood	2629.076	F-statistic	298.5558
Durbin-Watson stat	1.796329	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Diet Soft Drinks

Dependent Variable: LOGI_DSD
Method: Least Squares
Date: 10/14/09 Time: 14:26
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.613955	0.003259	188.3746	0.0000
DUM_DIETSOFTDNK	0.054152	0.004029	13.44022	0.0000

R-squared	0.045187	Mean dependent var	0.649390
Adjusted R-squared	0.044936	S.D. dependent var	0.121167
S.E. of regression	0.118413	Akaike info criterion	-1.428745
Sum squared resid	53.52102	Schwarz criterion	-1.425473
Log likelihood	2730.189	F-statistic	180.6396
Durbin-Watson stat	1.790278	Prob(F-statistic)	0.000000

[73] LOGI_DSD=probability diet soft drinks (logit model generated)
DUM_DIETSOFTDNK=dummy variable diet soft drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for High-Fat Milk[74]

Dependent Variable: PROB_HFM
Method: Least Squares
Date: 10/14/09 Time: 13:14
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.770248	0.003353	229.7105	0.0000
DUM_HIGHFATMILK	0.057142	0.003710	15.40357	0.0000

R-squared	0.058509	Mean dependent var	0.816934
Adjusted R-squared	0.058262	S.D. dependent var	0.091353
S.E. of regression	0.088652	Akaike info criterion	-2.007675
Sum squared resid	30.00628	Schwarz criterion	-2.004403
Log likelihood	3836.659	F-statistic	237.2700
Durbin-Watson stat	1.846114	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for High-Fat Milk

Dependent Variable: PROB_HFM
Method: Least Squares
Date: 10/14/09 Time: 13:37
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.779036	0.003336	233.5465	0.0000
DUM_HIGHFATMILK	0.044372	0.003666	12.10208	0.0000

R-squared	0.036953	Mean dependent var	0.815762
Adjusted R-squared	0.036700	S.D. dependent var	0.087180
S.E. of regression	0.085565	Akaike info criterion	-2.078554
Sum squared resid	27.94576	Schwarz criterion	-2.075282
Log likelihood	3970.999	F-statistic	146.4604
Durbin-Watson stat	1.850697	Prob(F-statistic)	0.000000

[74] PROB_HFM=probability high-fat milk (Probit model generated)
DUM_HIGHFATMILK=dummy variable high-fat milk
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for High-Fat Milk[75]

Dependent Variable: LOGI_HFM
Method: Least Squares
Date: 10/14/09 Time: 14:14
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.769429	0.003400	226.3135	0.0000
DUM_HIGHFATMILK	0.058245	0.003761	15.48516	0.0000

R-squared	0.059094	Mean dependent var	0.817016
Adjusted R-squared	0.058847	S.D. dependent var	0.092654
S.E. of regression	0.089887	Akaike info criterion	-1.980006
Sum squared resid	30.84812	Schwarz criterion	-1.976734
Log likelihood	3783.811	F-statistic	239.7902
Durbin-Watson stat	1.845810	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for High-Fat Milk

Dependent Variable: LOGI_HFM
Method: Least Squares
Date: 10/14/09 Time: 14:27
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.778465	0.003378	230.4790	0.0000
DUM_HIGHFATMILK	0.045131	0.003713	12.15629	0.0000

R-squared	0.037272	Mean dependent var	0.815819
Adjusted R-squared	0.037020	S.D. dependent var	0.088290
S.E. of regression	0.086640	Akaike info criterion	-2.053577
Sum squared resid	28.65254	Schwarz criterion	-2.050305
Log likelihood	3923.306	F-statistic	147.7753
Durbin-Watson stat	1.849207	Prob(F-statistic)	0.000000

[75] LOGI_HFM=probability high-fat milk (logit model generated)
DUM_HIGHFATMILK=dummy variable high-fat milk
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Low-Fat Milk[76]

Dependent Variable: PROB_LFM
Method: Least Squares
Date: 10/14/09 Time: 13:16
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.573699	0.003006	190.8356	0.0000
DUM_LOWFATMILK	0.060135	0.003848	15.62919	0.0000

R-squared	0.060132	Mean dependent var	0.610410
Adjusted R-squared	0.059886	S.D. dependent var	0.119601
S.E. of regression	0.115965	Akaike info criterion	-1.470536
Sum squared resid	51.34387	Schwarz criterion	-1.467265
Log likelihood	2810.724	F-statistic	244.2717
Durbin-Watson stat	1.828118	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Low-Fat Milk

Dependent Variable: PROB_LFM
Method: Least Squares
Date: 10/14/09 Time: 13:37
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.569570	0.003056	186.3822	0.0000
DUM_LOWFATMILK	0.062745	0.003823	16.41172	0.0000

R-squared	0.065913	Mean dependent var	0.609658
Adjusted R-squared	0.065669	S.D. dependent var	0.117402
S.E. of regression	0.113481	Akaike info criterion	-1.513831
Sum squared resid	49.15551	Schwarz criterion	-1.510559
Log likelihood	2892.659	F-statistic	269.3445
Durbin-Watson stat	1.775989	Prob(F-statistic)	0.000000

[76] PROB_LFM=probability low-fat milk (probit model gerated)
DUM_LOWFATMILK=dummy variable low-fat milk
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Low-Fat Milk[77]

Dependent Variable: LOGI_LFM
Method: Least Squares
Date: 10/14/09 Time: 14:15
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.573735	0.003007	190.8040	0.0000
DUM_LOWFATMILK	0.060177	0.003848	15.63637	0.0000

R-squared	0.060184	Mean dependent var	0.610471
Adjusted R-squared	0.059938	S.D. dependent var	0.119632
S.E. of regression	0.115991	Akaike info criterion	-1.470080
Sum squared resid	51.36729	Schwarz criterion	-1.466809
Log likelihood	2809.853	F-statistic	244.4960
Durbin-Watson stat	1.828102	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Low-Fat Milk

Dependent Variable: LOGI_LFM
Method: Least Squares
Date: 10/14/09 Time: 14:28
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.569518	0.003058	186.2164	0.0000
DUM_LOWFATMILK	0.062795	0.003826	16.41179	0.0000

R-squared	0.065914	Mean dependent var	0.609638
Adjusted R-squared	0.065669	S.D. dependent var	0.117496
S.E. of regression	0.113572	Akaike info criterion	-1.512234
Sum squared resid	49.23405	Schwarz criterion	-1.508962
Log likelihood	2889.611	F-statistic	269.3470
Durbin-Watson stat	1.776005	Prob(F-statistic)	0.000000

[77]LOGI_LFM=probability low-fat milk (logit model genetrated
DUM_LOWFATMILK=dummy variable low-fat milk
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Fruit Drinks[78]

Dependent Variable: PROB_FD
Method: Least Squares
Date: 10/14/09 Time: 13:16
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.679878	0.004130	164.6056	0.0000
DUM_FRUITDNK	0.094014	0.004768	19.71565	0.0000

R-squared	0.092402	Mean dependent var	0.750413
Adjusted R-squared	0.092164	S.D. dependent var	0.133893
S.E. of regression	0.127574	Akaike info criterion	-1.279723
Sum squared resid	62.13803	Schwarz criterion	-1.276452
Log likelihood	2446.272	F-statistic	388.7069
Durbin-Watson stat	1.815557	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Fruit Drinks

Dependent Variable: PROB_FD
Method: Least Squares
Date: 10/14/09 Time: 13:36
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.706112	0.003394	208.0293	0.0000
DUM_FRUITDNK	0.062021	0.003880	15.98566	0.0000

R-squared	0.062747	Mean dependent var	0.753582
Adjusted R-squared	0.062502	S.D. dependent var	0.104934
S.E. of regression	0.101602	Akaike info criterion	-1.734980
Sum squared resid	39.40291	Schwarz criterion	-1.731708
Log likelihood	3314.944	F-statistic	255.5412
Durbin-Watson stat	1.852908	Prob(F-statistic)	0.000000

[78] PROB_FD=probability fruit drinks (probit model generated)
DUM_FRUITDNK=dummy variable fruit drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Fruit Drinks[79]

Dependent Variable: LOGI_FD
Method: Least Squares
Date: 10/14/09 Time: 14:17
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.679914	0.004126	164.7964	0.0000
DUM_FRUITDNK	0.093764	0.004763	19.68510	0.0000

R-squared	0.092142	Mean dependent var	0.750262
Adjusted R-squared	0.091904	S.D. dependent var	0.133726
S.E. of regression	0.127433	Akaike info criterion	-1.281936
Sum squared resid	62.00072	Schwarz criterion	-1.278664
Log likelihood	2450.497	F-statistic	387.5030
Durbin-Watson stat	1.817158	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Fruit Drinks

Dependent Variable: LOGI_FD
Method: Least Squares
Date: 10/14/09 Time: 14:29
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.705993	0.003389	208.3128	0.0000
DUM_FRUITDNK	0.061966	0.003874	15.99586	0.0000

R-squared	0.062822	Mean dependent var	0.753420
Adjusted R-squared	0.062577	S.D. dependent var	0.104778
S.E. of regression	0.101447	Akaike info criterion	-1.738042
Sum squared resid	39.28243	Schwarz criterion	-1.734770
Log likelihood	3320.791	F-statistic	255.8675
Durbin-Watson stat	1.852226	Prob(F-statistic)	0.000000

[79] LOGI_FD=probability fruit drinks (logit model generated)
DUM_FRUITDNK=dummy variable fruit drinks
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Fruit Juices[80]

Dependent Variable: PROB_FJ
Method: Least Squares
Date: 10/14/09 Time: 13:17
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.886459	0.003288	269.5895	0.0000
DUM_FRUITJUICE	0.047492	0.003409	13.93322	0.0000

R-squared	0.048387	Mean dependent var	0.930656
Adjusted R-squared	0.048138	S.D. dependent var	0.054865
S.E. of regression	0.053528	Akaike info criterion	-3.016712
Sum squared resid	10.93939	Schwarz criterion	-3.013440
Log likelihood	5763.919	F-statistic	194.1347
Durbin-Watson stat	1.869734	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Fruit Juices

Dependent Variable: PROB_FJ
Method: Least Squares
Date: 10/14/09 Time: 13:36
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.893502	0.003403	262.5492	0.0000
DUM_FRUITJUICE	0.041004	0.003513	11.67205	0.0000

R-squared	0.034462	Mean dependent var	0.931982
Adjusted R-squared	0.034209	S.D. dependent var	0.053086
S.E. of regression	0.052170	Akaike info criterion	-3.068105
Sum squared resid	10.38866	Schwarz criterion	-3.064833
Log likelihood	5860.547	F-statistic	136.2366
Durbin-Watson stat	1.832231	Prob(F-statistic)	0.000000

[80] PROB_FJ=probability fruit juice (probit model generated)
DUM_FRUITJUICE=dummy variable fruit juice
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Fruit Juices[81]

Dependent Variable: LOGI_FJ
Method: Least Squares
Date: 10/14/09 Time: 14:17
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.882029	0.003515	250.9211	0.0000
DUM_FRUITJUICE	0.052222	0.003644	14.33167	0.0000

R-squared	0.051051	Mean dependent var	0.930628
Adjusted R-squared	0.050802	S.D. dependent var	0.058734
S.E. of regression	0.057223	Akaike info criterion	-2.883208
Sum squared resid	12.50181	Schwarz criterion	-2.879936
Log likelihood	5508.927	F-statistic	205.3969
Durbin-Watson stat	1.888991	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Fruit Juices

Dependent Variable: LOGI_FJ
Method: Least Squares
Date: 10/14/09 Time: 14:30
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.890490	0.003602	247.2236	0.0000
DUM_FRUITJUICE	0.044582	0.003718	11.99027	0.0000

R-squared	0.036298	Mean dependent var	0.932329
Adjusted R-squared	0.036045	S.D. dependent var	0.056240
S.E. of regression	0.055217	Akaike info criterion	-2.954567
Sum squared resid	11.63773	Schwarz criterion	-2.951295
Log likelihood	5643.745	F-statistic	143.7666
Durbin-Watson stat	1.858135	Prob(F-statistic)	0.000000

[81] LOGI_FJ=probability fruit juice (logit model generated)
DUM_FRUITJUICE=dummy variable fruit juice
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Bottled Water[82]

Dependent Variable: PROB_BW
Method: Least Squares
Date: 10/14/09 Time: 13:17
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.657202	0.003410	192.7158	0.0000
DUM_BOTWATER	0.067752	0.004062	16.68121	0.0000

R-squared	0.067931	Mean dependent var	0.704965
Adjusted R-squared	0.067687	S.D. dependent var	0.118567
S.E. of regression	0.114484	Akaike info criterion	-1.496248
Sum squared resid	50.04056	Schwarz criterion	-1.492977
Log likelihood	2859.833	F-statistic	278.2628
Durbin-Watson stat	1.824939	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Bottled Water

Dependent Variable: PROB_BW
Method: Least Squares
Date: 10/14/09 Time: 13:35
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.671682	0.002957	227.1190	0.0000
DUM_BOTWATER	0.051298	0.003530	14.53330	0.0000

R-squared	0.052434	Mean dependent var	0.707694
Adjusted R-squared	0.052186	S.D. dependent var	0.102475
S.E. of regression	0.099766	Akaike info criterion	-1.771460
Sum squared resid	37.99139	Schwarz criterion	-1.768188
Log likelihood	3384.602	F-statistic	211.2167
Durbin-Watson stat	1.912229	Prob(F-statistic)	0.000000

[82] PROB_BW=probability bottled water (probit model generated)
DUM_BOTWATER=dummy variable bottled water
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Bottled Water[83]

Dependent Variable: LOGI_BW
Method: Least Squares
Date: 10/14/09 Time: 14:19
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.656986	0.003420	192.1137	0.0000
DUM_BOTWATER	0.068070	0.004073	16.71260	0.0000

R-squared	0.068169	Mean dependent var	0.704974
Adjusted R-squared	0.067925	S.D. dependent var	0.118914
S.E. of regression	0.114805	Akaike info criterion	-1.490644
Sum squared resid	50.32176	Schwarz criterion	-1.487373
Log likelihood	2849.130	F-statistic	279.3109
Durbin-Watson stat	1.826566	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Bottled Water

Dependent Variable: LOGI_BW
Method: Least Squares
Date: 10/14/09 Time: 14:30
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.671465	0.002987	224.8309	0.0000
DUM_BOTWATER	0.051870	0.003564	14.55189	0.0000

R-squared	0.052561	Mean dependent var	0.707878
Adjusted R-squared	0.052313	S.D. dependent var	0.103492
S.E. of regression	0.100748	Akaike info criterion	-1.751856
Sum squared resid	38.74352	Schwarz criterion	-1.748584
Log likelihood	3347.169	F-statistic	211.7575
Durbin-Watson stat	1.911388	Prob(F-statistic)	0.000000

[83] LOGI_BW=probability bottled water (logit model generated)
DUM_BOTWATER=dummy variable bottled water
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Coffee[84]

Dependent Variable: PROB_COF
Method: Least Squares
Date: 10/14/09 Time: 13:18
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.617661	0.005147	120.0023	0.0000
DUM_COFFEE	0.162211	0.005999	27.03938	0.0000

R-squared	0.160718	Mean dependent var	0.737069
Adjusted R-squared	0.160498	S.D. dependent var	0.178353
S.E. of regression	0.163415	Akaike info criterion	-0.784529
Sum squared resid	101.9571	Schwarz criterion	-0.781258
Log likelihood	1500.450	F-statistic	731.1280
Durbin-Watson stat	1.871289	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Coffee

Dependent Variable: PROB_COF
Method: Least Squares
Date: 10/14/09 Time: 13:35
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.630862	0.005134	122.8739	0.0000
DUM_COFFEE	0.140131	0.006055	23.14387	0.0000

R-squared	0.123061	Mean dependent var	0.731622
Adjusted R-squared	0.122831	S.D. dependent var	0.179570
S.E. of regression	0.168180	Akaike info criterion	-0.727038
Sum squared resid	107.9622	Schwarz criterion	-0.723766
Log likelihood	1390.279	F-statistic	535.6388
Durbin-Watson stat	1.793215	Prob(F-statistic)	0.000000

[84] PROB_COF=probability Coffee (probit model generated)
DUM_COFFEE=dummy variable coffee
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Coffee[85]

Dependent Variable: LOGI_COF
Method: Least Squares
Date: 10/14/09 Time: 14:19
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.616226	0.005176	119.0634	0.0000
DUM_COFFEE	0.162879	0.006032	27.00093	0.0000

R-squared	0.160335	Mean dependent var	0.736126
Adjusted R-squared	0.160115	S.D. dependent var	0.179301
S.E. of regression	0.164321	Akaike info criterion	-0.773470
Sum squared resid	103.0909	Schwarz criterion	-0.770199
Log likelihood	1479.328	F-statistic	729.0505
Durbin-Watson stat	1.877598	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Coffee

Dependent Variable: LOGI_COF
Method: Least Squares
Date: 10/14/09 Time: 14:31
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.629016	0.005165	121.7744	0.0000
DUM_COFFEE	0.141074	0.006092	23.15880	0.0000

R-squared	0.123200	Mean dependent var	0.730453
Adjusted R-squared	0.122970	S.D. dependent var	0.180675
S.E. of regression	0.169202	Akaike info criterion	-0.714923
Sum squared resid	109.2782	Schwarz criterion	-0.711651
Log likelihood	1367.145	F-statistic	536.3298
Durbin-Watson stat	1.799084	Prob(F-statistic)	0.000000

[85] LOGI_COF=probability Coffee (logit model generated)
DUM_COFFEE=dummy variable coffee
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Within-Sample for Tea[86]

Dependent Variable: PROB_TEA
Method: Least Squares
Date: 10/14/09 Time: 13:19
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.683422	0.003062	223.1699	0.0000
DUM_TEA	0.051861	0.003607	14.37676	0.0000

R-squared	0.051356	Mean dependent var	0.720797
Adjusted R-squared	0.051107	S.D. dependent var	0.102690
S.E. of regression	0.100031	Akaike info criterion	-1.766146
Sum squared resid	38.20382	Schwarz criterion	-1.762875
Log likelihood	3375.339	F-statistic	206.6913
Durbin-Watson stat	1.552314	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Probit Out-of-Sample for Tea

Dependent Variable: PROB_TEA
Method: Least Squares
Date: 10/14/09 Time: 13:38
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.693931	0.002910	238.4884	0.0000
DUM_TEA	0.040821	0.003407	11.98047	0.0000

R-squared	0.036240	Mean dependent var	0.723700
Adjusted R-squared	0.035988	S.D. dependent var	0.095295
S.E. of regression	0.093564	Akaike info criterion	-1.899815
Sum squared resid	33.41498	Schwarz criterion	-1.896543
Log likelihood	3629.697	F-statistic	143.5316
Durbin-Watson stat	1.450423	Prob(F-statistic)	0.000000

[86] PROB_TEA=probability Tea (probit model generated)
DUM_TEA=dummy variable Tea
C=intercept coefficient

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Within-Sample for Tea[87]

Dependent Variable: LOGI_TEA
Method: Least Squares
Date: 10/14/09 Time: 14:20
Sample: 1 3820
Included observations: 3820

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.683360	0.003061	223.2546	0.0000
DUM_TEA	0.051785	0.003606	14.36224	0.0000

R-squared	0.051257	Mean dependent var	0.720681
Adjusted R-squared	0.051009	S.D. dependent var	0.102636
S.E. of regression	0.099984	Akaike info criterion	-1.767085
Sum squared resid	38.16798	Schwarz criterion	-1.763813
Log likelihood	3377.132	F-statistic	206.2741
Durbin-Watson stat	1.556231	Prob(F-statistic)	0.000000

Covariance Regression of Forecast Probabilities and Outcome Indexes: Logit Out-of-Sample for Tea

Dependent Variable: LOGI_TEA
Method: Least Squares
Date: 10/14/09 Time: 14:31
Sample: 1 3819
Included observations: 3819

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.694016	0.002907	238.7530	0.0000
DUM_TEA	0.040662	0.003404	11.94542	0.0000

R-squared	0.036036	Mean dependent var	0.723668
Adjusted R-squared	0.035784	S.D. dependent var	0.095191
S.E. of regression	0.093472	Akaike info criterion	-1.901789
Sum squared resid	33.34908	Schwarz criterion	-1.898517
Log likelihood	3633.466	F-statistic	142.6931
Durbin-Watson stat	1.451210	Prob(F-statistic)	0.000000

[87] LOGI_TEA=probability Tea (logit model generated)
DUM_TEA=dummy variable Tea
C=intercept coefficient

APPENDIX 5

DERIVATION OF ELASTICITY FORMULAE AND PARAMETER ESTIMATES FOR LA/QUAIDS, BARTEN AND STATE ADJUSTMENT MODELS

Expenditure, own-price and cross-price elasticity formule are derived for linear approximated QUAIDS (LA/QUAIDS), Batern Synthetic and Houthakker and Taylor State Adjustment models. Parameter estimates for each of aforementioned models also are reported.

Derivation of expenditure elasticity formula for QUAIDS model

Let us start with the QUAIDS model expressed as follows:

(6A.1) $$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{m}{f(\mathbf{p})}\right] + \frac{\lambda_i}{g(\mathbf{p})}\left\{\ln\left[\frac{m}{f(\mathbf{p})}\right]\right\}^2$$

Differentiating above equation 6A.1 with respect to $\ln m$ we get the following relationship:

(6A.2) $$\frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{g(\mathbf{p})}\left(\ln m - \ln f(\mathbf{p})\right)$$

Expenditure elasticity e_i can be defined as follows:

(6A.3) $$e_i = \frac{\partial \ln q_i}{\partial \ln m}$$

where q_i is the quantity of the good consumed. However, QUAIDS is written in terms of budget shares, w_i. Therefore, we can derive the elasticity formula taking budget shares into account as follows:

(6A.4) $$w_i = \frac{p_i q_i}{m}$$

Writing above 6A.4 in *log-log* form:

(6A.5) $$\ln w_i = \ln p_i + \ln q_i - \ln m$$

Re-writing above 6A.5 in terms of $\ln q_i$, we get the following:

(6A.6) $$\ln q_i = \ln w_i - \ln p_i + \ln m$$

(6A.7) $$\partial \ln q_i = \partial \ln w_i - \partial \ln p_i + \partial \ln m$$

divide 6A.7 through by $\partial \ln m$ to obtain the following relationship for the expenditure elasticity:

(6A.8) $$\frac{\partial \ln q_i}{\partial \ln m} = \frac{\partial \ln w_i}{\partial \ln m} - \frac{\partial \ln p_i}{\partial \ln m} + \frac{\partial \ln m}{\partial \ln m}$$

(6A.9) $$\frac{\partial \ln q_i}{\partial \ln m} = \frac{\partial w_i}{\partial \ln m}\left(\frac{1}{w_i}\right) - \frac{\partial \ln p_i}{\partial \ln m} + \frac{\partial \ln m}{\partial \ln m}$$

Substituting 6A.2 into 6A.9 and simplifying would result the following relationship:

(6A.10) $$\frac{\partial \ln q_i}{\partial \ln m} = \left(\beta_i + \frac{2\lambda_i}{g(\mathbf{p})}(\ln m - \ln f(\mathbf{p}))\right)\left(\frac{1}{w_i}\right) - 0 + 1$$

(6A.11) $$e_i = \left(\beta_i + \frac{2\lambda_i}{g(\mathbf{p})}(\ln m - \ln f(\mathbf{p}))\right)\left(\frac{1}{w_i}\right) + 1$$

Above 6A.11 shows the expression for the expenditure elasticity of demand for a given good for derived through the QUAIDS model.

Derivation of uncompensated price elasticity formula for QUAIDS model

First let us substitute equations 6.2, 6.3 and 6.4 from Chapter VI above into the equation 6A.1:

$$\text{(6A.12)}\quad w_i = \alpha_i + \sum_{j=1}^{n}\gamma_{ij}\ln p_j + \beta_i \ln\left[\frac{m}{\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j}\right] + \frac{\lambda_i}{\prod_{i=1}^{n} p_i^{\beta_i}}\left\{\ln\left[\frac{m}{\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j}\right]\right\}^2$$

through some simplification we get the following:

$$\text{(6A.13)}\quad \begin{aligned} w_i &= \alpha_i + \sum_{j=1}^{n}\gamma_{ij}\ln p_j + \beta_i\left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j\right)\right] + \\ &\frac{\lambda_i}{\sum_{i=1}^{n}\beta_i \ln p_i}\left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j\right)\right]^2 \end{aligned}$$

$$\text{(6A.14)}\quad \begin{aligned} w_i &= \alpha_i + \sum_{j=1}^{n}\gamma_{ij}\ln p_j + \beta_i\left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j\right)\right] + \\ &\lambda_i\left(\sum_{i=1}^{n}\beta_i \ln p_i\right)^{-1}\left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\gamma_{ij}\ln p_i \ln p_j\right)\right]^2 \end{aligned}$$

Next we differentiate above equation 6A.14 with respect to $\ln p_j$ we get the following relationship:

(6A.15)

$$\frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \beta_i \alpha_j - \beta_i \sum_{i=1}^{n} \gamma_{ij} \ln p_i + 2\lambda_i \left(\sum_{i=1}^{n} \beta_i \ln p_i \right)^{-1} \left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1} \gamma_{ij} \ln p_i \ln p_j \right) \right]$$

$$\left(-\alpha_j - \sum_{i=1}^{n} \gamma_{ij} \ln p_i \right) -$$

$$\left[\ln m - \left(\alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1} \gamma_{ij} \ln p_i \ln p_j \right) \right]^2 \lambda_i \beta_j \left(\sum_{i=1}^{n} \beta_i \ln p_i \right)^{-2}$$

Further simplification would result in the following expression:

(6A.16)
$$\frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \beta_i \left(\alpha_j - \sum_{i=1}^{n} \gamma_{ij} \ln p_i \right) + \frac{2\lambda_i}{g(\mathbf{p})} [\ln m - \ln f(\mathbf{p})] * \left[- \left(\alpha_j + \sum_{i=1}^{n} \gamma_{ij} \ln p_i \right) \right] - \frac{\lambda_i \beta_j}{g(\mathbf{p})} [\ln m - \ln f(\mathbf{p})]^2$$

One more step of simplification follows:

(6A.17)
$$\frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \left(\alpha_j + \sum_{i=1}^{n} \gamma_{ij} \ln p_i \right) \left[\beta_i + \frac{2\lambda_i}{g(\mathbf{p})} [\ln m - \ln f(\mathbf{p})] \right] - \frac{\lambda_i \beta_j}{g(\mathbf{p})} [\ln m - \ln f(\mathbf{p})]^2$$

Along the same logic which was used in deriving the expenditure elasticity formula above, we use the equation 6A.9 with expenditure variable replaced by the price variable in the denominator:

(6A.18)
$$\frac{\partial \ln q_i}{\partial \ln p_j} = \frac{\partial w_i}{\partial \ln p_j} \left(\frac{1}{w_i} \right) - \frac{\partial \ln p_i}{\partial \ln p_j} + \frac{\partial \ln m}{\partial \ln p_j}$$

Uncompensated price elasticity formula can be written as following (combine 6A.17 and 6A.18):

$$e_{ij}^{U} = \left\{ \gamma_{ij} - \left(\alpha_j + \sum_{i=1}^{n} \gamma_{ij} \ln p_i \right) \left[\beta_i + \frac{2\lambda_i}{g(\mathbf{p})} \left[\ln m - \ln f(\mathbf{p}) \right] \right] - \frac{\lambda_i \beta_j}{g(\mathbf{p})} \left[\ln m - \ln f(\mathbf{p}) \right]^2 \right\} \frac{1}{w_i} - \delta_{ij} \tag{6A.19}$$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1$ $If\, i = j$ and $\delta_{ij} = 0$ $if\, i \neq j$).

<u>Derivation of expenditure elasticity formula for linear approximated QUAIDS model (LA/QUAIDS)</u>

Let us begin with the following expression that shows the LA/QUAIDS model:

(6A.20) $$w_{it} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_{it}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{ti}\right] + \frac{\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left[\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right]^2$$

Differentiating above equation 6A.20 with respect to $\ln m$ gives us the following expression for the slope:

(6A.21) $$\frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right)$$

Using expression 6A.9 we obtain the following expression for expenditure elasticity for LA/QUAIDS model:

(6A.22) $$\frac{\partial \ln q_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right)\left(\frac{1}{w_i}\right) - 0 + 1$$

Further simplification follows; e_i is the expenditure elasticity:

(6A.23) $$e_i = \left\{\beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}_{it-2}^{0})(\ln p_{it-1} - \ln p_{it-2}^{0})}\left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it}\right)\right\}\left(\frac{1}{w_i}\right) + 1$$

Derivation of uncompensated price elasticity formulae for linear approximated QUAIDS model (LA/QUAIDS)

Let us differentiate above 6A.20 with respect to $\ln p_j$ to obtain the expression for slope as follows:

(6A.24)
$$\frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \left\{ \beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^0_{it-2})(\ln p_{it-1} - \ln p^0_{it-2})} \left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it} \right) \right\} w_{jt-1} - \frac{\lambda_i (\overline{w}_{jt-1} - \overline{w}^0_{jt-2})}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^0_{it-2})(\ln p_{it-1} - \ln p^0_{it-2})} \left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it} \right)^2$$

Uncompensated price elasticity formula (we used above equation 6A.18 to derive it) for linear approximated QUAIDS model is specified as follows:

(6A.25)
$$e^U_{ij} = \left[\gamma_{ij} - \left\{ \beta_i + \frac{2\lambda_i}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^0_{it-2})(\ln p_{it-1} - \ln p^0_{it-2})} \left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it} \right) \right\} w_{jt-1} - \frac{\lambda_i (\overline{w}_{jt-1} - \overline{w}^0_{jt-2})}{\sum_{i=1}^{n} (\overline{w}_{it-1} - \overline{w}^0_{it-2})(\ln p_{it-1} - \ln p^0_{it-2})} \left(\ln m - \sum_{i=1}^{n} w_{it-1} \ln p_{it} \right)^2 \right] \frac{1}{w_j} - \delta_{ij}$$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1 \ If i = j$ and $\delta_{ij} = 0 \ if i \neq j$).

<u>Derivation of compensated price elasticity formula for the Barten synthetic model</u>

Lets write the Barten synthetic model as follows:

(6A.26) $$w_i d\ln q_i = (\beta_i + \lambda w_i) d\ln Q + \sum_{j=1}^{n} [\gamma_{ij} - \mu w_i (\delta_{ij} - w_j)] d\ln p_j$$

Divide above equation 6A.26 through by w_i to get the following:

(6A.27) $$d\ln q_i = \left(\frac{\beta_i}{w_i} + \lambda\right) d\ln Q + \sum_{j=1}^{n} \left[\frac{\gamma_{ij}}{w_i} - \mu(\delta_{ij} - w_j)\right] d\ln p_j$$

Now, let us differentiate above equation 6A.27 with respect to $d\ln p_j$, to obtain the compensated price elasticity formula:

(6A.28) $$\frac{d\ln q_i}{d\ln p_j} \equiv e_{ij}^{C} = \left[\frac{\gamma_{ij}}{w_i} - \mu(\delta_{ij} - w_j)\right]$$

<u>Derivation of expenditure elasticity formula for the Barten synthetic model</u>

We know that:

(6A.29) $$d\ln m = d\ln P + d\ln Q$$

Write above equation 6A.29 in terms of $d\ln Q$:

(6A.30) $$d\ln Q = d\ln m - d\ln P$$

Applying above result from equation 6A.30 into equation 6A.26 gives us the following:

(6A.31) $$w_i d\ln q_i = (\beta_i + \lambda w_i)(d\ln m - d\ln P) + \sum_{j=1}^{n} [\gamma_{ij} - \mu w_i (\delta_{ij} - w_j)] d\ln p_j$$

Simplifying equation 6A.31 further would result in the following:

(6A.32) $$w_i d\ln q_i = (\beta_i + \lambda w_i) d\ln m - (\beta_i + \lambda w_i) d\ln P + \sum_{j=1}^{n} [\gamma_{ij} - \mu w_i (\delta_{ij} - w_j)] d\ln p_j$$

Dividing above equation 6A.32 through by w_i would give us the following expression:

(6A.33) $$d\ln q_i = \left(\frac{\beta_i}{w_i} + \lambda\right) d\ln m - \left(\frac{\beta_i}{w_i} + \lambda\right) d\ln P + \sum_{j=1}^{n} \left[\frac{\gamma_{ij}}{w_i} - \mu\left(\delta_{ij} - w_j\right)\right] d\ln p_j$$

Now, differentiating equation 6A.33 with respect to $d\ln m$ would give us the formula for expenditure elasticity:

(6A.34) $$\frac{d\ln q_i}{d\ln m} \equiv e_i = \left(\frac{\beta_i}{w_i} + \lambda\right)$$

<u>Derivation of the formula for Diversion Ration (DR)</u>

Let us consider two goods, i and j. We want to find out the change of quantity of good j for a change of quantity of good i. Mathematically, we can write the above statement at follows:

(6A.35) $$DR_{ji} = \frac{\partial q_j}{\partial q_i}$$

Let us assume that the price of *i*th good changes. It is going to affect both good i and good j. Now, DR can be further written as follows:

(6A.36) $$DR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}}{\frac{\partial q_i}{\partial p_i}}$$

Multiplying both numerator and denominator by p_i / q_j and further simplification would result as following:

(6A.37) $$DR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}\frac{p_i}{q_j}}{\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_j}} = \frac{e_{ji}}{\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_j}\frac{q_i}{q_i}} = \frac{e_{ji}}{e_{ii}}\frac{q_j}{q_i}$$

Final expression for Diversion Ratio can be written as follows (e_{ji} is the cross-price elasticity of demand *i*th and *j*th goods; e_{ii} is the own-price elasticity of demand for *i*th good; $\overline{q}_j$ is the average quantity of *j*th good; $\overline{q}_i$ is the average quantity of *i*th good):

(6A.38) $$DR_{ji} = \frac{e_{ji}}{e_{ii}}\frac{\overline{q}_j}{\overline{q}_i}$$

Derivation of the finite approximation (the reduced form equation), short-run effects, and long-run effects using the short-run demand and stock depreciation function of Houthakker and Taylor (1970)

Let us write a basic State Adjustment Model with quantity variable on the left-hand side and state variable, income/expenditure and price on the right-hand side as follows:

Short-run demand equation

(6A.39) $$q(t) = \alpha + \beta S(t) + \gamma X(t) + \eta P(t)$$

where, $q(t)$ is the rate of demand at time *t*; $S(t)$ is the state of good at time *t*; $X(t)$ is the rate of income or expenditure at time *t*; $P(t)$ is the rate of price of good at time *t*.

$\alpha, \beta, \gamma, \eta$ are short run coefficients:

Stock depreciation equation

(6A.40) $$\dot{S}(t) = q(t) - \delta S(t)$$

where, $\dot{S}(t)$ is the rate of change in physical or psychological stock; δ is the constant depreciation rate. Now, to eliminate $S(t)$ from 6A.40, solve 6A.39 for $S(t)$ and substitute in 6A.40:

(6A.41) $$\dot{S}(t) = q(t) - \frac{\delta}{\beta}\left[q(t) - \alpha - \gamma X(t) - \eta P(t)\right]$$

Now, differentiate 6A.39 with respect to time and substitute 6A.41 for $\dot{S}(t)$:

(6A.42) $$\frac{dq(t)}{dt} = \beta \frac{dS(t)}{dt} + \gamma \frac{X(t)}{dt} + \eta \frac{P(t)}{dt}$$

Further simplification of 6A.42 would results in the following:

(6A.43) $$\dot{q}(t) = \beta \dot{S}(t) + \gamma \dot{X}(t) + \eta \dot{P}(t)$$

Now, solve equation 6A.43 for $\dot{S}(t)$ and substitute in 6A.41 to get the following equation after some simplification:

(6A.44) $$\dot{q}(t) = \delta\alpha + (\beta - \delta)q(t) + \gamma\dot{X}(t) + \delta\gamma X(t) + \eta\dot{P}(t) + \delta\eta P(t)$$

Equation 6A.44 is a first order differential equation involving observable variables quantity, income/expenditure and price.

<u>*Derivation of the short-run effect*</u>

Short-term derivative of consumption with respect to income/expenditure is given by:

(6A.45) $$\frac{d\dot{q}(t)}{d\dot{X}(t)} = \gamma$$

Short-term derivative of consumption with respect to price is given by:

(6A.46) $$\frac{d\dot{q}(t)}{d\dot{P}(t)} = \eta$$

Short-term derivative tells us the instantaneous adjustment of consumption before state variables have a chance to adjust.

<u>*Derivation of the long-run effect*</u>

To derive the long-run effect we set the $\dot{S}(t)$ in equation 6A.40 into zero. Then we obtain the following:

(6A.47) $$q(t) = \delta S(t)$$

Now, substituting equation 6A.47 in 6A.39 would result in the following relationship:

(6A.48) $$q(t) = \alpha + \beta\frac{q(t)}{\delta} + \gamma X(t) + \eta P(t)$$

Simplifying equation 6A.48 would result in the following:

(6A.49) $$q = \frac{\delta\alpha}{(\delta - \beta)} + \frac{\delta\gamma}{(\delta - \beta)}X + \frac{\delta\eta}{(\delta - \beta)}P$$

To obtain the long-run effects, let us differentiate equation 6A.50 with respect to *X* and *P*:

(6A.50) $$\frac{dq}{dX} = \frac{\delta\gamma}{(\delta - \beta)}$$

(6A.51) $$\frac{dq}{dP} = \frac{\delta\eta}{(\delta - \beta)}$$

<u>Finite approximation to the equation 6A.44</u>

If we want to be able to estimate equation 6A.44, we need to approximate above continuous form into a discrete form (use discrete intervals of time) or in other words, a finite approximation of 6A.44 would result in the following equation (it should be noted that Houthakker and Taylor (1970) used a calculus based approach to derive the finite approximation to above 6A.44 and alternatively, Winder (1971) used a non-calculus approach to arrive at the same result).

Reduced form equation is defined as follows:

(6A.52) $$q_t = A_0 + A_1 q_{t-1} + A_2 \Delta X_t + A_3 X_{t-1} + A_4 \Delta P_t + A_5 P_{t-1}$$

where, $\Delta X_t = X_t - X_{t-1}$ and $\Delta P_t = P_t - P_{t-1}$. Parameters defined through A's have following non-linear definitions.

(6A.53) $$A_0 = \frac{\alpha\delta}{1 - \frac{1}{2}(\beta - \delta)}$$

(6A.54) $$A_1 = \frac{1 + \frac{1}{2}(\beta - \delta)}{1 - \frac{1}{2}(\beta - \delta)}$$

(6A.55) $$A_2 = \frac{\gamma\left(1 + \frac{\delta}{2}\right)}{1 - \frac{1}{2}(\beta - \delta)}$$

(6A.56) $$A_3 = \frac{\gamma\delta}{1 - \frac{1}{2}(\beta - \delta)}$$

(6A.57) $$A_4 = \frac{\eta\left(1 + \frac{\delta}{2}\right)}{1 - \frac{1}{2}(\beta - \delta)}$$

(6A.58) $$A_5 = \frac{\eta\delta}{1 - \frac{1}{2}(\beta - \delta)}$$

Parameter Estimates of LA/QUAIDS Model for U.S. Non-alcoholic Beverages Consumed At Home: January 1998-December 2003[88]

Parameter	Estimate	P-Value		Parameter	Estimate	P-Value
g11	**-0.0258**	0.0009		**a1**	0.0099	0.4917
g12	-0.0008	0.9456		**b1**	0.0016	0.7783
g13	0.0201	0.1142		**L1**	-3.2E-09	0.4514
g14	-0.0075	0.3480		**d11**	**0.0024**	0.0010
g15	0.0049	0.5007		**d12**	**0.0041**	<.0001
g16	**-0.0221**	0.0017		**d13**	**0.0023**	0.0003
g17	**0.0181**	0.0767		**a2**	-0.0149	0.8026
g18	0.0035	0.6113		**b2**	**0.0990**	0.0019
g19	0.0097	0.1726		**L2**	3.5E-08	0.1494
g110	0.0001	0.9881		**d21**	**-0.0063**	0.0693
g22	**-0.2208**	<.0001		**d22**	**0.0064**	0.0573
g23	**-0.1056**	0.0049		**d23**	-0.0039	0.1980
g24	0.0214	0.3397		**a3**	0.0625	0.1328
g25	**0.0541**	0.0076		**b3**	**0.0336**	0.0785
g26	-0.0242	0.1806		**L3**	-2.5E-09	0.8666
g27	**0.2145**	<.0001		**d31**	0.0007	0.7579
g28	-0.0038	0.8499		**d32**	0.0030	0.1617
g29	**0.0500**	0.0281		**d33**	-0.0016	0.4117
g210	0.0153	0.2284		**a4**	**0.2228**	<.0001
g33	-0.0312	0.4540		**b4**	**-0.0260**	0.0615
g34	**0.0550**	0.0096		**L4**	7.2E-09	0.5046
g35	-0.0196	0.2824		**d41**	-0.0001	0.9752
g36	**0.0514**	0.0040		**d42**	**-0.0054**	0.0011
g37	-0.0068	0.7869		**d43**	1.1E-05	0.9938
g38	**0.0346**	0.0469		**a5**	**0.1138**	<.0001
g39	0.0022	0.9055		**b5**	-0.0129	0.2598
g310	2.6E-05	0.9979		**L5**	-5.1E-09	0.5633
g44	0.0288	0.3245		**d51**	0.0014	0.2861
g45	0.0377	0.1608		**d52**	-0.0020	0.1150
g46	**-0.0317**	0.0044		**d53**	**0.0022**	0.0534
g47	**-0.0789**	<.0001		**a6**	-0.0065	0.8386
g48	0.0006	0.9569		**b6**	0.0187	0.1325
g49	-0.0047	0.7029		**L6**	2.8E-09	0.7631
g410	**-0.0207**	0.0030		**d61**	**0.0138**	<.0001
g55	0.0056	0.8311		**d62**	**0.0122**	<.0001
g56	-0.0139	0.1244		**d63**	**0.0071**	<.0001
g57	**-0.0438**	0.0031		**a7**	**0.2632**	<.0001
g58	-0.0145	0.1135		**b7**	-0.0337	0.1610
g59	-0.0029	0.7672		**L7**	**-5.0E-08**	0.0090
g510	-0.0077	0.1485		**d71**	**-0.0068**	0.0139

[88] Parameter estimates that are in bold are significant at alpha level 0.10
g=estimated parameters in the LA/QUAIDS model (*gamas*)

Parameter Estimates of LA/QUAIDS Model for U.S. Non-alcoholic Beverages Consumed At Home: January 1998-December 2003 (Continued)

g66	**0.0250**	0.0802		**d72**	**-0.0170**	<.0001
g67	0.0092	0.5546		**d73**	**-0.0043**	0.0730
Parameter[89]	**Estimate**	**P-Value**		**Parameter**	**Estimate**	**P-Value**
g68	**-0.0250**	0.0415		**a8**	**0.0673**	0.0619
g69	**0.0374**	0.0095		**b8**	**-0.0310**	0.0403
g610	-0.0060	0.3868		**L8**	1.8E-08	0.1157
g77	-0.0356	0.2930		**d81**	**0.0077**	<.0001
g78	-0.0155	0.3877		**d82**	**0.0093**	<.0001
g79	**-0.0463**	0.0187		**d83**	**0.0066**	<.0001
g710	-0.0149	0.1846		**a9**	**0.1797**	<.0001
g88	0.0142	0.4551		**b9**	**-0.0452**	0.0119
g89	-0.0056	0.6970		**L9**	-7.7E-09	0.5698
g810	0.0115	0.1750		**d91**	**-0.0114**	<.0001
g99	**-0.0581**	0.0072		**d92**	**-0.0100**	<.0001
g910	**0.0183**	0.0448		**d93**	**-0.0060**	0.0011
g1010	0.0041	0.5771		**a10**	**0.1022**	0.0000
				b10	-0.0041	0.6737
				L10	5.5E-09	0.4656
				rho1	**0.5379**	<.0001
				rho2	**0.3559**	<.0001

[89] g=estimated parameters in the LA/QUAIDS model (*gamas*)
d=coefficients associated with seasonal dummy variable
L=lambda in the LA/QUAIDS model

Joint Hypothesis Tests for Seasonal (Quarterly) Dummies and Lambda

null hypothesis	Chi-Square	P-value
d11=d12=d13=0	34.17	0.0000
d21=d22=d23=0	17.04	0.0007
d31=d32=d33=0	5.69	0.1278
d41=d42=d43=0	18.95	0.0003
d51=d52=d53=0	15.31	0.0016
d61=d62=d63=0	111.41	0.0000
d71=d72=d73=0	46.26	0.0000
d81=d82=d83=0	34.24	0.0000
d91=d92=d93=0	38.76	0.0000
L1=L2=L3=L4=L5=L6=L7=L8=L9=0	26.92	0.0014

Parameter Estimates of Barten Synthetic Model for U.S. Non-alcoholic Beverages Consumed At Home: January 1998-December 2003[90]

Parameter	Estimate	p-value		Parameter	Estimate	p-value
g11	**-0.0471**	0.0000		b1	0.0053	0.1759
g12	**0.0217**	0.0767		d11	-0.0005	0.3068
g13	0.0159	0.1773		d12	**0.0016**	0.0046
g14	-0.0116	0.1377		d13	0.0002	0.6337
g15	0.0057	0.4209		b2	0.0130	0.7958
g16	**-0.0296**	0.0003		d21	**-0.0082**	0.0020
g17	0.0177	0.1287		d22	**0.0077**	0.0028
g18	0.0066	0.3973		d23	**-0.0040**	0.0789
g19	**0.0182**	0.0165		b3	0.0192	0.5351
g110	0.0025	0.5435		d31	-0.0015	0.2325
g22	**-0.3730**	0.0003		d32	**0.0037**	0.0078
g23	-0.0507	0.1883		d33	**-0.0019**	0.0880
g24	**0.0601**	0.0318		b4	-0.0421	0.2205
g25	**0.0484**	0.0368		d41	**0.0026**	0.0261
g26	0.0251	0.2904		d42	**-0.0049**	0.0000
g27	**0.1652**	0.0000		d43	0.0014	0.1760
g28	**0.0478**	0.0400		b5	-0.0250	0.3150
g29	0.0309	0.2081		d51	0.0011	0.2337
g210	**0.0245**	0.0669		d52	**-0.0038**	0.0000
g33	**-0.1680**	0.0172		d53	**0.0016**	0.0413
g34	**0.0516**	0.0283		b6	0.0228	0.2114
g35	0.0078	0.7114		d61	**0.0048**	0.0011
g36	**0.0723**	0.0002		d62	**0.0055**	0.0002
g37	0.0027	0.9181		d63	0.0003	0.7848
g38	**0.0362**	0.0343		b7	**-0.0819**	0.0793
g39	0.0214	0.2153		d71	**0.0037**	0.0952
g310	0.0108	0.2426		d72	**-0.0117**	0.0000
g44	**-0.1339**	0.0447		d73	0.0014	0.4892
g45	0.0459	0.1021		b8	-0.0018	0.8926
g46	**-0.0270**	0.0497		d81	0.0017	0.2013
g47	0.0093	0.6649		d82	**0.0050**	0.0010
g48	-0.0060	0.5978		d83	**0.0021**	0.0789
g49	0.0217	0.1126		b9	**-0.0508**	0.0458
g410	-0.0101	0.1499		d91	**-0.0039**	0.0119
g55	**-0.1186**	0.0233		d92	**-0.0045**	0.0038
g56	-0.0095	0.3774		d93	-0.0006	0.6423
g57	0.0024	0.8889		b10	-0.0016	0.8868
g58	-0.0032	0.7361		g1010	**-0.0557**	0.0130

[90] Parameter estimates that are in bold are significant at alpha level 0.10
g,b,d and lambda=estimated parameters in the Barten Synthetic model

Parameter Estimates of Barten Synthetic Model for U.S. Non-alcoholic Beverages Consumed At Home: January 1998-December 2003 (Continued)

Parameter[91]	Estimate	p-value		Parameter	Estimate	p-value
g59	**0.0226**	0.0380		lambda	**1.1427**	0.0000
g510	-0.0015	0.7850		mu	-0.5384	0.2839
g66	**-0.0876**	0.0270		rho1	**-0.3925**	0.0000
g67	0.0302	0.1652		rho2	**-0.1976**	0.0001
g68	-0.0231	0.1468		rho3	**-0.0996**	0.0355
g69	**0.0544**	0.0024				
g610	-0.0053	0.5211				
g77	**-0.2311**	0.0080				
g78	-0.0030	0.8911				
g79	-0.0109	0.6331				
g710	0.0176	0.1565				
g88	**-0.0507**	0.0590				
g89	-0.0044	0.7728				
g810	-0.0002	0.9814				
g99	**-0.1714**	0.0004				
g910	**0.0174**	0.0547				

Joint Hypothesis Tests for Seasonal (Quarterly) Dummies, Lambda and Mu

null hypothesis	Chi-Square	p-value
d11=d12=d13=0	9.46	0.0238
d21=d22=d23=0	22.09	0.0000
d31=d32=d33=0	11.35	0.0100
d41=d42=d43=0	24.28	0.0000
d51=d52=d53=0	23.96	0.0000
d61=d62=d63=0	29.53	0.0000
d71=d72=d73=0	33.11	0.0000
d81=d82=d83=0	17.92	0.0005
d91=d92=d93=0	16.82	0.0008
lambda=0,mu=0	25.16	0.0000
lambda=1,mu=1	10.1	0.0064
lambda=1,mu=0	1.6	0.4499
lambda=0,mu=1	34.43	0.0000

[91] g,b,d, rho, mu and lambda=estimated parameters in the Barten Synthetic model

Reduced-form Parameter Estimates: Houthakker and Taylor Model

Variable	Isotonics		Regular Soft Drinks		Diet Soft Drinks		High Fat Milk		Low Fat Milk	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-0.0317	0.5650	1.8628	0.0006	1.0216	0.0003	0.5711	0.0009	0.4900	0.0138
G[92]1	0.3760	0.0003	-0.0488	0.6457	0.0000	0.9998	-0.1495	0.3160	-0.5054	0.0000
G2	0.0056	0.0000	0.1738	0.0000	0.1041	0.0000	0.0779	0.0000	0.0524	0.0000
G3	0.0065	0.0005	0.1916	0.0000	0.0890	0.0000	0.0940	0.0000	0.0785	0.0000
G4	-0.0229	0.0047	0.0566	0.3181	-0.0602	0.0476	0.0334	0.0864	0.0164	0.4560
G5	0.0033	0.9289	-1.3161	0.0000	-0.3120	0.0606	0.1681	0.1680	0.2594	0.0284
G6	0.0445	0.2531	-0.2431	0.4151	-0.3250	0.0688	-0.0898	0.4897	-0.1093	0.3416
G7	0.0120	0.7663	0.0247	0.9426	0.2612	0.1461	-0.1054	0.3635	0.1310	0.3379
G8	-0.0081	0.8385	-0.3180	0.3495	-0.2785	0.1176	0.0028	0.9800	-0.1996	0.1346
G9	-0.0726	0.0000	-0.5063	0.0000	-0.0458	0.4137	0.0720	0.0973	0.1364	0.0013
G10	0.0350	0.0050	0.1758	0.1090	-0.0669	0.1116	-0.1339	0.0008	-0.1668	0.0011
G11	0.0135	0.5318	0.0135	0.9372	-0.0658	0.4592	-0.0839	0.2116	-0.0836	0.2299
G12	0.0514	0.0226	0.9911	0.0000	0.3812	0.0004	-0.2380	0.0005	-0.1965	0.0347
G13	0.0022	0.8708	0.3499	0.0017	0.1544	0.0169	-0.2289	0.0000	-0.1668	0.0002
Quarter 1	0.0024	0.1117	-0.0440	0.0000	-0.0129	0.0573	0.0220	0.0000	0.0147	0.0000
Quarter 2	0.0057	0.0008	-0.0098	0.3699	0.0080	0.3423	0.0005	0.9074	0.0021	0.5713
Quarter 3	0.0036	0.0336	-0.0238	0.0183	-0.0162	0.0582	0.0119	0.0118	0.0083	0.0128
rho1	-0.0808	0.5160	0.6065	0.0000	-0.1032	0.5097	0.1756	0.3074	0.9591	0.0000
rho2	0.6285	0.0000	0.2754	0.0052	0.2422	0.0014	0.0591	0.4853	0.0459	0.7278
R-Squared (Adjusted)	0.9020		0.9344		0.9168		0.9745		0.9818	

[92] Gs=reduced form parameter estimates for Houthakker and Taylor model

Continued..

Variable	Fruit Drinks		Fruit Juices		Bottled Water		Coffee		Tea	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	0.0600	0.7358	-0.0303	0.5019	0.8220	0.0006	2.5129	0.0072	0.4071	0.0367
G[93]1	0.0536	0.5309	0.7542	0.0000	0.6584	0.0000	-0.2920	0.0107	-0.1168	0.4794
G2	0.0415	0.0000	0.0718	0.0000	0.0180	0.0244	0.1202	0.0000	0.0422	0.0000
G3	0.0424	0.0000	0.0180	0.0000	0.0135	0.0474	0.1537	0.0000	0.0385	0.0000
G4	-0.0725	0.0017	-0.0123	0.0500	-0.0314	0.3092	0.2468	0.0212	0.0096	0.6921
G5	0.0406	0.6755	0.0559	0.0631	-0.1369	0.4595	-0.8884	0.0740	0.3219	0.0164
G6	0.1604	0.1286	0.0261	0.4105	-0.1189	0.5358	0.1542	0.7463	-0.2238	0.1225
G7	0.1123	0.3359	-0.0905	0.0348	0.2529	0.1012	-0.9866	0.0823	0.2549	0.0976
G8	-0.1890	0.1019	0.0776	0.0595	-0.3200	0.0378	0.8792	0.1105	-0.2891	0.0629
G9	-0.1092	0.0028	0.0682	0.0000	-0.1807	0.0018	0.4287	0.0112	-0.1640	0.0032
G10	-0.0504	0.2103	-0.0256	0.0412	0.0458	0.3389	-0.0817	0.6679	0.0851	0.0425
G11	0.0419	0.4922	0.0098	0.5904	-0.1501	0.1054	-0.4822	0.1131	0.1423	0.0810
G12	0.1309	0.1348	-0.1057	0.0002	-0.1009	0.1616	-2.3148	0.0000	-0.2157	0.0054
G13	0.1269	0.0028	-0.0287	0.0275	0.1531	0.0264	-0.4060	0.0279	-0.3363	0.0005
Quarter 1	0.0240	0.0000	-0.0219	0.0000	0.0677	0.0000	-0.0685	0.0003	0.0211	0.0049
Quarter 2	0.0271	0.0000	-0.0359	0.0000	0.0503	0.0000	-0.0962	0.0000	0.0150	0.0454
Quarter 3	0.0178	0.0002	-0.0186	0.0000	0.0486	0.0000	-0.0776	0.0001	0.0051	0.4709
rho1	0.3671	0.0000	-0.2976	0.0000	-0.5623	0.0000	0.4885	0.0000	0.4861	0.0077
rho2	0.6305	0.0000	-0.1494	0.0016	-0.1857	0.0423	0.5092	0.0000	-0.1954	0.1050
R-Squared (Adjusted)	0.9226		0.9073		0.8888		0.8933		0.8189	

[93] Gs=reduced form parameter estimates for Houthakker and Taylor model

Houthakker and Taylor Reduced-form Parameter Estimation: Joint Test for Significance of Model Seasonality Dummy Variables[94]

null hypothesis	Chi Square	p-value
d11=d12=d13=0	12.85	0.005
d21=d22=d23=0	39.1	0.000
d31=d32=d33=0	21.65	0.000
d41=d42=d43=0	43.47	0.000
d51=d52=d53=0	31.51	0.000
d61=d62=d63=0	44.35	0.000
d71=d72=d73=0	110	0.000
d81=d82=d83=0	104.02	0.000
d91=d92=d93=0	26.55	0.000
d101=d102=d103=0	10.95	0.012

[94] d=estimated dummy variable coefficient for Houthakker and Taylor model

Houthakker and Taylor Model: Short-Run Structural Parameter Estimates

Beverage	Structural Parameters[95]													
	alpha	**beta**	**gama**	**delta**	**k1**	**k2**	**k3**	**k4**	**k5**	**k6**	**k7**	**k8**	**k9**	**k10**
Isotonics	-0.0169	**1.8092**	**0.0035**	**2.7163**	**-0.0122**	0.0018	0.0238	0.0064	-0.0043	**-0.0388**	**0.0187**	0.0072	**0.0275**	0.0012
	0.5720	0.0361	0.0007	0.0076	0.0115	0.9293	0.2403	0.7651	0.8374	0.0005	0.0152	0.5367	0.0311	0.8696
Regular Soft Drinks	**1.5956**	**0.2495**	**0.1641**	**2.4546**	0.0485	**-1.1273**	-0.2082	0.0212	-0.2724	**-0.4337**	**0.1506**	0.0115	**0.8489**	**0.2997**
	0.0004	0.0589	0.0000	0.0000	0.3106	0.0000	0.4114	0.9425	0.3416	0.0000	0.1026	0.9371	0.0000	0.0017
Diet Soft Drinks	**1.3680**	**-0.5063**	**0.1192**	**1.4935**	**-0.0806**	**-0.4178**	**-0.4352**	**0.3498**	**-0.3729**	-0.0614	**-0.0896**	-0.0882	**0.5105**	**0.2068**
	0.0000	0.0364	0.0000	0.0020	0.0333	0.0422	0.0506	0.1380	0.1075	0.3990	0.1294	0.4634	0.0000	0.0087
High Fat Milk	**0.4405**	0.3459	**0.0725**	**3.0487**	**0.0257**	**0.1297**	-0.0692	-0.0813	0.0022	**0.0556**	**-0.1032**	**-0.0647**	**-0.1835**	**-0.1766**
	0.0001	0.2239	0.0000	0.0042	0.1078	0.1644	0.4951	0.3517	0.9800	0.0799	0.0000	0.1851	0.0000	0.0000
Low Fat Milk	**0.3324**	-0.1268	**0.0533**	**5.9607**	0.0111	**0.1760**	-0.0741	0.0889	**-0.1354**	**0.0925**	**-0.1132**	-0.0567	**-0.1333**	**-0.1131**
	0.0130	0.8061	0.0000	0.0005	0.4585	0.0291	0.3440	0.3377	0.1333	0.0019	0.0007	0.2234	0.0378	0.0004
Fruit Drinks	0.0546	**0.2889**	**0.0386**	**2.0855**	**-0.0660**	0.0370	**0.1460**	0.1022	**-0.1721**	**-0.0994**	-0.0459	0.0382	**0.1191**	**0.1155**
	0.7375	0.1793	0.0000	0.0000	0.0011	0.6753	0.1151	0.3299	0.0922	0.0013	0.2133	0.4914	0.1365	0.0010
Fruit Juices	-0.1204	0.0066	**0.0715**	**0.2869**	**-0.0489**	**0.2223**	0.1038	**-0.3598**	**0.3084**	**0.2710**	**-0.1017**	0.0389	**-0.4201**	**-0.1141**
	0.4989	0.7979	0.0000	0.0000	0.0323	0.0407	0.4110	0.0189	0.0408	0.0000	0.0198	0.5879	0.0000	0.0123
Bottled Water	**0.8289**	**0.7839**	**0.0136**	**1.1959**	-0.0317	-0.1380	-0.1199	**0.2550**	**-0.3227**	**-0.1823**	0.0462	**-0.1514**	**-0.1018**	**0.1544**
	0.0087	0.0244	0.0242	0.0022	0.3022	0.4542	0.5439	0.1504	0.0811	0.0108	0.3502	0.1555	0.1983	0.0254
Coffee	**2.0013**	-0.1026	**0.1224**	**3.5470**	**0.1965**	**-0.7075**	0.1228	**-0.7858**	**0.7002**	**0.3414**	-0.0651	**-0.3840**	**-1.8435**	**-0.3233**
	0.0057	0.7744	0.0000	0.0002	0.0194	0.0749	0.7479	0.0870	0.1175	0.0104	0.6672	0.1085	0.0000	0.0273
Tea	**0.5494**	**-0.8513**	**0.0520**	**1.6777**	0.0130	**0.4345**	**-0.3021**	**0.3441**	**-0.3902**	**-0.2213**	**0.1149**	**0.1921**	**-0.2911**	**-0.4540**
	0.0183	0.0181	0.0000	0.0098	0.6959	0.0078	0.1079	0.1081	0.0697	0.0003	0.0425	0.0651	0.0022	0.0000

[95] Alpha, beta, gama, delta, k1 through k10 are short-run structural parameter estimates of Houthakker and Taylor model for each non-alcoholic beverage. Number blow each estimated coefficient is the corresponding p-value

Houthakker and Taylor Model Long-Run Structural Parameter Estimates

Beverage	Structural Parameters[96]										
	eta	**theta1**	**theta2**	**theta3**	**theta4**	**theta5**	**theta6**	**theta7**	**theta8**	**theta9**	**theta10**
Isotonics	**0.0103**	**-0.0367**	0.0053	0.0713	0.0192	-0.0129	**-0.1163**	**0.0561**	0.0216	**0.0823**	0.0036
	0.0001	0.0015	0.9289	0.2404	0.7653	0.8380	0.0000	0.0077	0.5304	0.0162	0.8702
Regular Soft Drinks	**0.1826**	0.0540	**-1.2549**	-0.2318	0.0236	-0.3032	**-0.4828**	**0.1677**	0.0128	**0.9450**	**0.3692**
	0.0000	0.3095	0.0000	0.4121	0.9425	0.3395	0.0000	0.1062	0.9371	0.0000	0.0559
Diet Soft Drinks	**0.0890**	**-0.0602**	**-0.3120**	**-0.3250**	**0.2612**	**-0.2785**	-0.0458	**-0.0669**	-0.0658	**0.3812**	**0.1544**
	0.0000	0.0391	0.0446	0.0539	0.1231	0.0961	0.3920	0.1249	0.4607	0.0000	0.0091
High Fat Milk	**0.0818**	**0.0290**	**0.1463**	-0.0781	-0.0917	0.0024	**0.0627**	**-0.1165**	**-0.0730**	**-0.2070**	**-0.1991**
	0.0000	0.0930	0.1608	0.4953	0.3545	0.9800	0.0789	0.0000	0.1913	0.0000	0.0000
Low Fat Milk	**0.0522**	0.0109	**0.1723**	-0.0726	0.0870	**-0.1326**	**0.0906**	**-0.1108**	-0.0555	**-0.1305**	**-0.1108**
	0.0000	0.4564	0.0246	0.3441	0.3377	0.1348	0.0011	0.0006	0.2255	0.0350	0.0002
Fruit Drinks	**0.0448**	**-0.0766**	0.0429	**0.1694**	0.1186	**-0.1997**	**-0.1153**	-0.0533	0.0443	**0.1383**	**0.1341**
	0.0000	0.0007	0.6757	0.1137	0.3349	0.0993	0.0015	0.2033	0.4877	0.1380	0.0010
Fruit Juices	**0.0732**	**-0.0500**	**0.2276**	0.1063	**-0.3683**	**0.3157**	**0.2774**	**-0.1041**	0.0399	**-0.4300**	**-0.1168**
	0.0000	0.0383	0.0429	0.4083	0.0219	0.0438	0.0000	0.0309	0.5884	0.0000	0.0138
Bottled Water	**0.0395**	-0.0921	-0.4007	-0.3480	**0.7403**	**-0.9369**	**-0.5291**	0.1342	**-0.4396**	**-0.2954**	**0.4483**
	0.0498	0.2765	0.4656	0.5349	0.1011	0.0394	0.0072	0.3833	0.1148	0.1520	0.0200
Coffee	**0.1190**	**0.1910**	**-0.6876**	0.1194	**-0.7637**	**0.6805**	**0.3318**	-0.0633	**-0.3732**	**-1.7917**	**-0.3142**
	0.0000	0.0152	0.0685	0.7468	0.0773	0.1065	0.0092	0.6683	0.1057	0.0000	0.0221
Tea	**0.0345**	0.0086	**0.2882**	**-0.2004**	**0.2283**	**-0.2588**	**-0.1468**	**0.0762**	**0.1274**	**-0.1931**	**-0.3012**
	0.0000	0.6942	0.0072	0.1163	0.1000	0.0632	0.0011	0.0359	0.0593	0.0024	0.0000

Note: eta is associated with expenditure coefficient and theta's are associated with each price coefficient

[96] eta and theta1 through theta10 are long-run structural parameter estimates of Houthakker and Taylor model for each non-alcoholic beverage. Number blow each estimated coefficient is the corresponding p-value

APPENDIX 6

REGRESSION RESULTS FOR FACTORS AFFECTING CALORIC, CALCIUM, CAFFEINE, AND VITAMIN C INTAKE FOR EACH NON-ALCOHOLIC BEVERAGE

Regression results for factors affecting caloric, calcium, caffeine and vitamin C intake for each non-alcoholic beverage for each year are reported. Abbreviations used in regression analyses are as follows.

C	Constant
PRICE	Price
PRICE2	Price squared
AGEHH2529	Age of household head between 25-29 years
AGEHH3034	Age of household head between 30-34 years
AGEHH3544	Age of household head between 35-44 years
AGEHH4554	Age of household head between 45-54 years
AGEHH5564	Age of household head between 55-64 years
AGEHHGT64	Age of household head greater than 64 years
EMPHHPT	Part-time employed household head
EMPHHFT	Full-time employed household head
EDUHHHS	High-school educated household head
EDUHHU	Undergraduate educated household head
EDUHHPC	Post-college educated household head
REG_CENTRAL	Central (Midwest) region of the United States
REG_SOUTH	South region of the United States
REG_WEST	West region of the United States
RACE_BLACK	Black racial category
RACE_ORIENTAL	Oriental or Asian racial category
RACE_OTHER	Other racial category
HISP_YES	Presence of Hispanic household head
AGEPCLT6_ONLY	Age and presence of children less than 6 years
AGEPC6_12ONLY	Age and presence of children between 6-12 years
AGEPC13_17ONLY	Age and presence of children between 13-17 years
AGEPCLT6_6_12ONLY	Age and presence of children less than 6 and 6-12 years
AGEPCLT6_13_17ONLY	Age and presence of children less than 6 and 13-17 years
AGEPC6_12AND13_17ONLY	Age and presence of children between 6-12 and 13-17 years
AGEPCLT6_6_12AND13_17	Age and presence of children less than 6, 6-12 and 13-17years
MHONLY	Male only headed household head
FHONLY	Female only headed household head
POV185	Poverty households (less than 185% poverty)

Regression Results from Caloric Intake 1998

Dependent Variable: CALORIES

Included observations: 6087

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	130.8838	30.19166	4.335097	0.0000
PRICE	71.58935	13.92106	5.142521	0.0000
PRICE2	-10.76437	2.548607	-4.223628	0.0000
AGEHH2529	23.91501	21.41407	1.116790	0.2641
AGEHH3034	28.58343	20.42441	1.399474	0.1617
AGEHH3544	20.13143	19.91420	1.010908	0.3121
AGEHH4554	13.84138	19.91754	0.694934	0.4871
AGEHH5564	18.66853	20.22396	0.923090	0.3560
AGEHHGT64	15.55468	20.76455	0.749098	0.4538
EMPHHPT	-15.00713	6.160447	-2.436045	0.0149
EMPHHFT	-30.17687	5.484913	-5.501795	0.0000
EDUHHHS	12.15340	13.54724	0.897113	0.3697
EDUHHU	-5.225607	13.22151	-0.395235	0.6927
EDUHHPC	-4.393662	14.29925	-0.307265	0.7587
REG_CENTRAL	9.081195	5.969668	1.521223	0.1283
REG_SOUTH	4.393857	5.668904	0.775081	0.4383
REG_WEST	-21.14000	6.363192	-3.322231	0.0009
RACE_BLACK	7.482983	7.635276	0.980054	0.3271
RACE_ORIENTAL	-48.50519	17.63207	-2.750964	0.0060
RACE_OTHER	4.326686	11.81052	0.366342	0.7141
HISP_YES	-6.388155	9.133844	-0.699394	0.4843
AGEPCLT6_ONLY	-21.52900	9.638103	-2.233739	0.0255
AGEPC6_12ONLY	-35.69544	8.127964	-4.391683	0.0000
AGEPC13_17ONLY	3.172601	7.247164	0.437771	0.6616
AGEPCLT6_6_12ONLY	-48.94099	10.25789	-4.771060	0.0000
AGEPCLT6_13_17ONLY	-54.21328	24.49060	-2.213636	0.0269
AGEPC6_12AND13_17ONLY	-27.74432	9.399406	-2.951710	0.0032
AGEPCLT6_6_12AND13_17	-36.42093	22.64681	-1.608214	0.1078
MHONLY	77.35724	7.438307	10.39984	0.0000
FHONLY	-2.017869	5.362880	-0.376266	0.7067
POV185	17.11834	6.597240	2.594774	0.0095
		Weighted Statistics		
R-squared	0.047067	Mean dependent var		232.7599
Adjusted R-squared	0.042346	S.D. dependent var		157.8942
S.E. of regression	154.2710	Akaike info criterion		12.92038
Sum squared resid	1.44E+08	Schwarz criterion		12.95457
Log likelihood	-39292.17	F-statistic		9.970435
Durbin-Watson stat	1.976482	Prob(F-statistic)		0.000000

Regression Results from Caloric Intake 1999

Dependent Variable: CALORIES
Included observations: 6376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	119.9095	28.01256	4.280561	0.0000
PRICE	86.38859	12.45154	6.937983	0.0000
PRICE2	-11.48621	2.351405	-4.884826	0.0000
AGEHH2529	-8.447052	21.46057	-0.393608	0.6939
AGEHH3034	16.51404	20.64901	0.799750	0.4239
AGEHH3544	8.979021	20.04801	0.447876	0.6543
AGEHH4554	0.201219	19.97461	0.010074	0.9920
AGEHH5564	1.375779	20.18474	0.068159	0.9457
AGEHHGT64	-4.661747	20.59579	-0.226345	0.8209
EMPHHPT	-19.91079	5.890410	-3.380205	0.0007
EMPHHFT	-26.89457	5.191429	-5.180572	0.0000
EDUHHHS	14.57944	11.11461	1.311736	0.1897
EDUHHU	-6.366405	10.79894	-0.589540	0.5555
EDUHHPC	-11.48702	12.04792	-0.953444	0.3404
REG_CENTRAL	7.696289	5.614053	1.370897	0.1705
REG_SOUTH	-0.092250	5.322741	-0.017331	0.9862
REG_WEST	-26.39427	6.065968	-4.351204	0.0000
RACE_BLACK	8.317866	6.695137	1.242374	0.2141
RACE_ORIENTAL	-54.83401	17.66672	-3.103803	0.0019
RACE_OTHER	22.34575	11.02226	2.027330	0.0427
HISP_YES	-7.350457	8.433957	-0.871531	0.3835
AGEPCLT6_ONLY	-26.40397	9.794819	-2.695707	0.0070
AGEPC6_12ONLY	-30.14761	7.988653	-3.773804	0.0002
AGEPC13_17ONLY	2.420641	7.121094	0.339925	0.7339
AGEPCLT6_6_12ONLY	-51.93900	10.69678	-4.855574	0.0000
AGEPCLT6_13_17ONLY	-58.22345	22.62889	-2.572969	0.0101
AGEPC6_12AND13_17ONLY	-28.61477	9.208290	-3.107501	0.0019
AGEPCLT6_6_12AND13_17	-40.35088	20.75507	-1.944146	0.0519
MHONLY	52.30170	7.170478	7.294032	0.0000
FHONLY	1.856420	4.971929	0.373380	0.7089
POV185	4.526518	6.084258	0.743972	0.4569

Weighted Statistics

R-squared	0.045023	Mean dependent var	232.0124
Adjusted R-squared	0.040508	S.D. dependent var	154.3173
S.E. of regression	151.8027	Akaike info criterion	12.88789
Sum squared resid	1.46E+08	Schwarz criterion	12.92076
Log likelihood	-41055.59	F-statistic	9.971320
Durbin-Watson stat	1.974350	Prob(F-statistic)	0.000000

Regression Results from Caloric Intake 2000

Dependent Variable: CALORIES

Included observations: 6555

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	153.0955	38.60142	3.966059	0.0001
PRICE	79.22788	14.98470	5.287254	0.0000
PRICE2	-11.47873	2.646864	-4.336728	0.0000
AGEHH2529	-17.83836	31.60171	-0.564474	0.5725
AGEHH3034	-13.24994	29.96018	-0.442252	0.6583
AGEHH3544	-14.50259	29.36082	-0.493944	0.6214
AGEHH4554	-20.52357	29.34618	-0.699361	0.4844
AGEHH5564	-25.38809	29.58378	-0.858176	0.3908
AGEHHGT64	-15.96538	30.05010	-0.531292	0.5952
EMPHHPT	-1.101838	8.087964	-0.136232	0.8916
EMPHHFT	-22.02654	6.988018	-3.152045	0.0016
EDUHHHS	1.774249	15.26348	0.116241	0.9075
EDUHHU	-12.12816	14.94600	-0.811465	0.4171
EDUHHPC	-26.67581	16.70073	-1.597284	0.1103
REG_CENTRAL	16.75103	7.716581	2.170784	0.0300
REG_SOUTH	4.214139	7.181128	0.586835	0.5573
REG_WEST	-21.11556	7.985124	-2.644362	0.0082
RACE_BLACK	3.099181	8.664387	0.357692	0.7206
RACE_ORIENTAL	-41.79655	23.00827	-1.816588	0.0693
RACE_OTHER	18.64677	14.20519	1.312673	0.1893
HISP_YES	6.592830	12.51251	0.526899	0.5983
AGEPCLT6_ONLY	-33.12412	13.98708	-2.368194	0.0179
AGEPC6_12ONLY	-35.81707	10.83647	-3.305235	0.0010
AGEPC13_17ONLY	-6.054102	10.07590	-0.600850	0.5480
AGEPCLT6_6_12ONLY	-47.77484	15.06956	-3.170288	0.0015
AGEPCLT6_13_17ONLY	-39.61470	32.02343	-1.237053	0.2161
AGEPC6_12AND13_17ONLY	-32.84905	13.34589	-2.461362	0.0139
AGEPCLT6_6_12AND13_17	-46.29716	32.52507	-1.423430	0.1547
MHONLY	83.33983	9.171290	9.087034	0.0000
FHONLY	5.644783	6.668014	0.846546	0.3973
POV185	8.831394	8.326157	1.060681	0.2889

Weighted Statistics

R-squared	0.031339	Mean dependent var	235.8663
Adjusted R-squared	0.026884	S.D. dependent var	212.2829
S.E. of regression	209.6243	Akaike info criterion	13.53323
Sum squared resid	2.87E+08	Schwarz criterion	13.56533
Log likelihood	-44324.16	F-statistic	7.035575
Durbin-Watson stat	2.022997	Prob(F-statistic)	0.000000

Regression Results from Caloric Intake 2001

Dependent Variable: CALORIES

Included observations: 7103

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	150.7162	29.58637	5.094111	0.0000
PRICE	83.08611	9.095170	9.135190	0.0000
PRICE2	-11.98486	1.588695	-7.543838	0.0000
AGEHH2529	-1.440342	26.39745	-0.054564	0.9565
AGEHH3034	-10.62504	25.46705	-0.417207	0.6765
AGEHH3544	-10.20624	25.00410	-0.408183	0.6832
AGEHH4554	-10.79187	25.04184	-0.430954	0.6665
AGEHH5564	-14.74948	25.15256	-0.586401	0.5576
AGEHHGT64	-26.75568	25.39479	-1.053589	0.2921
EMPHHPT	-23.62719	5.557297	-4.251562	0.0000
EMPHHFT	-37.28328	4.880474	-7.639275	0.0000
EDUHHHS	-4.443772	9.918685	-0.448020	0.6542
EDUHHU	-21.64117	9.673818	-2.237086	0.0253
EDUHHPC	-34.93535	11.06909	-3.156117	0.0016
REG_CENTRAL	12.83582	5.549623	2.312918	0.0208
REG_SOUTH	2.496524	4.963107	0.503016	0.6150
REG_WEST	-18.97944	5.623567	-3.374983	0.0007
RACE_BLACK	20.14921	5.648572	3.567133	0.0004
RACE_ORIENTAL	-34.79540	12.09163	-2.877644	0.0040
RACE_OTHER	11.77748	11.30611	1.041692	0.2976
HISP_YES	1.323585	8.421246	0.157172	0.8751
AGEPCLT6_ONLY	-25.42528	9.741521	-2.609991	0.0091
AGEPC6_12ONLY	-35.90106	7.483434	-4.797405	0.0000
AGEPC13_17ONLY	7.083196	7.378139	0.960025	0.3371
AGEPCLT6_6_12ONLY	-49.44135	10.30634	-4.797177	0.0000
AGEPCLT6_13_17ONLY	-44.13332	22.08520	-1.998322	0.0457
AGEPC6_12AND13_17ONLY	-26.79876	9.502197	-2.820270	0.0048
AGEPCLT6_6_12AND13_17	-50.00161	21.08384	-2.371561	0.0177
MHONLY	91.43294	6.406877	14.27106	0.0000
FHONLY	8.738390	4.644607	1.881406	0.0600
POV185	5.311103	5.586541	0.950696	0.3418

Weighted Statistics

R-squared	0.067772	Mean dependent var	226.5852
Adjusted R-squared	0.063818	S.D. dependent var	157.5771
S.E. of regression	152.7741	Akaike info criterion	12.90015
Sum squared resid	1.65E+08	Schwarz criterion	12.93013
Log likelihood	-45783.89	F-statistic	17.13760
Durbin-Watson stat	1.988414	Prob(F-statistic)	0.000000

Regression Results from Caloric Intake 2002

Dependent Variable: CALORIES
Included observations: 7384

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	177.5659	28.05038	6.330251	0.0000
PRICE	60.79630	7.356423	8.264385	0.0000
PRICE2	-8.252006	1.201182	-6.869904	0.0000
AGEHH2529	-37.98918	25.68650	-1.478955	0.1392
AGEHH3034	-41.12564	24.74483	-1.661989	0.0966
AGEHH3544	-43.86862	24.39109	-1.798551	0.0721
AGEHH4554	-39.73328	24.39897	-1.628482	0.1035
AGEHH5564	-47.45911	24.48802	-1.938054	0.0527
AGEHHGT64	-55.55335	24.67059	-2.251805	0.0244
EMPHHPT	-11.57740	5.127784	-2.257779	0.0240
EMPHHFT	-24.19019	4.459659	-5.424225	0.0000
EDUHHHS	0.464751	9.094452	0.051103	0.9592
EDUHHU	-19.90984	8.856749	-2.247985	0.0246
EDUHHPC	-30.44417	10.10432	-3.012985	0.0026
REG_CENTRAL	5.223165	5.098542	1.024443	0.3057
REG_SOUTH	3.831533	4.488213	0.853688	0.3933
REG_WEST	-25.38504	5.157819	-4.921663	0.0000
RACE_BLACK	7.403418	5.008505	1.478169	0.1394
RACE_ORIENTAL	-37.41106	10.57690	-3.537052	0.0004
RACE_OTHER	14.20689	9.078893	1.564826	0.1177
HISP_YES	-7.296712	8.257288	-0.883669	0.3769
AGEPCLT6_ONLY	-17.82679	9.877456	-1.804796	0.0711
AGEPC6_12ONLY	-33.66655	6.961749	-4.835932	0.0000
AGEPC13_17ONLY	-7.950772	6.671195	-1.191806	0.2334
AGEPCLT6_6_12ONLY	-44.82419	9.526601	-4.705161	0.0000
AGEPCLT6_13_17ONLY	-20.46283	22.91162	-0.893120	0.3718
AGEPC6_12AND13_17ONLY	-23.46438	8.228879	-2.851467	0.0044
AGEPCLT6_6_12AND13_17	-41.31872	16.53864	-2.498315	0.0125
MHONLY	80.62607	5.794223	13.91491	0.0000
FHONLY	11.86024	4.165900	2.846981	0.0044
POV185	7.027463	5.203414	1.350548	0.1769

Weighted Statistics

R-squared	0.061321	Mean dependent var	200.0040
Adjusted R-squared	0.057491	S.D. dependent var	145.9172
S.E. of regression	141.8025	Akaike info criterion	12.75094
Sum squared resid	1.48E+08	Schwarz criterion	12.77993
Log likelihood	-47045.46	F-statistic	16.01160
Durbin-Watson stat	1.974478	Prob(F-statistic)	0.000000

Regression Results from Caloric Intake 2003

Dependent Variable: CALORIES

Included observations: 7566

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	205.6050	34.94770	5.883220	0.0000
PRICE	45.47725	6.092759	7.464147	0.0000
PRICE2	-6.180041	0.934033	-6.616516	0.0000
AGEHH2529	-29.75254	34.14285	-0.871413	0.3836
AGEHH3034	-36.78474	33.11087	-1.110957	0.2666
AGEHH3544	-37.11442	32.64859	-1.136785	0.2557
AGEHH4554	-37.50260	32.58106	-1.151055	0.2497
AGEHH5564	-42.60673	32.62237	-1.306059	0.1916
AGEHHGT64	-50.95771	32.76281	-1.555352	0.1199
EMPHHPT	-8.836185	5.229016	-1.689837	0.0911
EMPHHFT	-23.65696	4.517872	-5.236305	0.0000
EDUHHHS	-14.02419	9.629037	-1.456447	0.1453
EDUHHU	-30.49009	9.378664	-3.251006	0.0012
EDUHHPC	-45.68420	10.61317	-4.304484	0.0000
REG_CENTRAL	5.612279	5.361105	1.046851	0.2952
REG_SOUTH	2.053878	4.573451	0.449087	0.6534
REG_WEST	-26.01807	5.368191	-4.846711	0.0000
RACE_BLACK	16.50410	5.216461	3.163850	0.0016
RACE_ORIENTAL	-34.20030	10.69469	-3.197878	0.0014
RACE_OTHER	19.11282	8.719356	2.191998	0.0284
HISP_YES	-3.932552	7.864998	-0.500007	0.6171
AGEPCLT6_ONLY	-23.11723	9.941529	-2.325320	0.0201
AGEPC6_12ONLY	-34.00733	7.640193	-4.451109	0.0000
AGEPC13_17ONLY	0.447706	6.931844	0.064587	0.9485
AGEPCLT6_6_12ONLY	-36.71861	10.89116	-3.371414	0.0008
AGEPCLT6_13_17ONLY	-49.50335	23.28351	-2.126112	0.0335
AGEPC6_12AND13_17ONLY	-20.37695	8.876062	-2.295719	0.0217
AGEPCLT6_6_12AND13_17	-34.14145	17.96779	-1.900147	0.0575
MHONLY	85.49498	6.059682	14.10882	0.0000
FHONLY	10.87691	4.180400	2.601882	0.0093
POV185	-1.195516	5.351896	-0.223382	0.8232

Weighted Statistics

R-squared	0.054842	Mean dependent var	199.6900
Adjusted R-squared	0.051079	S.D. dependent var	151.0669
S.E. of regression	147.1396	Akaike info criterion	12.82473
Sum squared resid	1.63E+08	Schwarz criterion	12.85313
Log likelihood	-48484.95	F-statistic	14.57363
Durbin-Watson stat	2.010108	Prob(F-statistic)	0.000000

Regression Results from Caloric Intake 1998-2003

Dependent Variable: CALORIES, Sample 41071 obs				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	186.7295	12.71830	14.68195	0.0000
PRICE	53.21295	6.825841	7.795810	0.0000
PRICE2	-6.841931	1.183584	-5.780689	0.0000
AGEHH2529	-4.439407	8.299387	-0.534908	0.5927
AGEHH3034	-1.313496	8.076041	-0.162641	0.8708
AGEHH3544	-4.459229	7.830809	-0.569447	0.5691
AGEHH4554	-7.471375	7.859669	-0.950597	0.3418
AGEHH5564	-9.870013	7.940217	-1.243041	0.2139
AGEHHGT64	-15.34615	8.308071	-1.847138	0.0647
EMPHHPT	-13.44869	3.014845	-4.460824	0.0000
EMPHHFT	-27.35002	2.151495	-12.71210	0.0000
EDUHHHS	-0.874238	4.409471	-0.198264	0.8428
EDUHHU	-18.26923	4.364324	-4.186039	0.0000
EDUHHPC	-28.10405	4.833712	-5.814174	0.0000
REG_CENTRAL	9.254725	2.560502	3.614418	0.0003
REG_SOUTH	2.899378	2.034232	1.425294	0.1541
REG_WEST	-23.01746	2.294237	-10.03273	0.0000
RACE_BLACK	10.81992	2.502930	4.322902	0.0000
RACE_ORIENTAL	-40.61006	3.566127	-11.38772	0.0000
RACE_OTHER	15.36375	4.770420	3.220628	0.0013
HISP_YES	-3.805839	3.422253	-1.112086	0.2661
AGEPCLT6_ONLY	-22.67262	3.343884	-6.780324	0.0000
AGEPC6_12ONLY	-33.43181	2.549933	-13.11086	0.0000
AGEPC13_17ONLY	-0.156916	2.638165	-0.059479	0.9526
AGEPCLT6_6_12ONLY	-45.53180	3.162089	-14.39928	0.0000
AGEPCLT6_13_17ONLY	-44.80358	6.315909	-7.093765	0.0000
AGEPC6_12AND13_17ONLY	-25.84940	3.003904	-8.605268	0.0000
AGEPCLT6_6_12AND13_17	-42.12336	6.296236	-6.690245	0.0000
MHONLY	81.02755	3.568380	22.70710	0.0000
FHONLY	5.916651	2.227376	2.656333	0.0079
POV185	6.104240	2.572247	2.373115	0.0176
D2001	-8.353513	2.241836	-3.726192	0.0002
D2002	-36.17763	2.114581	-17.10866	0.0000
D2003	-37.20804	2.163528	-17.19786	0.0000
R-squared	0.055378	Mean dependent var		220.3985
Adjusted R-squared	0.054618	S.D. dependent var		164.7567
S.E. of regression	160.1941	Akaike info criterion		12.99148
Sum squared resid	1.05E+09	Schwarz criterion		12.99862
Log likelihood	-266752.5	F-statistic		72.90238
Durbin-Watson stat	1.993006	Prob(F-statistic)		0.000000

Regression Results from Caffeine Intake 1998

Dependent Variable: CAFFEINE
Included observations: 6087

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	311.7235	15.32319	20.34325	0.0000
PRICE	-144.5131	7.916911	-18.25373	0.0000
PRICE2	17.68611	1.333361	13.26431	0.0000
AGEHH2529	0.741880	8.573227	0.086534	0.9310
AGEHH3034	13.95395	8.105110	1.721624	0.0852
AGEHH3544	21.06888	7.916622	2.661348	0.0078
AGEHH4554	25.01126	7.930484	3.153812	0.0016
AGEHH5564	32.36829	8.083272	4.004355	0.0001
AGEHHGT64	18.81998	8.350170	2.253844	0.0242
EMPHHPT	-1.700665	2.752858	-0.617782	0.5367
EMPHHFT	-1.312961	2.432619	-0.539731	0.5894
EDUHHHS	2.841253	6.604413	0.430205	0.6671
EDUHHU	-5.444418	6.436237	-0.845901	0.3976
EDUHHPC	-6.587609	6.783897	-0.971066	0.3316
REG_CENTRAL	-4.420766	2.655708	-1.664628	0.0960
REG_SOUTH	-5.020193	2.482643	-2.022117	0.0432
REG_WEST	-0.905949	2.700050	-0.335530	0.7372
RACE_BLACK	-24.55054	3.276194	-7.493616	0.0000
RACE_ORIENTAL	-17.68621	6.813108	-2.595909	0.0095
RACE_OTHER	-13.33459	5.013535	-2.659717	0.0078
HISP_YES	0.267910	3.888545	0.068897	0.9451
AGEPCLT6_ONLY	-20.61723	3.999093	-5.155477	0.0000
AGEPC6_12ONLY	-26.73163	3.523820	-7.585979	0.0000
AGEPC13_17ONLY	-21.09664	3.196024	-6.600902	0.0000
AGEPCLT6_6_12ONLY	-35.21724	4.374827	-8.049973	0.0000
AGEPCLT6_13_17ONLY	-36.11010	10.92980	-3.303821	0.0010
AGEPC6_12AND13_17ONLY	-35.39575	4.227183	-8.373365	0.0000
AGEPCLT6_6_12AND13_17	-42.95321	9.749500	-4.405683	0.0000
MHONLY	15.18537	2.988960	5.080488	0.0000
FHONLY	5.554166	2.292178	2.423095	0.0154
POV185	-4.687258	3.026325	-1.548828	0.1215

Weighted Statistics

R-squared	0.212852	Mean dependent var	72.85438
Adjusted R-squared	0.208952	S.D. dependent var	73.37182
S.E. of regression	70.04477	Akaike info criterion	11.34123
Sum squared resid	29712367	Schwarz criterion	11.37542
Log likelihood	-34486.02	F-statistic	54.58651
Durbin-Watson stat	2.020346	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 1999

Dependent Variable: CAFFEINE
Included observations: 6376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	303.7204	15.04301	20.19013	0.0000
PRICE	-139.4307	7.682143	-18.14998	0.0000
PRICE2	16.94416	1.268496	13.35768	0.0000
AGEHH2529	6.760774	8.493230	0.796019	0.4261
AGEHH3034	15.67233	8.193763	1.912714	0.0558
AGEHH3544	23.32910	8.006663	2.913710	0.0036
AGEHH4554	25.65943	7.992604	3.210397	0.0013
AGEHH5564	26.34113	8.112236	3.247087	0.0012
AGEHHGT64	20.68237	8.334504	2.481536	0.0131
EMPHHPT	-7.203600	2.718637	-2.649710	0.0081
EMPHHFT	-4.179463	2.374173	-1.760387	0.0784
EDUHHHS	5.707089	5.562812	1.025936	0.3050
EDUHHU	-0.990321	5.390799	-0.183706	0.8543
EDUHHPC	-0.772687	5.789742	-0.133458	0.8938
REG_CENTRAL	-6.316682	2.566392	-2.461308	0.0139
REG_SOUTH	-8.635318	2.394014	-3.607046	0.0003
REG_WEST	-2.408308	2.610002	-0.922723	0.3562
RACE_BLACK	-26.35154	2.931277	-8.989782	0.0000
RACE_ORIENTAL	-21.80545	6.528149	-3.340220	0.0008
RACE_OTHER	-1.544143	4.714816	-0.327509	0.7433
HISP_YES	0.492541	3.684757	0.133670	0.8937
AGEPCLT6_ONLY	-22.94061	4.067119	-5.640508	0.0000
AGEPC6_12ONLY	-24.84385	3.556592	-6.985295	0.0000
AGEPC13_17ONLY	-23.34040	3.226645	-7.233643	0.0000
AGEPCLT6_6_12ONLY	-36.93599	4.706460	-7.847935	0.0000
AGEPCLT6_13_17ONLY	-34.86992	10.76702	-3.238586	0.0012
AGEPC6_12AND13_17ONLY	-31.73131	4.168931	-7.611379	0.0000
AGEPCLT6_6_12AND13_17	-27.91627	9.655151	-2.891334	0.0038
MHONLY	20.23300	2.922101	6.924128	0.0000
FHONLY	7.371989	2.190607	3.365273	0.0008
POV185	-5.564220	2.970392	-1.873227	0.0611

Weighted Statistics

R-squared	0.197771	Mean dependent var	72.08387
Adjusted R-squared	0.193978	S.D. dependent var	74.05316
S.E. of regression	71.34979	Akaike info criterion	11.37792
Sum squared resid	32301078	Schwarz criterion	11.41078
Log likelihood	-36241.80	F-statistic	52.14055
Durbin-Watson stat	1.995817	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 2000

Dependent Variable: CAFFEINE

Included observations: 6555

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	324.2359	22.89016	14.16486	0.0000
PRICE	-152.3022	11.00054	-13.84498	0.0000
PRICE2	18.64227	1.778129	10.48421	0.0000
AGEHH2529	3.635620	14.72369	0.246923	0.8050
AGEHH3034	11.88077	14.07696	0.843987	0.3987
AGEHH3544	22.69384	13.80881	1.643433	0.1003
AGEHH4554	25.16487	13.81171	1.821995	0.0685
AGEHH5564	25.59008	13.94695	1.834815	0.0666
AGEHHGT64	26.81913	14.19186	1.889754	0.0588
EMPHHPT	0.117535	4.109533	0.028601	0.9772
EMPHHFT	0.885713	3.560441	0.248765	0.8036
EDUHHHS	2.394815	8.052419	0.297403	0.7662
EDUHHU	-4.112437	7.829529	-0.525247	0.5994
EDUHHPC	-5.877083	8.478442	-0.693180	0.4882
REG_CENTRAL	-4.653187	3.934713	-1.182599	0.2370
REG_SOUTH	-7.381224	3.624572	-2.036440	0.0417
REG_WEST	-1.611921	3.870494	-0.416464	0.6771
RACE_BLACK	-25.50127	4.220085	-6.042832	0.0000
RACE_ORIENTAL	-17.37196	9.428117	-1.842569	0.0654
RACE_OTHER	1.059712	6.759887	0.156765	0.8754
HISP_YES	1.272843	5.969831	0.213213	0.8312
AGEPCLT6_ONLY	-22.01957	6.467659	-3.404565	0.0007
AGEPC6_12ONLY	-27.69386	5.383474	-5.144236	0.0000
AGEPC13_17ONLY	-19.36278	5.021051	-3.856321	0.0001
AGEPCLT6_6_12ONLY	-28.80049	7.184914	-4.008468	0.0001
AGEPCLT6_13_17ONLY	-48.95547	19.05758	-2.568819	0.0102
AGEPC6_12AND13_17ONLY	-33.17601	6.739518	-4.922609	0.0000
AGEPCLT6_6_12AND13_17	-38.28452	16.83588	-2.273983	0.0230
MHONLY	26.37375	4.281976	6.159246	0.0000
FHONLY	11.29457	3.283796	3.439486	0.0006
POV185	-4.663192	4.485958	-1.039509	0.2986

Weighted Statistics

R-squared	0.106839	Mean dependent var	74.71019
Adjusted R-squared	0.102732	S.D. dependent var	112.0755
S.E. of regression	109.9972	Akaike info criterion	12.24350
Sum squared resid	78936363	Schwarz criterion	12.27561
Log likelihood	-40097.09	F-statistic	26.01324
Durbin-Watson stat	1.971647	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 2001

Dependent Variable: CAFFEINE
Included observations: 7103

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	303.8606	14.77331	20.56821	0.0000
PRICE	-130.7129	5.899242	-22.15757	0.0000
PRICE2	15.32653	0.926646	16.53978	0.0000
AGEHH2529	4.771622	11.10026	0.429866	0.6673
AGEHH3034	6.408917	10.65344	0.601582	0.5475
AGEHH3544	15.19571	10.48795	1.448873	0.1474
AGEHH4554	20.82758	10.50696	1.982266	0.0475
AGEHH5564	18.25970	10.58274	1.725422	0.0845
AGEHHGT64	15.54726	10.71573	1.450882	0.1469
EMPHHPT	-5.125424	2.581738	-1.985261	0.0472
EMPHHFT	-4.834474	2.250359	-2.148312	0.0317
EDUHHHS	-2.100649	4.969972	-0.422668	0.6726
EDUHHU	-8.130153	4.812259	-1.689467	0.0912
EDUHHPC	-8.653864	5.252123	-1.647689	0.0995
REG_CENTRAL	-5.358939	2.603736	-2.058173	0.0396
REG_SOUTH	-6.128615	2.291940	-2.673986	0.0075
REG_WEST	1.166001	2.434183	0.479011	0.6319
RACE_BLACK	-20.43072	2.464711	-8.289295	0.0000
RACE_ORIENTAL	-11.72927	4.779794	-2.453927	0.0142
RACE_OTHER	-0.958638	4.766628	-0.201115	0.8406
HISP_YES	-3.129772	3.688049	-0.848625	0.3961
AGEPCLT6_ONLY	-22.70327	4.066061	-5.583604	0.0000
AGEPC6_12ONLY	-25.72855	3.391713	-7.585709	0.0000
AGEPC13_17ONLY	-18.01275	3.387484	-5.317441	0.0000
AGEPCLT6_6_12ONLY	-29.03917	4.432284	-6.551740	0.0000
AGEPCLT6_13_17ONLY	-31.53575	10.44435	-3.019408	0.0025
AGEPC6_12AND13_17ONLY	-31.88571	4.367139	-7.301280	0.0000
AGEPCLT6_6_12AND13_17	-44.19601	10.19550	-4.334855	0.0000
MHONLY	26.22475	2.679313	9.787862	0.0000
FHONLY	11.40849	2.104468	5.421082	0.0000
POV185	-6.019238	2.751338	-2.187750	0.0287

Weighted Statistics

R-squared	0.211829	Mean dependent var	73.89560
Adjusted R-squared	0.208485	S.D. dependent var	75.96546
S.E. of regression	72.94181	Akaike info criterion	11.42156
Sum squared resid	37626632	Schwarz criterion	11.45153
Log likelihood	-40532.66	F-statistic	63.35571
Durbin-Watson stat	2.002770	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 2002

Dependent Variable: CAFFEINE
Included observations: 7384

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	226.9023	12.29776	18.45071	0.0000
PRICE	-87.64929	4.045674	-21.66494	0.0000
PRICE2	9.182668	0.586460	15.65780	0.0000
AGEHH2529	4.612365	10.02419	0.460123	0.6454
AGEHH3034	3.351934	9.660405	0.346977	0.7286
AGEHH3544	11.95163	9.540062	1.252783	0.2103
AGEHH4554	12.29753	9.542450	1.288718	0.1975
AGEHH5564	15.48298	9.594083	1.613805	0.1066
AGEHHGT64	11.37905	9.678470	1.175708	0.2397
EMPHHPT	-3.881155	2.170701	-1.787973	0.0738
EMPHHFT	-5.299534	1.890158	-2.803752	0.0051
EDUHHHS	0.506279	4.291479	0.117973	0.9061
EDUHHU	-3.630886	4.154545	-0.873955	0.3822
EDUHHPC	-5.528115	4.530490	-1.220202	0.2224
REG_CENTRAL	-8.032807	2.228710	-3.604241	0.0003
REG_SOUTH	-6.606439	1.893404	-3.489186	0.0005
REG_WEST	-1.787801	2.028524	-0.881331	0.3782
RACE_BLACK	-19.12314	2.028888	-9.425430	0.0000
RACE_ORIENTAL	-11.07733	3.817561	-2.901676	0.0037
RACE_OTHER	3.793024	3.616045	1.048943	0.2942
HISP_YES	-9.563016	3.338214	-2.864711	0.0042
AGEPCLT6_ONLY	-18.48053	3.854895	-4.794041	0.0000
AGEPC6_12ONLY	-19.48964	2.791904	-6.980772	0.0000
AGEPC13_17ONLY	-15.41438	2.793869	-5.517216	0.0000
AGEPCLT6_6_12ONLY	-25.32839	3.846954	-6.584013	0.0000
AGEPCLT6_13_17ONLY	-28.98603	10.64527	-2.722902	0.0065
AGEPC6_12AND13_17ONLY	-26.95138	3.569943	-7.549528	0.0000
AGEPCLT6_6_12AND13_17	-39.11127	7.592916	-5.151021	0.0000
MHONLY	21.22942	2.241216	9.472277	0.0000
FHONLY	9.427534	1.736521	5.428977	0.0000
POV185	-2.951154	2.363300	-1.248743	0.2118

Weighted Statistics

R-squared	0.206747	Mean dependent var	60.75998
Adjusted R-squared	0.203511	S.D. dependent var	65.25650
S.E. of regression	62.77920	Akaike info criterion	11.12131
Sum squared resid	28979850	Schwarz criterion	11.15031
Log likelihood	-41028.89	F-statistic	63.88101
Durbin-Watson stat	1.976344	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 2003

Dependent Variable: CAFFEINE

Included observations: 7566

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	222.0313	14.90628	14.89515	0.0000
PRICE	-76.68937	3.133846	-24.47133	0.0000
PRICE2	7.275637	0.419592	17.33979	0.0000
AGEHH2529	-0.341993	13.82131	-0.024744	0.9803
AGEHH3034	3.500043	13.45391	0.260151	0.7948
AGEHH3544	13.74705	13.29328	1.034135	0.3011
AGEHH4554	13.77669	13.27186	1.038038	0.2993
AGEHH5564	18.64751	13.29465	1.402633	0.1608
AGEHHGT64	14.69026	13.36729	1.098971	0.2718
EMPHHPT	-0.941241	2.247519	-0.418791	0.6754
EMPHHFT	-1.377581	1.918096	-0.718202	0.4727
EDUHHHS	-9.567679	4.548718	-2.103379	0.0355
EDUHHU	-12.37399	4.402515	-2.810663	0.0050
EDUHHPC	-14.66042	4.763894	-3.077404	0.0021
REG_CENTRAL	-8.817976	2.389706	-3.689984	0.0002
REG_SOUTH	-5.515612	1.933856	-2.852133	0.0044
REG_WEST	-4.736845	2.112779	-2.241998	0.0250
RACE_BLACK	-20.97678	2.113403	-9.925595	0.0000
RACE_ORIENTAL	-12.46204	3.798812	-3.280509	0.0010
RACE_OTHER	-0.518960	3.468081	-0.149639	0.8811
HISP_YES	-6.104313	3.181180	-1.918883	0.0550
AGEPCLT6_ONLY	-19.92225	3.921083	-5.080802	0.0000
AGEPC6_12ONLY	-20.73912	3.155871	-6.571600	0.0000
AGEPC13_17ONLY	-18.61255	2.878041	-6.467091	0.0000
AGEPCLT6_6_12ONLY	-25.55703	4.458145	-5.732661	0.0000
AGEPCLT6_13_17ONLY	-36.37453	10.23815	-3.552843	0.0004
AGEPC6_12AND13_17ONLY	-33.16335	3.922303	-8.455069	0.0000
AGEPCLT6_6_12AND13_17	-33.65585	8.309251	-4.050407	0.0001
MHONLY	12.50137	2.345266	5.330472	0.0000
FHONLY	8.991094	1.751580	5.133135	0.0000
POV185	-5.322449	2.425093	-2.194740	0.0282

Weighted Statistics

R-squared	0.212710	Mean dependent var	64.35591
Adjusted R-squared	0.209575	S.D. dependent var	67.60698
S.E. of regression	65.25778	Akaike info criterion	11.19866
Sum squared resid	32088385	Schwarz criterion	11.22706
Log likelihood	-42333.52	F-statistic	67.86017
Durbin-Watson stat	2.013948	Prob(F-statistic)	0.000000

Regression Results from Caffeine Intake 1998-2003

Dependent Variable: CAFFEINE, Sample 41071				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	280.1262	12.42305	22.54891	0.0000
PRICE	-110.4775	8.926570	-12.37626	0.0000
PRICE2	10.41906	1.555096	6.699949	0.0000
AGEHH2529	5.782497	3.274113	1.766126	0.0774
AGEHH3034	13.65759	3.040816	4.491423	0.0000
AGEHH3544	25.93581	3.090420	8.392325	0.0000
AGEHH4554	31.98228	3.114359	10.26930	0.0000
AGEHH5564	31.82670	3.197432	9.953833	0.0000
AGEHHGT64	28.07924	3.928302	7.147934	0.0000
EMPHHPT	-3.351864	2.552804	-1.313013	0.1892
EMPHHFT	-4.949177	1.376522	-3.595422	0.0003
EDUHHHS	0.873532	2.709847	0.322355	0.7472
EDUHHU	-4.389159	2.645501	-1.659103	0.0971
EDUHHPC	-6.579419	2.936946	-2.240224	0.0251
REG_CENTRAL	-9.681585	1.786453	-5.419445	0.0000
REG_SOUTH	-8.136026	1.254542	-6.485258	0.0000
REG_WEST	-4.837558	1.395316	-3.466997	0.0005
RACE_BLACK	-32.96292	1.214124	-27.14956	0.0000
RACE_ORIENTAL	-20.01157	1.984954	-10.08163	0.0000
RACE_OTHER	-7.129630	2.761493	-2.581803	0.0098
HISP_YES	-3.666225	1.992821	-1.839716	0.0658
AGEPCLT6_ONLY	-27.93732	1.453039	-19.22682	0.0000
AGEPC6_12ONLY	-31.61904	1.323166	-23.89650	0.0000
AGEPC13_17ONLY	-29.59181	1.320865	-22.40335	0.0000
AGEPCLT6_6_12ONLY	-38.74531	1.464741	-26.45199	0.0000
AGEPCLT6_13_17ONLY	-47.09167	3.034645	-15.51802	0.0000
AGEPC6_12AND13_17ONLY	-43.67521	1.467835	-29.75484	0.0000
AGEPCLT6_6_12AND13_17	-48.79084	2.485431	-19.63074	0.0000
MHONLY	26.76743	2.084120	12.84352	0.0000
FHONLY	15.81772	1.733133	9.126664	0.0000
POV185	-12.32193	1.503648	-8.194688	0.0000
D2001	1.480556	1.482715	0.998544	0.3180
D2002	-12.70057	1.376362	-9.227642	0.0000
D2003	-11.08967	1.392683	-7.962808	0.0000
R-squared	0.170674	Mean dependent var		83.16632
Adjusted R-squared	0.170007	S.D. dependent var		118.2735
S.E. of regression	107.7518	Akaike info criterion		12.19837
Sum squared resid	4.76E+08	Schwarz criterion		12.20550
Log likelihood	-250465.6	F-statistic		255.9194
Durbin-Watson stat	1.981823	Prob(F-statistic)		0.000000

Regression Results from Calcium Intake 1998

Dependent Variable: CALCIUM
Included observations: 6087

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	161.6710	29.79958	5.425277	0.0000
PRICE	49.04242	10.80113	4.540489	0.0000
PRICE2	-10.29596	1.750764	-5.880841	0.0000
AGEHH2529	7.602347	22.60021	0.336384	0.7366
AGEHH3034	18.78240	21.53869	0.872031	0.3832
AGEHH3544	10.49657	21.00031	0.499829	0.6172
AGEHH4554	6.450703	21.00229	0.307143	0.7587
AGEHH5564	17.40813	21.32293	0.816405	0.4143
AGEHHGT64	36.79334	21.89346	1.680563	0.0929
EMPHHPT	-21.95514	6.508994	-3.373047	0.0007
EMPHHFT	-31.77179	5.794441	-5.483151	0.0000
EDUHHHS	3.308754	14.27096	0.231852	0.8167
EDUHHU	0.502765	13.92542	0.036104	0.9712
EDUHHPC	-0.594492	15.04925	-0.039503	0.9685
REG_CENTRAL	22.39922	6.299717	3.555592	0.0004
REG_SOUTH	5.331701	5.977873	0.891906	0.3725
REG_WEST	7.768983	6.704477	1.158775	0.2466
RACE_BLACK	-86.96713	8.034549	-10.82415	0.0000
RACE_ORIENTAL	-67.51300	18.49873	-3.649602	0.0003
RACE_OTHER	-28.56547	12.46906	-2.290908	0.0220
HISP_YES	-24.63044	9.647118	-2.553139	0.0107
AGEPCLT6_ONLY	1.009030	10.21359	0.098793	0.9213
AGEPC6_12ONLY	-22.27375	8.605800	-2.588226	0.0097
AGEPC13_17ONLY	-6.892745	7.666149	-0.899114	0.3686
AGEPCLT6_6_12ONLY	-21.48676	10.87604	-1.975605	0.0482
AGEPCLT6_13_17ONLY	-37.79271	26.00520	-1.453275	0.1462
AGEPC6_12AND13_17ONLY	-12.51848	9.956320	-1.257340	0.2087
AGEPCLT6_6_12AND13_17	-27.18241	23.91798	-1.136484	0.2558
MHONLY	46.37821	7.772740	5.966777	0.0000
FHONLY	-4.584403	5.648453	-0.811621	0.4170
POV185	-1.494150	6.935868	-0.215424	0.8294

Weighted Statistics

R-squared	0.061947	Mean dependent var	207.6933
Adjusted R-squared	0.057300	S.D. dependent var	167.1983
S.E. of regression	162.7345	Akaike info criterion	13.02720
Sum squared resid	1.60E+08	Schwarz criterion	13.06139
Log likelihood	-39617.28	F-statistic	13.33081
Durbin-Watson stat	1.963591	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 1999

Dependent Variable: CALCIUM
Included observations: 6376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	91.75916	29.56208	3.103949	0.0019
PRICE	94.41131	12.27289	7.692671	0.0000
PRICE2	-17.05433	2.219015	-7.685538	0.0000
AGEHH2529	-29.16812	22.79663	-1.279493	0.2008
AGEHH3034	7.270561	21.94080	0.331372	0.7404
AGEHH3544	0.031781	21.31586	0.001491	0.9988
AGEHH4554	-2.692744	21.24186	-0.126766	0.8991
AGEHH5564	9.694593	21.47191	0.451501	0.6516
AGEHHGT64	16.25280	21.91981	0.741466	0.4584
EMPHHPT	-28.78218	6.332803	-4.544935	0.0000
EMPHHFT	-29.14470	5.576272	-5.226557	0.0000
EDUHHHS	21.80272	12.03128	1.812170	0.0700
EDUHHU	13.90299	11.68830	1.189480	0.2343
EDUHHPC	14.43231	12.98930	1.111093	0.2666
REG_CENTRAL	20.03464	6.030661	3.322130	0.0009
REG_SOUTH	4.814824	5.710034	0.843222	0.3991
REG_WEST	3.365722	6.484118	0.519072	0.6037
RACE_BLACK	-91.79170	7.169398	-12.80326	0.0000
RACE_ORIENTAL	-62.79375	18.63428	-3.369798	0.0008
RACE_OTHER	-23.06425	11.77666	-1.958472	0.0502
HISP_YES	-21.13751	9.025658	-2.341935	0.0192
AGEPCLT6_ONLY	-8.951426	10.43512	-0.857817	0.3910
AGEPC6_12ONLY	-12.97968	8.552748	-1.517603	0.1292
AGEPC13_17ONLY	-7.893256	7.641120	-1.032997	0.3016
AGEPCLT6_6_12ONLY	-24.86649	11.43742	-2.174134	0.0297
AGEPCLT6_13_17ONLY	-49.45919	24.41809	-2.025514	0.0429
AGEPC6_12AND13_17ONLY	-10.40459	9.874983	-1.053631	0.2921
AGEPCLT6_6_12AND13_17	-18.07046	22.33633	-0.809017	0.4185
MHONLY	28.71199	7.624586	3.765711	0.0002
FHONLY	-1.692472	5.326459	-0.317748	0.7507
POV185	0.501824	6.570961	0.076370	0.9391

Weighted Statistics

R-squared	0.062557	Mean dependent var	203.1871
Adjusted R-squared	0.058125	S.D. dependent var	167.4464
S.E. of regression	162.3776	Akaike info criterion	13.02258
Sum squared resid	1.67E+08	Schwarz criterion	13.05545
Log likelihood	-41484.97	F-statistic	14.11377
Durbin-Watson stat	1.987476	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 2000

Dependent Variable: CALCIUM
Included observations: 6555

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	154.8637	32.65603	4.742269	0.0000
PRICE	65.96528	10.87808	6.064053	0.0000
PRICE2	-12.45666	1.756987	-7.089785	0.0000
AGEHH2529	-29.69146	27.47990	-1.080479	0.2800
AGEHH3034	-30.58851	26.06121	-1.173718	0.2406
AGEHH3544	-19.80398	25.54261	-0.775331	0.4382
AGEHH4554	-29.30096	25.52922	-1.147742	0.2511
AGEHH5564	-23.90438	25.73620	-0.928823	0.3530
AGEHHGT64	3.967273	26.14598	0.151735	0.8794
EMPHHPT	-11.85872	7.065290	-1.678448	0.0933
EMPHHFT	-22.21420	6.108396	-3.636666	0.0003
EDUHHHS	2.552319	13.38508	0.190684	0.8488
EDUHHU	-0.191007	13.10368	-0.014577	0.9884
EDUHHPC	-1.625761	14.59474	-0.111394	0.9113
REG_CENTRAL	32.46127	6.737048	4.818323	0.0000
REG_SOUTH	13.58274	6.261101	2.169384	0.0301
REG_WEST	6.692456	6.935520	0.964954	0.3346
RACE_BLACK	-94.84375	7.537650	-12.58267	0.0000
RACE_ORIENTAL	-71.79481	19.79818	-3.626334	0.0003
RACE_OTHER	-25.65848	12.28259	-2.089011	0.0367
HISP_YES	-7.274159	10.87617	-0.668816	0.5036
AGEPCLT6_ONLY	-16.31895	12.17061	-1.340849	0.1800
AGEPC6_12ONLY	-10.87242	9.465300	-1.148660	0.2507
AGEPC13_17ONLY	-7.736892	8.819658	-0.877233	0.3804
AGEPCLT6_6_12ONLY	-30.16608	13.15677	-2.292818	0.0219
AGEPCLT6_13_17ONLY	-50.57482	28.21694	-1.792357	0.0731
AGEPC6_12AND13_17ONLY	-9.805406	11.69884	-0.838152	0.4020
AGEPCLT6_6_12AND13_17	-20.08867	28.54299	-0.703804	0.4816
MHONLY	56.30558	7.916919	7.112056	0.0000
FHONLY	0.400372	5.807785	0.068937	0.9450
POV185	0.251988	7.290342	0.034565	0.9724

Weighted Statistics

R-squared	0.062360	Mean dependent var	203.7432
Adjusted R-squared	0.058049	S.D. dependent var	187.8594
S.E. of regression	182.7220	Akaike info criterion	13.25853
Sum squared resid	2.18E+08	Schwarz criterion	13.29063
Log likelihood	-43423.82	F-statistic	14.46320
Durbin-Watson stat	2.010366	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 2001

Dependent Variable: CALCIUM
Included observations: 7103

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	122.0635	30.76133	3.968082	0.0001
PRICE	65.99406	7.761104	8.503179	0.0000
PRICE2	-10.79130	1.238743	-8.711497	0.0000
AGEHH2529	6.986196	28.12602	0.248389	0.8038
AGEHH3034	-3.862844	27.14134	-0.142323	0.8868
AGEHH3544	-1.375219	26.64865	-0.051606	0.9588
AGEHH4554	0.765897	26.68851	0.028698	0.9771
AGEHH5564	3.880729	26.80538	0.144774	0.8849
AGEHHGT64	15.30903	27.06150	0.565712	0.5716
EMPHHPT	-30.90231	5.902330	-5.235613	0.0000
EMPHHFT	-35.58147	5.180944	-6.867758	0.0000
EDUHHHS	3.673998	10.51866	0.349284	0.7269
EDUHHU	-3.453028	10.25987	-0.336557	0.7365
EDUHHPC	-7.825265	11.74191	-0.666439	0.5052
REG_CENTRAL	34.64601	5.892276	5.879903	0.0000
REG_SOUTH	11.42640	5.268303	2.168896	0.0301
REG_WEST	8.957899	5.968743	1.500802	0.1335
RACE_BLACK	-78.27719	5.997126	-13.05245	0.0000
RACE_ORIENTAL	-62.87362	12.81936	-4.904585	0.0000
RACE_OTHER	-21.92782	12.00043	-1.827253	0.0677
HISP_YES	-13.40621	8.950987	-1.497736	0.1342
AGEPCLT6_ONLY	-15.86424	10.37373	-1.529270	0.1262
AGEPC6_12ONLY	-17.36990	7.963890	-2.181082	0.0292
AGEPC13_17ONLY	-3.041089	7.843987	-0.387697	0.6983
AGEPCLT6_6_12ONLY	-35.96382	10.97003	-3.278369	0.0010
AGEPCLT6_13_17ONLY	-15.95998	23.51409	-0.678741	0.4973
AGEPC6_12AND13_17ONLY	-12.46528	10.11566	-1.232275	0.2179
AGEPCLT6_6_12AND13_17	-20.18985	22.40448	-0.901152	0.3675
MHONLY	62.43550	6.787803	9.198190	0.0000
FHONLY	-0.422453	4.928496	-0.085716	0.9317
POV185	-4.734630	5.922233	-0.799467	0.4240

Weighted Statistics

R-squared	0.076350	Mean dependent var	191.4540
Adjusted R-squared	0.072432	S.D. dependent var	168.2974
S.E. of regression	162.2235	Akaike info criterion	13.02018
Sum squared resid	1.86E+08	Schwarz criterion	13.05016
Log likelihood	-46210.18	F-statistic	19.48604
Durbin-Watson stat	1.997920	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 2002

Dependent Variable: CALCIUM
Included observations: 7384

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	147.9461	27.66089	5.348565	0.0000
PRICE	20.64740	4.782002	4.317731	0.0000
PRICE2	-3.811658	0.602719	-6.324106	0.0000
AGEHH2529	31.77107	26.06393	1.218967	0.2229
AGEHH3034	8.534548	25.12659	0.339662	0.7341
AGEHH3544	8.449806	24.76900	0.341144	0.7330
AGEHH4554	10.79175	24.77593	0.435574	0.6632
AGEHH5564	16.67785	24.86901	0.670628	0.5025
AGEHHGT64	20.96880	25.05585	0.836883	0.4027
EMPHHPT	-21.96859	5.245164	-4.188351	0.0000
EMPHHFT	-24.30734	4.560657	-5.329789	0.0000
EDUHHHS	2.214022	9.380813	0.236016	0.8134
EDUHHU	-11.88700	9.131715	-1.301727	0.1931
EDUHHPC	-9.700523	10.36492	-0.935899	0.3494
REG_CENTRAL	31.81817	5.230139	6.083620	0.0000
REG_SOUTH	17.46222	4.589647	3.804698	0.0001
REG_WEST	4.178379	5.239054	0.797545	0.4252
RACE_BLACK	-77.52999	5.111956	-15.16640	0.0000
RACE_ORIENTAL	-53.13136	10.65326	-4.987331	0.0000
RACE_OTHER	-21.64462	9.209138	-2.350342	0.0188
HISP_YES	-10.05350	8.403701	-1.196318	0.2316
AGEPCLT6_ONLY	7.267841	10.06398	0.722164	0.4702
AGEPC6_12ONLY	-13.80429	7.098013	-1.944811	0.0518
AGEPC13_17ONLY	-3.056766	6.830327	-0.447528	0.6545
AGEPCLT6_6_12ONLY	-22.81398	9.711899	-2.349075	0.0188
AGEPCLT6_13_17ONLY	-5.804012	23.63627	-0.245555	0.8060
AGEPC6_12AND13_17ONLY	-9.536350	8.445032	-1.129226	0.2588
AGEPCLT6_6_12AND13_17	-22.69239	17.04742	-1.331133	0.1832
MHONLY	52.71600	5.869013	8.982089	0.0000
FHONLY	5.371283	4.253465	1.262802	0.2067
POV185	-3.674502	5.338097	-0.688354	0.4913

Weighted Statistics

R-squared	0.074137	Mean dependent var	167.5062
Adjusted R-squared	0.070359	S.D. dependent var	149.8029
S.E. of regression	144.7341	Akaike info criterion	12.79186
Sum squared resid	1.54E+08	Schwarz criterion	12.82086
Log likelihood	-47196.56	F-statistic	19.62585
Durbin-Watson stat	1.977244	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 2003

Dependent Variable: CALCIUM
Included observations: 7566

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	194.1418	35.00540	5.546052	0.0000
PRICE	2.030825	4.366680	0.465073	0.6419
PRICE2	-1.390719	0.507651	-2.739521	0.0062
AGEHH2529	4.220672	34.51702	0.122278	0.9027
AGEHH3034	-4.992291	33.48797	-0.149077	0.8815
AGEHH3544	-8.214053	33.03441	-0.248651	0.8036
AGEHH4554	-14.22525	32.96916	-0.431471	0.6661
AGEHH5564	-10.80662	33.01271	-0.327347	0.7434
AGEHHGT64	2.641878	33.16171	0.079666	0.9365
EMPHHPT	-15.95736	5.357515	-2.978501	0.0029
EMPHHFT	-24.28070	4.617546	-5.258355	0.0000
EDUHHHS	3.328979	10.01522	0.332392	0.7396
EDUHHU	-3.740185	9.746029	-0.383765	0.7012
EDUHHPC	-8.899622	10.93628	-0.813770	0.4158
REG_CENTRAL	27.89337	5.515513	5.057258	0.0000
REG_SOUTH	18.30770	4.669368	3.920809	0.0001
REG_WEST	0.664172	5.416714	0.122615	0.9024
RACE_BLACK	-69.96508	5.294487	-13.21470	0.0000
RACE_ORIENTAL	-57.85396	10.61082	-5.452355	0.0000
RACE_OTHER	-12.28359	8.823653	-1.392120	0.1639
HISP_YES	-10.70265	7.974701	-1.342076	0.1796
AGEPCLT6_ONLY	2.014407	10.01689	0.201101	0.8406
AGEPC6_12ONLY	-19.28992	7.758488	-2.486299	0.0129
AGEPC13_17ONLY	6.552040	7.038399	0.930899	0.3519
AGEPCLT6_6_12ONLY	-20.90228	11.03378	-1.894389	0.0582
AGEPCLT6_13_17ONLY	-21.03224	23.82777	-0.882677	0.3774
AGEPC6_12AND13_17ONLY	-6.325138	9.114713	-0.693948	0.4877
AGEPCLT6_6_12AND13_17	-9.166958	18.50440	-0.495393	0.6203
MHONLY	56.37022	6.095931	9.247188	0.0000
FHONLY	-3.752230	4.262208	-0.880349	0.3787
POV185	-8.322655	5.529393	-1.505166	0.1323

Weighted Statistics

R-squared	0.063425	Mean dependent var	167.5464
Adjusted R-squared	0.059697	S.D. dependent var	154.3618
S.E. of regression	149.9274	Akaike info criterion	12.86227
Sum squared resid	1.69E+08	Schwarz criterion	12.89067
Log likelihood	-48626.96	F-statistic	17.00916
Durbin-Watson stat	2.004448	Prob(F-statistic)	0.000000

Regression Results from Calcium Intake 1998-2003

Dependent Variable: CALCIUM, Sample 41071				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	174.2000	14.58163	11.94654	0.0000
PRICE	35.71132	8.745381	4.083449	0.0000
PRICE2	-6.676035	1.544955	-4.321183	0.0000
AGEHH2529	-2.269514	8.386077	-0.270629	0.7867
AGEHH3034	0.778613	8.095921	0.096174	0.9234
AGEHH3544	-0.393800	7.859397	-0.050106	0.9600
AGEHH4554	-2.841569	7.882406	-0.360495	0.7185
AGEHH5564	3.273848	7.959541	0.411311	0.6808
AGEHHGT64	16.51263	8.199939	2.013751	0.0440
EMPHHPT	-21.94699	2.649480	-8.283505	0.0000
EMPHHFT	-28.07659	2.242268	-12.52152	0.0000
EDUHHHS	5.577363	4.426069	1.260117	0.2076
EDUHHU	-1.240365	4.352978	-0.284946	0.7757
EDUHHPC	-2.838073	4.958070	-0.572415	0.5670
REG_CENTRAL	28.65519	2.546310	11.25362	0.0000
REG_SOUTH	12.28513	2.018324	6.086800	0.0000
REG_WEST	5.667196	2.564518	2.209848	0.0271
RACE_BLACK	-82.11059	1.868169	-43.95245	0.0000
RACE_ORIENTAL	-62.26044	4.016542	-15.50101	0.0000
RACE_OTHER	-20.94081	4.358730	-4.804337	0.0000
HISP_YES	-14.75330	3.260051	-4.525482	0.0000
AGEPCLT6_ONLY	-3.771439	3.381551	-1.115299	0.2647
AGEPC6_12ONLY	-15.17378	2.750154	-5.517430	0.0000
AGEPC13_17ONLY	-3.331614	2.824858	-1.179392	0.2382
AGEPCLT6_6_12ONLY	-24.78588	3.380089	-7.332906	0.0000
AGEPCLT6_13_17ONLY	-30.74507	6.484968	-4.740975	0.0000
AGEPC6_12AND13_17ONLY	-9.358931	3.330907	-2.809724	0.0050
AGEPCLT6_6_12AND13_17	-20.13569	6.550376	-3.073975	0.0021
MHONLY	50.92491	3.749508	13.58176	0.0000
FHONLY	-0.954939	2.022755	-0.472098	0.6369
POV185	-3.201248	2.586528	-1.237662	0.2158
D2001	-10.54347	2.412107	-4.371064	0.0000
D2002	-33.35776	2.197898	-15.17712	0.0000
D2003	-33.97321	2.207345	-15.39098	0.0000
R-squared	0.070772	Mean dependent var		189.1905
Adjusted R-squared	0.070025	S.D. dependent var		166.8522
S.E. of regression	160.9043	Akaike info criterion		13.00032
Sum squared resid	1.06E+09	Schwarz criterion		13.00746
Log likelihood	-266934.2	F-statistic		94.71114
Durbin-Watson stat	1.991104	Prob(F-statistic)		0.000000

Regression Results from Vitamin C Intake 1998

Dependent Variable: VITC
Included observations: 6087

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	26.49210	8.985041	2.948467	0.0032
PRICE	4.620584	4.539295	1.017908	0.3088
PRICE2	2.263247	0.915092	2.473246	0.0134
AGEHH2529	3.659972	6.528006	0.560657	0.5751
AGEHH3034	7.754002	6.232739	1.244076	0.2135
AGEHH3544	5.506874	6.065524	0.907897	0.3640
AGEHH4554	5.947778	6.062949	0.981004	0.3266
AGEHH5564	10.38274	6.147725	1.688874	0.0913
AGEHHGT64	14.66979	6.302897	2.327467	0.0200
EMPHHPT	-3.456396	1.814351	-1.905031	0.0568
EMPHHFT	-8.453969	1.617099	-5.227860	0.0000
EDUHHHS	6.084949	3.850157	1.580442	0.1141
EDUHHU	6.931875	3.756598	1.845253	0.0650
EDUHHPC	11.07929	4.112443	2.694089	0.0071
REG_CENTRAL	-7.368769	1.757973	-4.191628	0.0000
REG_SOUTH	-5.595975	1.677254	-3.336391	0.0009
REG_WEST	-13.70766	1.906518	-7.189889	0.0000
RACE_BLACK	19.13370	2.266944	8.440305	0.0000
RACE_ORIENTAL	-6.322523	5.477845	-1.154199	0.2485
RACE_OTHER	5.041437	3.536824	1.425414	0.1541
HISP_YES	-1.838681	2.734090	-0.672502	0.5013
AGEPCLT6_ONLY	-5.552713	2.927468	-1.896763	0.0579
AGEPC6_12ONLY	-7.274494	2.425598	-2.999052	0.0027
AGEPC13_17ONLY	-3.714191	2.145179	-1.731413	0.0834
AGEPCLT6_6_12ONLY	-10.47498	3.099956	-3.379072	0.0007
AGEPCLT6_13_17ONLY	-14.81077	7.264526	-2.038780	0.0415
AGEPC6_12AND13_17ONLY	-3.375796	2.766523	-1.220231	0.2224
AGEPCLT6_6_12AND13_17	-3.491568	6.723745	-0.519289	0.6036
MHONLY	16.67537	2.267878	7.352849	0.0000
FHONLY	1.032279	1.598845	0.645641	0.5185
POV185	-1.744933	1.916054	-0.910691	0.3625

Weighted Statistics

R-squared	0.082223	Mean dependent var	52.83571
Adjusted R-squared	0.077676	S.D. dependent var	47.41791
S.E. of regression	46.21888	Akaike info criterion	10.50973
Sum squared resid	12936735	Schwarz criterion	10.54393
Log likelihood	-31955.37	F-statistic	18.08508
Durbin-Watson stat	1.990454	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 1999

Dependent Variable: VITC
Included observations: 6376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.73232	8.397849	1.635219	0.1021
PRICE	11.88488	4.249868	2.796529	0.0052
PRICE2	1.380684	0.873649	1.580363	0.1141
AGEHH2529	0.275913	6.372661	0.043296	0.9655
AGEHH3034	5.964527	6.126481	0.973565	0.3303
AGEHH3544	3.936971	5.938998	0.662902	0.5074
AGEHH4554	3.959165	5.914406	0.669410	0.5033
AGEHH5564	9.119800	5.972143	1.527057	0.1268
AGEHHGT64	14.14809	6.086707	2.324424	0.0201
EMPHHPT	-2.575802	1.700906	-1.514370	0.1300
EMPHHFT	-7.462248	1.501784	-4.968921	0.0000
EDUHHHS	8.372492	3.158435	2.650836	0.0080
EDUHHU	9.136223	3.069190	2.976753	0.0029
EDUHHPC	11.37503	3.456308	3.291092	0.0010
REG_CENTRAL	-7.243429	1.623342	-4.462047	0.0000
REG_SOUTH	-5.454589	1.543208	-3.534578	0.0004
REG_WEST	-14.09368	1.772942	-7.949320	0.0000
RACE_BLACK	20.06990	1.949194	10.29651	0.0000
RACE_ORIENTAL	-6.538251	5.299096	-1.233843	0.2173
RACE_OTHER	7.826967	3.224937	2.427014	0.0153
HISP_YES	-1.521865	2.463206	-0.617839	0.5367
AGEPCLT6_ONLY	-5.885677	2.891766	-2.035323	0.0419
AGEPC6_12ONLY	-6.509762	2.333281	-2.789960	0.0053
AGEPC13_17ONLY	-0.868527	2.066764	-0.420235	0.6743
AGEPCLT6_6_12ONLY	-10.38845	3.136193	-3.312440	0.0009
AGEPCLT6_13_17ONLY	-11.57361	6.477606	-1.786712	0.0740
AGEPC6_12AND13_17ONLY	-5.960467	2.678778	-2.225069	0.0261
AGEPCLT6_6_12AND13_17	-7.887143	5.977175	-1.319543	0.1870
MHONLY	10.40276	2.117029	4.913847	0.0000
FHONLY	0.909375	1.445397	0.629152	0.5293
POV185	-4.304036	1.737024	-2.477821	0.0132

Weighted Statistics

R-squared	0.100169	Mean dependent var	53.25410
Adjusted R-squared	0.095914	S.D. dependent var	45.76068
S.E. of regression	44.53018	Akaike info criterion	10.43506
Sum squared resid	12581732	Schwarz criterion	10.46793
Log likelihood	-33235.98	F-statistic	23.54408
Durbin-Watson stat	1.974018	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 2000

Dependent Variable: VITC
Included observations: 6555

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.04983	9.174583	2.403360	0.0163
PRICE	18.50084	4.083714	4.530397	0.0000
PRICE2	-0.480370	0.803304	-0.597993	0.5499
AGEHH2529	-8.022645	7.490136	-1.071095	0.2842
AGEHH3034	-3.850940	7.080201	-0.543903	0.5865
AGEHH3544	-5.902560	6.932870	-0.851388	0.3946
AGEHH4554	-3.908295	6.927098	-0.564204	0.5726
AGEHH5564	-0.788382	6.979508	-0.112957	0.9101
AGEHHGT64	5.686574	7.086417	0.802461	0.4223
EMPHHPT	-1.112520	1.870308	-0.594832	0.5520
EMPHHFT	-6.707480	1.614725	-4.153946	0.0000
EDUHHHS	3.320602	3.488098	0.951980	0.3411
EDUHHU	3.912145	3.420355	1.143783	0.2528
EDUHHPC	4.690961	3.862426	1.214512	0.2246
REG_CENTRAL	-6.824836	1.783421	-3.826822	0.0001
REG_SOUTH	-6.042071	1.663332	-3.632510	0.0003
REG_WEST	-13.13948	1.869440	-7.028567	0.0000
RACE_BLACK	20.01920	2.020938	9.905899	0.0000
RACE_ORIENTAL	-0.834549	5.670204	-0.147181	0.8830
RACE_OTHER	9.537776	3.358275	2.840082	0.0045
HISP_YES	-0.199500	2.951811	-0.067586	0.9461
AGEPCLT6_ONLY	-8.506357	3.320966	-2.561410	0.0104
AGEPC6_12ONLY	-8.744448	2.528244	-3.458704	0.0005
AGEPC13_17ONLY	-3.908282	2.344281	-1.667156	0.0955
AGEPCLT6_6_12ONLY	-8.457115	3.546014	-2.384964	0.0171
AGEPCLT6_13_17ONLY	-4.596866	7.144537	-0.643410	0.5200
AGEPC6_12AND13_17ONLY	-7.409330	3.101416	-2.389015	0.0169
AGEPCLT6_6_12AND13_17	-9.471125	7.454840	-1.270467	0.2040
MHONLY	18.76333	2.169754	8.647677	0.0000
FHONLY	0.241884	1.552554	0.155798	0.8762
POV185	-3.220510	1.897272	-1.697443	0.0897

Weighted Statistics

R-squared	0.087883	Mean dependent var	55.21346
Adjusted R-squared	0.083689	S.D. dependent var	50.51614
S.E. of regression	49.17523	Akaike info criterion	10.63338
Sum squared resid	15776360	Schwarz criterion	10.66548
Log likelihood	-34819.89	F-statistic	20.95304
Durbin-Watson stat	1.997215	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 2001

Dependent Variable: VITC
Included observations: 7103

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.18250	9.236604	1.102408	0.2703
PRICE	23.02417	3.359229	6.854006	0.0000
PRICE2	-1.679952	0.657512	-2.555012	0.0106
AGEHH2529	-2.189501	8.176229	-0.267789	0.7889
AGEHH3034	0.261477	7.896357	0.033114	0.9736
AGEHH3544	0.656899	7.747799	0.084785	0.9324
AGEHH4554	2.671983	7.759239	0.344362	0.7306
AGEHH5564	5.885034	7.789308	0.755527	0.4500
AGEHHGT64	8.014078	7.859745	1.019636	0.3079
EMPHHPT	-5.706757	1.680089	-3.396698	0.0007
EMPHHFT	-9.951905	1.478047	-6.733144	0.0000
EDUHHHS	3.854289	2.945590	1.308495	0.1907
EDUHHU	6.024049	2.876590	2.094163	0.0363
EDUHHPC	8.283876	3.336826	2.482562	0.0131
REG_CENTRAL	-6.027221	1.674969	-3.598408	0.0003
REG_SOUTH	-6.534393	1.501569	-4.351711	0.0000
REG_WEST	-12.41717	1.727672	-7.187224	0.0000
RACE_BLACK	23.49844	1.727587	13.60189	0.0000
RACE_ORIENTAL	-1.547787	3.795348	-0.407812	0.6834
RACE_OTHER	6.971401	3.510945	1.985620	0.0471
HISP_YES	2.843236	2.587113	1.099000	0.2718
AGEPCLT6_ONLY	-5.744362	3.030608	-1.895449	0.0581
AGEPC6_12ONLY	-9.276447	2.281532	-4.065885	0.0000
AGEPC13_17ONLY	-1.785752	2.240558	-0.797012	0.4255
AGEPCLT6_6_12ONLY	-9.422797	3.184782	-2.958694	0.0031
AGEPCLT6_13_17ONLY	-8.146776	6.667161	-1.221926	0.2218
AGEPC6_12AND13_17ONLY	-5.743961	2.892528	-1.985793	0.0471
AGEPCLT6_6_12AND13_17	-9.842349	6.330428	-1.554768	0.1200
MHONLY	20.87122	1.982601	10.52719	0.0000
FHONLY	1.835406	1.409505	1.302164	0.1929
POV185	-3.469417	1.666466	-2.081901	0.0374

Weighted Statistics

R-squared	0.105072	Mean dependent var	53.53232
Adjusted R-squared	0.101276	S.D. dependent var	48.57282
S.E. of regression	46.87236	Akaike info criterion	10.53709
Sum squared resid	15537313	Schwarz criterion	10.56706
Log likelihood	-37391.47	F-statistic	27.67719
Durbin-Watson stat	1.976470	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 2002

Dependent Variable: VITC

Included observations: 7384

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16.16475	8.744659	1.848528	0.0646
PRICE	21.84605	2.656616	8.223262	0.0000
PRICE2	-1.482200	0.503911	-2.941395	0.0033
AGEHH2529	-10.41771	8.042228	-1.295377	0.1952
AGEHH3034	-8.038650	7.741451	-1.038391	0.2991
AGEHH3544	-7.832221	7.625323	-1.027133	0.3044
AGEHH4554	-5.142294	7.627294	-0.674196	0.5002
AGEHH5564	-3.591147	7.649539	-0.469459	0.6388
AGEHHGT64	-1.597692	7.701818	-0.207443	0.8357
EMPHHPT	-1.155801	1.549225	-0.746051	0.4557
EMPHHFT	-5.549400	1.345292	-4.125054	0.0000
EDUHHHS	0.489149	2.646857	0.184804	0.8534
EDUHHU	1.033146	2.582057	0.400125	0.6891
EDUHHPC	1.526292	3.000485	0.508682	0.6110
REG_CENTRAL	-6.908061	1.526691	-4.524859	0.0000
REG_SOUTH	-6.226975	1.355602	-4.593514	0.0000
REG_WEST	-14.68187	1.592799	-9.217659	0.0000
RACE_BLACK	17.26629	1.529097	11.29182	0.0000
RACE_ORIENTAL	-4.711675	3.380328	-1.393851	0.1634
RACE_OTHER	5.591851	2.784879	2.007933	0.0447
HISP_YES	0.629689	2.514729	0.250400	0.8023
AGEPCLT6_ONLY	-5.919119	3.096985	-1.911252	0.0560
AGEPC6_12ONLY	-8.481713	2.159166	-3.928237	0.0001
AGEPC13_17ONLY	-3.015430	2.036194	-1.480915	0.1387
AGEPCLT6_6_12ONLY	-8.569882	2.945683	-2.909302	0.0036
AGEPCLT6_13_17ONLY	-2.003972	6.830468	-0.293387	0.7692
AGEPC6_12AND13_17ONLY	-2.672938	2.479645	-1.077952	0.2811
AGEPCLT6_6_12AND13_17	-4.196263	4.958688	-0.846245	0.3974
MHONLY	19.63145	1.787679	10.98153	0.0000
FHONLY	2.192871	1.260735	1.739360	0.0820
POV185	-0.393198	1.532932	-0.256500	0.7976

Weighted Statistics

R-squared	0.095990	Mean dependent var	47.40408
Adjusted R-squared	0.092302	S.D. dependent var	44.94345
S.E. of regression	43.66794	Akaike info criterion	10.39530
Sum squared resid	14021358	Schwarz criterion	10.42429
Log likelihood	-38348.43	F-statistic	26.02531
Durbin-Watson stat	1.995186	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 2003

Dependent Variable: VITC
Included observations: 7566

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.721611	11.12144	0.874132	0.3821
PRICE	24.35887	2.830918	8.604584	0.0000
PRICE2	-2.286337	0.532978	-4.289740	0.0000
AGEHH2529	-0.612260	10.68557	-0.057298	0.9543
AGEHH3034	-4.528747	10.35926	-0.437169	0.6620
AGEHH3544	-2.735370	10.21043	-0.267900	0.7888
AGEHH4554	-0.750780	10.18794	-0.073693	0.9413
AGEHH5564	0.506590	10.19984	0.049666	0.9604
AGEHHGT64	4.978603	10.23989	0.486197	0.6268
EMPHHPT	-1.186923	1.589569	-0.746695	0.4553
EMPHHFT	-5.288510	1.378425	-3.836631	0.0001
EDUHHHS	-0.835722	2.862152	-0.291991	0.7703
EDUHHU	0.174008	2.791295	0.062340	0.9503
EDUHHPC	0.979349	3.199838	0.306062	0.7596
REG_CENTRAL	-6.932178	1.622057	-4.273695	0.0000
REG_SOUTH	-7.583540	1.399221	-5.419829	0.0000
REG_WEST	-14.40347	1.667732	-8.636563	0.0000
RACE_BLACK	21.34704	1.607317	13.28117	0.0000
RACE_ORIENTAL	-0.118466	3.401029	-0.034833	0.9722
RACE_OTHER	6.318003	2.695565	2.343851	0.0191
HISP_YES	2.307227	2.432089	0.948661	0.3428
AGEPCLT6_ONLY	-7.545521	3.113238	-2.423689	0.0154
AGEPC6_12ONLY	-5.873741	2.358377	-2.490586	0.0128
AGEPC13_17ONLY	-2.091866	2.139171	-0.977886	0.3282
AGEPCLT6_6_12ONLY	-5.977653	3.389315	-1.763676	0.0778
AGEPCLT6_13_17ONLY	-11.78322	7.151499	-1.647657	0.0995
AGEPC6_12AND13_17ONLY	-2.642792	2.697997	-0.979538	0.3273
AGEPCLT6_6_12AND13_17	-6.545995	5.470370	-1.196628	0.2315
MHONLY	22.75387	1.887692	12.05380	0.0000
FHONLY	1.969172	1.277956	1.540876	0.1234
POV185	-3.059171	1.603118	-1.908262	0.0564

Weighted Statistics

R-squared	0.092860	Mean dependent var	47.32526
Adjusted R-squared	0.089249	S.D. dependent var	46.98280
S.E. of regression	45.48710	Akaike info criterion	10.47682
Sum squared resid	15590487	Schwarz criterion	10.50522
Log likelihood	-39602.82	F-statistic	25.71094
Durbin-Watson stat	1.977550	Prob(F-statistic)	0.000000

Regression Results from Vitamin C Intake 1998-2003

Dependent Variable: VITC, Sample 41071				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	8.039403	3.254840	2.469984	0.0135
PRICE	26.35925	1.370028	19.23994	0.0000
PRICE2	-2.205926	0.235995	-9.347360	0.0000
AGEHH2529	-0.568071	2.474184	-0.229599	0.8184
AGEHH3034	2.538888	2.433695	1.043224	0.2969
AGEHH3544	2.243050	2.338046	0.959369	0.3374
AGEHH4554	3.982678	2.327386	1.711223	0.0870
AGEHH5564	7.519329	2.369140	3.173864	0.0015
AGEHHGT64	11.56808	2.419384	4.781414	0.0000
EMPHHPT	-2.800693	0.704071	-3.977858	0.0001
EMPHHFT	-7.430502	0.636551	-11.67307	0.0000
EDUHHHS	2.135779	1.366011	1.563515	0.1179
EDUHHU	3.539535	1.343041	2.635463	0.0084
EDUHHPC	5.439838	1.536133	3.541255	0.0004
REG_CENTRAL	-7.978416	0.701934	-11.36634	0.0000
REG_SOUTH	-7.020787	0.675428	-10.39458	0.0000
REG_WEST	-14.74113	0.753570	-19.56174	0.0000
RACE_BLACK	19.73532	0.905813	21.78742	0.0000
RACE_ORIENTAL	-2.607269	1.370198	-1.902842	0.0571
RACE_OTHER	6.697346	1.297090	5.163363	0.0000
HISP_YES	0.193967	0.966463	0.200698	0.8409
AGEPCLT6_ONLY	-6.317468	1.008552	-6.263898	0.0000
AGEPC6_12ONLY	-8.234359	0.752595	-10.94128	0.0000
AGEPC13_17ONLY	-3.169057	0.731586	-4.331765	0.0000
AGEPCLT6_6_12ONLY	-9.516934	0.941517	-10.10808	0.0000
AGEPCLT6_13_17ONLY	-9.536684	1.992993	-4.785107	0.0000
AGEPC6_12AND13_17ONLY	-5.248878	0.888585	-5.907008	0.0000
AGEPCLT6_6_12AND13_17	-8.952999	1.702248	-5.259516	0.0000
MHONLY	21.89107	1.217687	17.97759	0.0000
FHONLY	0.833064	0.595924	1.397936	0.1621
POV185	-2.880594	0.732375	-3.933221	0.0001
D2001	-2.020553	0.681896	-2.963137	0.0030
D2002	-9.017309	0.651603	-13.83865	0.0000
D2003	-10.17065	0.651147	-15.61960	0.0000
R-squared	0.103682	Mean dependent var		52.88420
Adjusted R-squared	0.102961	S.D. dependent var		50.54896
S.E. of regression	47.87600	Akaike info criterion		10.57593
Sum squared resid	94061372	Schwarz criterion		10.58307
Log likelihood	-217148.1	F-statistic		143.8474
Durbin-Watson stat	1.982100	Prob(F-statistic)		0.000000

Seemingly Unrelated Regression (SUR) Results for Calories System

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	139.3709	29.25981	4.76	<.0001
price_98	64.10038	12.04523	5.32	<.0001
price2_98	-9.22505	2.101033	-4.39	<.0001
pov185_98	17.22358	6.658887	2.59	0.0097
agehh2529_98	24.57128	21.54157	1.14	0.2541
agehh3034_98	30.69322	20.53076	1.49	0.135
agehh3544_98	21.31853	20.00917	1.07	0.2867
agehh4554_98	14.57481	20.00995	0.73	0.4664
agehh5564_98	18.93934	20.31699	0.93	0.3513
agehhgt64_98	16.41492	20.86428	0.79	0.4315
emphhpt_98	-15.7697	6.231727	-2.53	0.0114
emphhft_98	-29.9831	5.54625	-5.41	<.0001
eduhhhs_98	11.11812	13.6049	0.82	0.4138
eduhhu_98	-5.37896	13.27631	-0.41	0.6854
eduhhpc_98	-4.12368	14.37905	-0.29	0.7743
reg_Central_98	8.403287	6.031069	1.39	0.1636
reg_South_98	4.679069	5.731683	0.82	0.4143
reg_West_98	-21.5468	6.426092	-3.35	0.0008
race_Black_98	7.773032	7.701268	1.01	0.3129
race_Oriental_98	-48.2716	17.79271	-2.71	0.0067
race_Other_98	2.748801	11.91328	0.23	0.8175
hisp_yes_98	-6.03833	9.249499	-0.65	0.5139
agepclt6_only_98	-21.255	9.778433	-2.17	0.0298
agepc6_12only_98	-36.2197	8.265014	-4.38	<.0001
agepc13_17only_98	3.300486	7.345133	0.45	0.6532
agepclt6_6_12only_98	-48.2289	10.38661	-4.64	<.0001
agepclt6_13_17only_98	-57.9984	24.93973	-2.33	0.0201
agepc6_12and13_17only_98	-27.4203	9.473093	-2.89	0.0038
agepclt6_6_12and13_17_98	-30.4947	22.95972	-1.33	0.1842
fhonly_98	-2.83931	5.41536	-0.52	0.6001
mhonly_98	78.84832	7.498801	10.51	<.0001

SUR Results for Calories System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	117.719	29.00885	4.06	<.0001
price_99	84.71743	10.99593	7.7	<.0001
price2_99	-10.8583	1.902587	-5.71	<.0001
pov185_99	5.357132	6.480374	0.83	0.4085
agehh2529_99	-2.32375	22.7931	-0.1	0.9188
agehh3034_99	25.05583	22.0106	1.14	0.255
agehh3544_99	13.74546	21.4155	0.64	0.521
agehh4554_99	6.235705	21.34753	0.29	0.7702
agehh5564_99	6.611495	21.56583	0.31	0.7592
agehhgt64_99	-0.29822	21.99453	-0.01	0.9892
emphhpt_99	-20.1156	6.229961	-3.23	0.0012
emphhft_99	-27.2759	5.459494	-5	<.0001
eduhhhs_99	12.2581	11.9257	1.03	0.3041
eduhhu_99	-8.63023	11.5853	-0.74	0.4563
eduhhpc_99	-13.8291	12.81223	-1.08	0.2805
reg_Central_99	6.41477	5.887896	1.09	0.276
reg_South_99	-0.40699	5.555198	-0.07	0.9416
reg_West_99	-27.7876	6.317173	-4.4	<.0001
race_Black_99	7.41484	6.969073	1.06	0.2874
race_Oriental_99	-58.6645	18.06824	-3.25	0.0012
race_Other_99	20.63975	11.45235	1.8	0.0716
hisp_yes_99	-8.20871	8.767107	-0.94	0.3492
agepclt6_only_99	-23.9868	10.10865	-2.37	0.0177
agepc6_12only_99	-30.0694	8.34247	-3.6	0.0003
agepc13_17only_99	0.080368	7.471865	0.01	0.9914
agepclt6_6_12only_99	-53.504	11.27297	-4.75	<.0001
agepclt6_13_17only_99	-58.8662	23.77921	-2.48	0.0133
agepc6_12and13_17only_99	-30.4891	9.619739	-3.17	0.0015
agepclt6_6_12and13_17_99	-42.1287	21.63611	-1.95	0.0516
fhonly_99	2.833303	5.191102	0.55	0.5852
mhonly_99	58.11067	7.389808	7.86	<.0001

SUR Results for Calories System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	154.8571	40.4442	3.83	0.0001
price_00	75.86393	15.14194	5.01	<.0001
price2_00	-10.9479	2.580757	-4.24	<.0001
pov185_00	14.0049	8.879617	1.58	0.1148
agehh2529_00	-12.5763	33.08118	-0.38	0.7038
agehh3034_00	-14.7835	31.2739	-0.47	0.6364
agehh3544_00	-12.6942	30.6216	-0.41	0.6785
agehh4554_00	-21.575	30.59309	-0.71	0.4807
agehh5564_00	-24.3799	30.87364	-0.79	0.4298
agehhgt64_00	-13.3539	31.3705	-0.43	0.6704
emphhpt_00	-4.93828	8.556027	-0.58	0.5638
emphhft_00	-22.7617	7.406743	-3.07	0.0021
eduhhhs_00	4.039513	16.12205	0.25	0.8022
eduhhu_00	-8.33887	15.77122	-0.53	0.597
eduhhpc_00	-21.1581	17.59714	-1.2	0.2293
reg_Central_00	16.8736	8.150473	2.07	0.0385
reg_South_00	3.797698	7.593677	0.5	0.617
reg_West_00	-19.8186	8.400763	-2.36	0.0183
race_Black_00	2.241378	9.201583	0.24	0.8076
race_Oriental_00	-42.766	24.24323	-1.76	0.0778
race_Other_00	22.45341	14.93743	1.5	0.1328
hisp_yes_00	10.24948	13.10887	0.78	0.4343
agepclt6_only_00	-36.5638	14.61374	-2.5	0.0124
agepc6_12only_00	-38.1726	11.47563	-3.33	0.0009
agepc13_17only_00	-10.1159	10.68729	-0.95	0.3439
agepclt6_6_12only_00	-51.461	15.85439	-3.25	0.0012
agepclt6_13_17only_00	-36.9748	35.85104	-1.03	0.3024
agepc6_12and13_17only_00	-35.6309	14.11107	-2.53	0.0116
agepclt6_6_12and13_17_00	-45.9534	34.3168	-1.34	0.1806
fhonly_00	4.792773	7.032549	0.68	0.4956
mhonly_00	80.69425	9.678439	8.34	<.0001

SUR Results for Calories System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	154.8188	30.07858	5.15	<.0001
price_01	76.00538	8.641862	8.8	<.0001
price2_01	-10.5666	1.40756	-7.51	<.0001
pov185_01	3.858025	6.022494	0.64	0.5218
agehh2529_01	0.969238	26.86211	0.04	0.9712
agehh3034_01	-20.1079	25.78835	-0.78	0.4356
agehh3544_01	-12.2579	25.2597	-0.49	0.6275
agehh4554_01	-10.2124	25.2947	-0.4	0.6864
agehh5564_01	-16.6579	25.4149	-0.66	0.5122
agehhgt64_01	-30.4662	25.71116	-1.18	0.2361
emphhpt_01	-28.5749	5.960212	-4.79	<.0001
emphhft_01	-39.062	5.231751	-7.47	<.0001
eduhhhs_01	0.639636	10.67206	0.06	0.9522
eduhhu_01	-17.4999	10.39187	-1.68	0.0922
eduhhpc_01	-27.7065	11.81401	-2.35	0.019
reg_Central_01	17.13597	5.915905	2.9	0.0038
reg_South_01	3.62307	5.28628	0.69	0.4931
reg_West_01	-13.2616	5.97439	-2.22	0.0265
race_Black_01	19.10642	5.996647	3.19	0.0014
race_Oriental_01	-37.7072	12.89026	-2.93	0.0035
race_Other_01	17.51845	12.1343	1.44	0.1489
hisp_yes_01	-10.2918	8.962285	-1.15	0.2509
agepclt6_only_01	-19.8307	10.33325	-1.92	0.055
agepc6_12only_01	-35.518	8.086989	-4.39	<.0001
agepc13_17only_01	1.357222	7.88956	0.17	0.8634
agepclt6_6_12only_01	-43.6633	10.73386	-4.07	<.0001
agepclt6_13_17only_01	-38.8339	23.48375	-1.65	0.0983
agepc6_12and13_17only_01	-29.7298	10.0507	-2.96	0.0031
agepclt6_6_12and13_17_01	-61.8991	22.72072	-2.72	0.0065
fhonly_01	4.178818	4.950782	0.84	0.3987
mhonly_01	96.61041	6.761153	14.29	<.0001

SUR Results for Calories System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	200.3725	30.89037	6.49	<.0001
price_02	57.19622	7.207478	7.94	<.0001
price2_02	-7.46979	1.106011	-6.75	<.0001
pov185_02	6.952513	5.852493	1.19	0.2349
agehh2529_02	-50.2184	28.56817	-1.76	0.0788
agehh3034_02	-57.2387	27.50022	-2.08	0.0374
agehh3544_02	-62.7611	27.104	-2.32	0.0206
agehh4554_02	-59.2216	27.12023	-2.18	0.029
agehh5564_02	-64.5875	27.23012	-2.37	0.0177
agehhgt64_02	-74.9957	27.45398	-2.73	0.0063
emphhpt_02	-11.5974	5.690285	-2.04	0.0416
emphhft_02	-23.0664	4.955798	-4.65	<.0001
eduhhhs_02	-1.37415	9.991455	-0.14	0.8906
eduhhu_02	-18.6573	9.739942	-1.92	0.0555
eduhhpc_02	-33.1467	11.11684	-2.98	0.0029
reg_Central_02	3.312893	5.695922	0.58	0.5608
reg_South_02	1.245292	4.994922	0.25	0.8031
reg_West_02	-26.0495	5.675791	-4.59	<.0001
race_Black_02	7.931584	5.593241	1.42	0.1562
race_Oriental_02	-37.2803	11.59334	-3.22	0.0013
race_Other_02	16.84153	10.28288	1.64	0.1015
hisp_yes_02	-7.07944	9.345199	-0.76	0.4488
agepclt6_only_02	-11.5085	11.09226	-1.04	0.2995
agepc6_12only_02	-30.6668	7.707414	-3.98	<.0001
agepc13_17only_02	-6.92894	7.561559	-0.92	0.3595
agepclt6_6_12only_02	-49.5972	10.62667	-4.67	<.0001
agepclt6_13_17only_02	-25.6719	27.22875	-0.94	0.3458
agepc6_12and13_17only_02	-27.7086	9.185504	-3.02	0.0026
agepclt6_6_12and13_17_02	-49.2153	18.79642	-2.62	0.0089
fhonly_02	12.07895	4.654059	2.6	0.0095
mhonly_02	82.38466	6.378057	12.92	<.0001

SUR Results for Calories System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	216.1826	37.01413	5.84	<.0001
price_03	27.22022	5.424933	5.02	<.0001
price2_03	-3.53976	0.704147	-5.03	<.0001
pov185_03	-5.34491	6.069752	-0.88	0.3786
agehh2529_03	-41.2815	37.32826	-1.11	0.2688
agehh3034_03	-45.7787	36.06645	-1.27	0.2044
agehh3544_03	-49.2903	35.54315	-1.39	0.1656
agehh4554_03	-49.5087	35.46544	-1.4	0.1628
agehh5564_03	-53.7097	35.5189	-1.51	0.1306
agehhgt64_03	-59.231	35.7102	-1.66	0.0972
emphhpt_03	-8.86039	5.963585	-1.49	0.1374
emphhft_03	-24.711	5.128049	-4.82	<.0001
eduhhhs_03	11.06292	4.733993	2.34	0.0195
eduhhpc_03	-15.5438	6.340511	-2.45	0.0143
reg_Central_03	6.541009	6.143464	1.06	0.2871
reg_South_03	3.785137	5.215158	0.73	0.468
reg_West_03	-24.8428	6.055121	-4.1	<.0001
race_Black_03	14.69435	5.928953	2.48	0.0132
race_Oriental_03	-34.7373	11.61978	-2.99	0.0028
race_Other_03	24.44398	9.834472	2.49	0.013
hisp_yes_03	-1.40075	8.915265	-0.16	0.8752
agepclt6_only_03	-21.8602	11.2018	-1.95	0.051
agepc6_12only_03	-33.9145	8.612256	-3.94	<.0001
agepc13_17only_03	-4.03088	7.904781	-0.51	0.6101
agepclt6_6_12only_03	-41.077	12.27768	-3.35	0.0008
agepclt6_13_17only_03	-54.8191	26.33018	-2.08	0.0374
agepc6_12and13_17only_03	-21.2183	10.00709	-2.12	0.034
agepclt6_6_12and13_17_03	-34.6514	19.9357	-1.74	0.0822
fhonly_03	13.51988	4.74432	2.85	0.0044
mhonly_03	84.16657	6.867696	12.26	<.0001

Seemingly Unrelated Regression (SUR) Results for Caffeine System

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	319.865	16.66706	19.19	<.0001
price_98	-144.887	6.861223	-21.12	<.0001
price2_98	16.18861	1.196793	13.53	<.0001
pov185_98	-9.33675	3.793039	-2.46	0.0139
agehh2529_98	8.009762	12.27054	0.65	0.5139
agehh3034_98	20.91737	11.69477	1.79	0.0737
agehh3544_98	32.61816	11.39765	2.86	0.0042
agehh4554_98	42.2515	11.3981	3.71	0.0002
agehh5564_98	45.41066	11.573	3.92	<.0001
agehhgt64_98	31.39779	11.88475	2.64	0.0083
emphhpt_98	-4.31476	3.549729	-1.22	0.2242
emphhft_98	-1.70381	3.159264	-0.54	0.5897
eduhhhs_98	1.388786	7.74964	0.18	0.8578
eduhhu_98	-7.87137	7.56247	-1.04	0.298
eduhhpc_98	-11.2066	8.190618	-1.37	0.1713
reg_Central_98	-9.14091	3.43543	-2.66	0.0078
reg_South_98	-6.82421	3.264895	-2.09	0.0366
reg_West_98	-4.19857	3.660445	-1.15	0.2514
race_Black_98	-35.4079	4.386807	-8.07	<.0001
race_Oriental_98	-22.2098	10.1351	-2.19	0.0285
race_Other_98	-21.6808	6.786054	-3.19	0.0014
hisp_yes_98	0.745629	5.268711	0.14	0.8875
agepclt6_only_98	-26.9005	5.570001	-4.83	<.0001
agepc6_12only_98	-35.3086	4.707925	-7.5	<.0001
agepc13_17only_98	-33.8483	4.183944	-8.09	<.0001
agepclt6_6_12only_98	-42.1062	5.916435	-7.12	<.0001
agepclt6_13_17only_98	-47.9286	14.2062	-3.37	0.0007
agepc6_12and13_17only_98	-47.9387	5.396078	-8.88	<.0001
agepclt6_6_12and13_17_98	-55.9356	13.07834	-4.28	<.0001
fhonly_98	7.664106	3.084703	2.48	0.013
mhonly_98	20.43183	4.271473	4.78	<.0001

SUR Results for Caffeine System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	335.2302	17.65361	18.99	<.0001
price_99	-152.116	6.691669	-22.73	<.0001
price2_99	17.22142	1.157836	14.87	<.0001
pov185_99	-12.5211	3.943691	-3.17	0.0015
agehh2529_99	5.785476	13.87094	0.42	0.6766
agehh3034_99	18.92353	13.39475	1.41	0.1578
agehh3544_99	29.66755	13.03259	2.28	0.0229
agehh4554_99	36.67394	12.99123	2.82	0.0048
agehh5564_99	35.76649	13.12408	2.73	0.0064
agehhgt64_99	33.37253	13.38497	2.49	0.0127
emphhpt_99	-8.01755	3.791299	-2.11	0.0345
emphhft_99	-7.7589	3.322424	-2.34	0.0196
eduhhhs_99	5.58273	7.257492	0.77	0.4418
eduhhu_99	-2.0863	7.050336	-0.3	0.7673
eduhhpc_99	5.019916	7.796995	0.64	0.5197
reg_Central_99	-9.94268	3.583133	-2.77	0.0055
reg_South_99	-13.5888	3.380666	-4.02	<.0001
reg_West_99	-9.24887	3.844375	-2.41	0.0162
race_Black_99	-39.545	4.241094	-9.32	<.0001
race_Oriental_99	-26.6562	10.99559	-2.42	0.0154
race_Other_99	-10.4648	6.96943	-1.5	0.1333
hisp_yes_99	1.594025	5.3353	0.3	0.7651
agepclt6_only_99	-26.2039	6.151709	-4.26	<.0001
agepc6_12only_99	-29.8815	5.076884	-5.89	<.0001
agepc13_17only_99	-32.2625	4.547069	-7.1	<.0001
agepclt6_6_12only_99	-46.6024	6.860269	-6.79	<.0001
agepclt6_13_17only_99	-57.8771	14.47105	-4	<.0001
agepc6_12and13_17only_99	-42.7804	5.854177	-7.31	<.0001
agepclt6_6_12and13_17_99	-46.7006	13.16685	-3.55	0.0004
fhonly_99	14.3482	3.159093	4.54	<.0001
mhonly_99	22.72119	4.497133	5.05	<.0001

SUR Results for Caffeine System (Contined)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	351.8128	34.29171	10.26	<.0001
price_00	-167.858	12.83851	-13.07	<.0001
price2_00	19.39171	2.188165	8.86	<.0001
pov185_00	-21.6525	7.528826	-2.88	0.004
agehh2529_00	-1.82962	28.04879	-0.07	0.948
agehh3034_00	4.34812	26.51643	0.16	0.8698
agehh3544_00	18.60447	25.96336	0.72	0.4737
agehh4554_00	21.14958	25.93919	0.82	0.4149
agehh5564_00	22.20545	26.17706	0.85	0.3963
agehhgt64_00	33.2305	26.59834	1.25	0.2116
emphhpt_00	6.243142	7.254463	0.86	0.3895
emphhft_00	-0.09103	6.280011	-0.01	0.9884
eduhhhs_00	8.45218	13.66953	0.62	0.5364
eduhhu_00	3.024355	13.37206	0.23	0.8211
eduhhpc_00	-3.44016	14.92022	-0.23	0.8177
reg_Central_00	3.582214	6.910602	0.52	0.6042
reg_South_00	-2.0798	6.438507	-0.32	0.7467
reg_West_00	2.252356	7.122818	0.32	0.7518
race_Black_00	-37.1625	7.801814	-4.76	<.0001
race_Oriental_00	-24.1013	20.55529	-1.17	0.241
race_Other_00	0.468923	12.66511	0.04	0.9705
hisp_yes_00	0.534338	11.11472	0.05	0.9617
agepclt6_only_00	-28.0084	12.39066	-2.26	0.0238
agepc6_12only_00	-35.1184	9.729933	-3.61	0.0003
agepc13_17only_00	-26.163	9.061512	-2.89	0.0039
agepclt6_6_12only_00	-36.6685	13.44258	-2.73	0.0064
agepclt6_13_17only_00	-54.7987	30.39729	-1.8	0.0715
agepc6_12and13_17only_00	-40.0541	11.96446	-3.35	0.0008
agepclt6_6_12and13_17_00	-46.6089	29.09644	-1.6	0.1092
fhonly_00	22.8899	5.96274	3.84	0.0001
mhonly_00	40.61386	8.206129	4.95	<.0001

SUR Results for Caffeine System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	330.8265	19.36643	17.08	<.0001
price_01	-141.237	5.564158	-25.38	<.0001
price2_01	15.19119	0.906273	16.76	<.0001
pov185_01	-15.3551	3.877649	-3.96	<.0001
agehh2529_01	5.836315	17.29547	0.34	0.7358
agehh3034_01	9.61396	16.60411	0.58	0.5626
agehh3544_01	21.08043	16.26373	1.3	0.195
agehh4554_01	28.6153	16.28627	1.76	0.079
agehh5564_01	25.27009	16.36366	1.54	0.1226
agehhgt64_01	26.1707	16.55441	1.58	0.114
emphhpt_01	-8.59856	3.837548	-2.24	0.0251
emphhft_01	-7.22958	3.36852	-2.15	0.0319
eduhhhs_01	-5.80854	6.871321	-0.85	0.398
eduhhu_01	-8.45906	6.69092	-1.26	0.2062
eduhhpc_01	-7.00799	7.606578	-0.92	0.3569
reg_Central_01	-6.87644	3.809021	-1.81	0.0711
reg_South_01	-6.67501	3.40363	-1.96	0.0499
reg_West_01	0.982766	3.846677	0.26	0.7984
race_Black_01	-29.7403	3.861008	-7.7	<.0001
race_Oriental_01	-17.762	8.299534	-2.14	0.0324
race_Other_01	-3.05722	7.812803	-0.39	0.6956
hisp_yes_01	-8.46055	5.770466	-1.47	0.1427
agepclt6_only_01	-28.9976	6.653178	-4.36	<.0001
agepc6_12only_01	-33.988	5.206896	-6.53	<.0001
agepc13_17only_01	-28.1212	5.07978	-5.54	<.0001
agepclt6_6_12only_01	-34.0303	6.911113	-4.92	<.0001
agepclt6_13_17only_01	-39.3692	15.12027	-2.6	0.0092
agepc6_12and13_17only_01	-44.2477	6.471251	-6.84	<.0001
agepclt6_6_12and13_17_01	-53.4563	14.62899	-3.65	0.0003
fhonly_01	16.97811	3.187615	5.33	<.0001
mhonly_01	34.59592	4.353243	7.95	<.0001

SUR Results for Caffeine System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	249.2368	18.14153	13.74	<.0001
price_02	-95.7024	4.232859	-22.61	<.0001
price2_02	9.112968	0.649546	14.03	<.0001
pov185_02	-11.5482	3.437089	-3.36	0.0008
agehh2529_02	7.50137	16.77773	0.45	0.6548
agehh3034_02	9.619864	16.15053	0.6	0.5514
agehh3544_02	19.30806	15.91784	1.21	0.2252
agehh4554_02	20.89395	15.92737	1.31	0.1896
agehh5564_02	22.47882	15.99191	1.41	0.1599
agehhgt64_02	14.12681	16.12337	0.88	0.381
emphhpt_02	-9.32181	3.341828	-2.79	0.0053
emphhft_02	-7.14201	2.910469	-2.45	0.0142
eduhhhs_02	0.186523	5.867853	0.03	0.9746
eduhhu_02	-4.86938	5.720139	-0.85	0.3947
eduhhpc_02	-6.10775	6.528769	-0.94	0.3496
reg_Central_02	-12.3248	3.345137	-3.68	0.0002
reg_South_02	-5.16634	2.933453	-1.76	0.0783
reg_West_02	-5.23173	3.33332	-1.57	0.1166
race_Black_02	-32.1256	3.284835	-9.78	<.0001
race_Oriental_02	-20.1129	6.808621	-2.95	0.0031
race_Other_02	-11.4486	6.039003	-1.9	0.058
hisp_yes_02	-4.58393	5.488312	-0.84	0.4036
agepclt6_only_02	-26.6864	6.514335	-4.1	<.0001
agepc6_12only_02	-25.2827	4.526465	-5.59	<.0001
agepc13_17only_02	-24.1123	4.440801	-5.43	<.0001
agepclt6_6_12only_02	-34.1247	6.240898	-5.47	<.0001
agepclt6_13_17only_02	-36.9397	15.99111	-2.31	0.0209
agepc6_12and13_17only_02	-38.6582	5.394529	-7.17	<.0001
agepclt6_6_12and13_17_02	-43.0294	11.03888	-3.9	<.0001
fhonly_02	19.35483	2.73327	7.08	<.0001
mhonly_02	26.22885	3.74575	7	<.0001

SUR Results for Caffeine System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	235.5275	22.02632	10.69	<.0001
price_03	-77.0602	3.228267	-23.87	<.0001
price2_03	5.780559	0.419023	13.8	<.0001
pov185_03	-8.6769	3.611984	-2.4	0.0163
agehh2529_03	-6.04941	22.21327	-0.27	0.7854
agehh3034_03	-5.23251	21.4624	-0.24	0.8074
agehh3544_03	9.694656	21.15099	0.46	0.6467
agehh4554_03	14.02807	21.10474	0.66	0.5063
agehh5564_03	12.44961	21.13656	0.59	0.5559
agehhgt64_03	9.796684	21.2504	0.46	0.6448
emphhpt_03	-2.00429	3.548805	-0.56	0.5722
emphhft_03	-3.44724	3.051598	-1.13	0.2587
eduhhhs_03	-1.43138	2.817104	-0.51	0.6114
eduhhpc_03	-7.95396	3.773106	-2.11	0.0351
reg_Central_03	-13.233	3.655847	-3.62	0.0003
reg_South_03	-8.99127	3.103434	-2.9	0.0038
reg_West_03	-9.76562	3.603277	-2.71	0.0067
race_Black_03	-31.7517	3.528195	-9	<.0001
race_Oriental_03	-16.5921	6.914686	-2.4	0.0164
race_Other_03	-3.61643	5.852289	-0.62	0.5366
hisp_yes_03	-7.22505	5.305286	-1.36	0.1733
agepclt6_only_03	-27.9666	6.66596	-4.2	<.0001
agepc6_12only_03	-28.4375	5.124976	-5.55	<.0001
agepc13_17only_03	-30.6823	4.703975	-6.52	<.0001
agepclt6_6_12only_03	-35.2638	7.30619	-4.83	<.0001
agepclt6_13_17only_03	-47.0872	15.66856	-3.01	0.0027
agepc6_12and13_17only_03	-45.4988	5.955015	-7.64	<.0001
agepclt6_6_12and13_17_03	-43.7527	11.86333	-3.69	0.0002
fhonly_03	17.13396	2.823245	6.07	<.0001
mhonly_03	16.20419	4.086824	3.96	<.0001

Seemingly Unrelated Regression (SUR) Results for Vitamin C System

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	5.684364	9.01945	0.63	0.5286
price_98	20.62311	3.712987	5.55	<.0001
price2_98	-0.88132	0.647651	-1.36	0.1736
pov185_98	-1.25882	2.052627	-0.61	0.5397
agehh2529_98	4.32273	6.64027	0.65	0.5151
agehh3034_98	9.999871	6.328685	1.58	0.1141
agehh3544_98	7.530009	6.1679	1.22	0.2222
agehh4554_98	8.35127	6.168142	1.35	0.1758
agehh5564_98	12.62836	6.262788	2.02	0.0438
agehhgt64_98	16.40464	6.431492	2.55	0.0108
emphhpt_98	-4.43718	1.920953	-2.31	0.0209
emphhft_98	-8.89286	1.709652	-5.2	<.0001
eduhhhs_98	6.735354	4.193762	1.61	0.1083
eduhhu_98	8.415456	4.092473	2.06	0.0398
eduhhpc_98	12.68074	4.432397	2.86	0.0042
reg_Central_98	-8.75034	1.8591	-4.71	<.0001
reg_South_98	-6.19619	1.766813	-3.51	0.0005
reg_West_98	-14.1079	1.980868	-7.12	<.0001
race_Black_98	17.9433	2.373945	7.56	<.0001
race_Oriental_98	-5.31242	5.48467	-0.97	0.3328
race_Other_98	5.375796	3.672312	1.46	0.1433
hisp_yes_98	-2.45693	2.851193	-0.86	0.3889
agepclt6_only_98	-6.12547	3.014238	-2.03	0.0422
agepc6_12only_98	-9.00539	2.547721	-3.53	0.0004
agepc13_17only_98	-4.48954	2.264164	-1.98	0.0474
agepclt6_6_12only_98	-12.0947	3.201711	-3.78	0.0002
agepclt6_13_17only_98	-15.005	7.687763	-1.95	0.051
agepc6_12and13_17only_98	-5.53604	2.920117	-1.9	0.058
agepclt6_6_12and13_17_98	-8.36131	7.077421	-1.18	0.2375
fhonly_98	0.873309	1.669305	0.52	0.6009
mhonly_98	19.60685	2.311533	8.48	<.0001

SUR Results for Vitamin C System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-5.23995	8.882737	-0.59	0.5553
price_99	27.74073	3.367037	8.24	<.0001
price2_99	-1.65743	0.582587	-2.84	0.0045
pov185_99	-4.60082	1.984341	-2.32	0.0205
agehh2529_99	2.641264	6.979422	0.38	0.7051
agehh3034_99	9.377446	6.739814	1.39	0.1642
agehh3544_99	5.978615	6.557592	0.91	0.362
agehh4554_99	6.701892	6.53678	1.03	0.3053
agehh5564_99	11.81587	6.603624	1.79	0.0736
agehhgt64_99	16.96462	6.734896	2.52	0.0118
emphhpt_99	-2.68809	1.907662	-1.41	0.1589
emphhft_99	-8.19088	1.671739	-4.9	<.0001
eduhhhs_99	6.206368	3.651741	1.7	0.0893
eduhhu_99	7.438801	3.547506	2.1	0.036
eduhhpc_99	9.497717	3.923202	2.42	0.0155
reg_Central_99	-8.3254	1.802918	-4.62	<.0001
reg_South_99	-5.64647	1.701044	-3.32	0.0009
reg_West_99	-15.3737	1.934367	-7.95	<.0001
race_Black_99	19.55487	2.133983	9.16	<.0001
race_Oriental_99	-8.61597	5.532633	-1.56	0.1195
race_Other_99	7.170535	3.506797	2.04	0.0409
hisp_yes_99	-1.81847	2.684555	-0.68	0.4982
agepclt6_only_99	-6.31111	3.095344	-2.04	0.0415
agepc6_12only_99	-6.49343	2.554527	-2.54	0.011
agepc13_17only_99	-2.22118	2.287941	-0.97	0.3317
agepclt6_6_12only_99	-12.8687	3.451869	-3.73	0.0002
Agepclt6_13_17only_99	-12.5266	7.281373	-1.72	0.0854
agepc6_12and13_17only_99	-7.08262	2.945637	-2.4	0.0162
Agepclt6_6_12and13_17_99	-9.61782	6.625142	-1.45	0.1466
fhonly_99	0.977556	1.589555	0.61	0.5386
Mhonly_99	15.9488	2.262815	7.05	<.0001

SUR Results for Vitamin C System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	4.766544	9.707836	0.49	0.6234
price_00	31.35966	3.634525	8.63	<.0001
price2_00	-2.9535	0.61946	-4.77	<.0001
pov185_00	-2.01838	2.131377	-0.95	0.3437
agehh2529_00	-1.23032	7.94049	-0.15	0.8769
agehh3034_00	-0.08453	7.506685	-0.01	0.991
agehh3544_00	-1.17125	7.350113	-0.16	0.8734
agehh4554_00	0.183635	7.343271	0.03	0.9801
agehh5564_00	4.772537	7.410611	0.64	0.5196
agehhgt64_00	11.05659	7.529874	1.47	0.1421
emphhpt_00	-1.88734	2.053706	-0.92	0.3581
emphhft_00	-6.50273	1.777844	-3.66	0.0003
eduhhhs_00	1.383211	3.869782	0.36	0.7208
Eduhhu_00	2.462832	3.78557	0.65	0.5153
eduhhpc_00	4.207098	4.223848	1	0.3193
reg_Central_00	-8.96088	1.956363	-4.58	<.0001
reg_South_00	-7.41366	1.822714	-4.07	<.0001
reg_West_00	-14.0438	2.016439	-6.96	<.0001
race_Black_00	20.33303	2.20866	9.21	<.0001
race_Oriental_00	1.574341	5.819112	0.27	0.7867
race_Other_00	10.66979	3.585437	2.98	0.0029
hisp_yes_00	0.462332	3.146528	0.15	0.8832
Agepclt6_only_00	-10.2611	3.507742	-2.93	0.0035
agepc6_12only_00	-9.78429	2.754501	-3.55	0.0004
agepc13_17only_00	-6.00962	2.565274	-2.34	0.0192
Agepclt6_6_12only_00	-10.3027	3.805536	-2.71	0.0068
Agepclt6_13_17only_00	-4.03682	8.60534	-0.47	0.639
agepc6_12and13_17only_00	-9.29876	3.387085	-2.75	0.0061
Agepclt6_6_12and13_17_00	-11.8778	8.237072	-1.44	0.1494
fhonly_00	-0.74337	1.688025	-0.44	0.6597
Mhonly_00	19.77558	2.32312	8.51	<.0001

SUR Results for Vitamin C System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.601646	9.807468	0.16	0.8703
price_01	28.9464	2.817778	10.27	<.0001
price2_01	-2.7851	0.458951	-6.07	<.0001
pov185_01	-4.14087	1.963704	-2.11	0.035
agehh2529_01	-0.11956	8.7587	-0.01	0.9891
agehh3034_01	-0.61609	8.40859	-0.07	0.9416
agehh3544_01	1.740145	8.236216	0.21	0.8327
agehh4554_01	3.171706	8.247628	0.38	0.7006
agehh5564_01	7.752101	8.286822	0.94	0.3496
agehhgt64_01	8.441416	8.38342	1.01	0.314
emphhpt_01	-8.01771	1.943396	-4.13	<.0001
emphhft_01	-10.4607	1.705872	-6.13	<.0001
eduhhhs_01	5.700049	3.479746	1.64	0.1015
eduhhu_01	8.005072	3.388388	2.36	0.0182
eduhhpc_01	10.40929	3.852093	2.7	0.0069
reg_Central_01	-6.58356	1.928949	-3.41	0.0006
reg_South_01	-8.05496	1.723653	-4.67	<.0001
reg_West_01	-12.1826	1.948018	-6.25	<.0001
race_Black_01	22.59679	1.955276	11.56	<.0001
race_Oriental_01	-1.92959	4.203017	-0.46	0.6462
race_Other_01	7.206059	3.956527	1.82	0.0686
hisp_yes_01	2.545367	2.922256	0.87	0.3838
agepclt6_only_01	-5.42201	3.369274	-1.61	0.1076
agepc6_12only_01	-10.2092	2.636855	-3.87	0.0001
agepc13_17only_01	-3.42853	2.572481	-1.33	0.1827
agepclt6_6_12only_01	-9.29941	3.499898	-2.66	0.0079
agepclt6_13_17only_01	-10.6093	7.657145	-1.39	0.1659
agepc6_12and13_17only_01	-8.21354	3.277145	-2.51	0.0122
agepclt6_6_12and13_17_01	-14.855	7.408351	-2.01	0.045
fhonly_01	0.820558	1.61426	0.51	0.6112
mhonly_01	23.98047	2.204551	10.88	<.0001

SUR Results for Vitamin C System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	13.01915	10.0368	1.3	0.1946
price_02	28.99408	2.341834	12.38	<.0001
price2_02	-2.69691	0.359362	-7.5	<.0001
pov185_02	-0.95613	1.901574	-0.5	0.6151
agehh2529_02	-17.0837	9.282292	-1.84	0.0658
agehh3034_02	-15.5115	8.935295	-1.74	0.0826
agehh3544_02	-13.5792	8.806556	-1.54	0.1231
agehh4554_02	-10.7969	8.811827	-1.23	0.2205
agehh5564_02	-8.01385	8.847533	-0.91	0.3651
agehhgt64_02	-6.06667	8.920267	-0.68	0.4965
emphhpt_02	-1.05821	1.84887	-0.57	0.5671
emphhft_02	-5.47143	1.610222	-3.4	0.0007
eduhhhs_02	0.424626	3.246397	0.13	0.8959
Eduhhu_02	2.486057	3.164675	0.79	0.4322
eduhhpc_02	3.130589	3.61205	0.87	0.3861
reg_Central_02	-10.0849	1.8507	-5.45	<.0001
reg_South_02	-8.58509	1.622934	-5.29	<.0001
reg_West_02	-17.6783	1.844161	-9.59	<.0001
race_Black_02	17.51372	1.817338	9.64	<.0001
race_Oriental_02	-5.23501	3.766877	-1.39	0.1647
race_Other_02	8.115759	3.341085	2.43	0.0152
hisp_yes_02	-0.01469	3.036414	0	0.9961
Agepclt6_only_02	-4.59774	3.604065	-1.28	0.2021
agepc6_12only_02	-7.17074	2.50427	-2.86	0.0042
agepc13_17only_02	-3.56562	2.45688	-1.45	0.1468
Agepclt6_6_12only_02	-8.80515	3.452786	-2.55	0.0108
Agepclt6_13_17only_02	-6.31352	8.847091	-0.71	0.4755
agepc6_12and13_17only_02	-4.30188	2.984528	-1.44	0.1495
Agepclt6_6_12and13_17_02	-11.0566	6.107278	-1.81	0.0703
fhonly_02	0.968248	1.512183	0.64	0.522
Mhonly_02	24.54535	2.07234	11.84	<.0001

SUR Results for Vitamin C System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	14.63248	11.74751	1.25	0.213
price_03	20.18939	1.721762	11.73	<.0001
price2_03	-1.6649	0.223482	-7.45	<.0001
pov185_03	-4.63949	1.926414	-2.41	0.0161
agehh2529_03	1.880345	11.84722	0.16	0.8739
agehh3034_03	-1.63131	11.44675	-0.14	0.8867
agehh3544_03	-0.26268	11.28066	-0.02	0.9814
agehh4554_03	1.633058	11.256	0.15	0.8846
agehh5564_03	2.862521	11.27297	0.25	0.7996
agehhgt64_03	8.878883	11.33368	0.78	0.4334
emphhpt_03	-1.14467	1.892718	-0.6	0.5454
emphhft_03	-6.0202	1.627538	-3.7	0.0002
eduhhhs_03	-2.37902	1.502472	-1.58	0.1134
eduhhpc_03	1.066961	2.012347	0.53	0.596
reg_Central_03	-6.50209	1.949808	-3.33	0.0009
reg_South_03	-7.71029	1.655184	-4.66	<.0001
reg_West_03	-15.2209	1.921771	-7.92	<.0001
race_Black_03	19.82593	1.881727	10.54	<.0001
race_Oriental_03	-1.32962	3.687877	-0.36	0.7185
race_Other_03	5.707529	3.121257	1.83	0.0675
hisp_yes_03	3.514545	2.829519	1.24	0.2142
agepclt6_only_03	-6.94775	3.55522	-1.95	0.0507
agepc6_12only_03	-5.53895	2.733353	-2.03	0.0428
agepc13_17only_03	-2.40256	2.508816	-0.96	0.3383
agepclt6_6_12only_03	-5.47829	3.896681	-1.41	0.1598
agepclt6_13_17only_03	-13.3958	8.356659	-1.6	0.109
agepc6_12and13_17only_03	-3.47168	3.176045	-1.09	0.2744
agepclt6_6_12and13_17_03	-7.13771	6.327182	-1.13	0.2593
fhonly_03	2.331614	1.505748	1.55	0.1216
mhonly_03	23.05724	2.179665	10.58	<.0001

Seemingly Unrelated Regression (SUR) Results for Calcium System

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	144.9308	30.82574	4.7	<.0001
price_98	61.42502	12.68984	4.84	<.0001
price2_98	-12.8447	2.213471	-5.8	<.0001
pov185_98	-1.64264	7.015237	-0.23	0.8149
agehh2529_98	8.811767	22.69439	0.39	0.6978
agehh3034_98	19.93041	21.62949	0.92	0.3569
agehh3544_98	11.64804	21.07998	0.55	0.5806
agehh4554_98	8.477964	21.0808	0.4	0.6876
agehh5564_98	18.91108	21.40428	0.88	0.377
agehhgt64_98	39.6289	21.98086	1.8	0.0715
emphhpt_98	-23.0495	6.565221	-3.51	0.0004
emphhft_98	-31.0267	5.843059	-5.31	<.0001
eduhhhs_98	4.636592	14.33295	0.32	0.7463
eduhhu_98	2.434755	13.98679	0.17	0.8618
eduhhpc_98	0.043102	15.14855	0	0.9977
reg_Central_98	21.96307	6.353837	3.46	0.0006
reg_South_98	5.635536	6.038423	0.93	0.3507
reg_West_98	6.923256	6.770003	1.02	0.3065
race_Black_98	-88.2535	8.113404	-10.88	<.0001
race_Oriental_98	-66.1687	18.74488	-3.53	0.0004
race_Other_98	-28.3099	12.55081	-2.26	0.0241
hisp_yes_98	-24.7473	9.744486	-2.54	0.0111
agepclt6_only_98	1.668619	10.30173	0.16	0.8713
agepc6_12only_98	-23.2254	8.707308	-2.67	0.0077
agepc13_17only_98	-7.13533	7.738201	-0.92	0.3565
agepclt6_6_12only_98	-20.9953	10.94244	-1.92	0.0551
agepclt6_13_17only_98	-44.5939	26.27438	-1.7	0.0897
agepc6_12and13_17only_98	-13.3204	9.980038	-1.33	0.182
agepclt6_6_12and13_17_98	-22.13	24.18839	-0.91	0.3603
fhonly_98	-4.32764	5.70516	-0.76	0.4482
mhonly_98	46.87385	7.900094	5.93	<.0001

SUR Results for Calcium System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	93.08692	30.11193	3.09	0.002
price_99	82.36685	11.41405	7.22	<.0001
price2_99	-14.5528	1.974933	-7.37	<.0001
pov185_99	3.69194	6.726793	0.55	0.5831
agehh2529_99	-19.4661	23.65981	-0.82	0.4107
agehh3034_99	18.88093	22.84755	0.83	0.4086
agehh3544_99	6.791252	22.22982	0.31	0.76
agehh4554_99	6.895142	22.15928	0.31	0.7557
agehh5564_99	18.47872	22.38588	0.83	0.4091
agehhgt64_99	23.90405	22.83088	1.05	0.2951
emphhpt_99	-29.6814	6.466856	-4.59	<.0001
emphhft_99	-27.7243	5.667092	-4.89	<.0001
eduhhhs_99	24.29288	12.37918	1.96	0.0498
eduhhu_99	16.37915	12.02583	1.36	0.1732
eduhhpc_99	17.35135	13.29941	1.3	0.1921
reg_Central_99	21.2227	6.111787	3.47	0.0005
reg_South_99	3.8721	5.766437	0.67	0.5019
reg_West_99	2.307763	6.557388	0.35	0.7249
race_Black_99	-92.7412	7.234074	-12.82	<.0001
race_Oriental_99	-61.6102	18.75529	-3.28	0.001
race_Other_99	-25.339	11.88783	-2.13	0.0331
hisp_yes_99	-20.3517	9.100475	-2.24	0.0254
agepclt6_only_99	-5.04891	10.49303	-0.48	0.6304
agepc6_12only_99	-13.0584	8.659693	-1.51	0.1316
agepc13_17only_99	-8.34448	7.755982	-1.08	0.282
agepclt6_6_12only_99	-22.3079	11.70162	-1.91	0.0566
agepclt6_13_17only_99	-53.183	24.68341	-2.15	0.0312
agepc6_12and13_17only_99	-10.0283	9.985531	-1	0.3153
agepclt6_6_12and13_17_99	-16.3224	22.45882	-0.73	0.4674
fhonly_99	-1.45369	5.388494	-0.27	0.7873
mhonly_99	25.40372	7.670806	3.31	0.0009

SUR Results for Calcium System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	142.8045	35.34579	4.04	<.0001
price_00	75.94607	13.23315	5.74	<.0001
price2_00	-14.5765	2.255427	-6.46	<.0001
pov185_00	3.248015	7.760253	0.42	0.6756
agehh2529_00	-31.2403	28.91097	-1.08	0.2799
agehh3034_00	-33.6375	27.33151	-1.23	0.2185
agehh3544_00	-19.963	26.76144	-0.75	0.4557
agehh4554_00	-31.0305	26.73652	-1.16	0.2458
agehh5564_00	-23.947	26.98171	-0.89	0.3748
agehhgt64_00	0.948241	27.41594	0.03	0.9724
emphhpt_00	-14.3594	7.477456	-1.92	0.0549
emphhft_00	-27.5584	6.473049	-4.26	<.0001
eduhhhs_00	4.670797	14.08971	0.33	0.7403
eduhhu_00	3.781875	13.7831	0.27	0.7838
eduhhpc_00	3.707428	15.37885	0.24	0.8095
reg_Central_00	36.35066	7.123025	5.1	<.0001
reg_South_00	13.96388	6.636418	2.1	0.0354
reg_West_00	8.121985	7.341763	1.11	0.2687
race_Black_00	-95.8996	8.041631	-11.93	<.0001
race_Oriental_00	-72.1155	21.18713	-3.4	0.0007
race_Other_00	-23.4571	13.05442	-1.8	0.0724
hisp_yes_00	-4.9384	11.45636	-0.43	0.6664
agepclt6_only_00	-18.4613	12.77153	-1.45	0.1484
agepc6_12only_00	-15.4835	10.02902	-1.54	0.1227
agepc13_17only_00	-9.61118	9.34005	-1.03	0.3035
agepclt6_6_12only_00	-30.746	13.85579	-2.22	0.0265
agepclt6_13_17only_00	-43.6802	31.33166	-1.39	0.1633
agepc6_12and13_17only_00	-12.6872	12.33223	-1.03	0.3036
agepclt6_6_12and13_17_00	-15.9383	29.99082	-0.53	0.5951
fhonly_00	3.969671	6.146025	0.65	0.5184
mhonly_00	62.41472	8.458375	7.38	<.0001

SUR Results for Calcium System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	111.9983	32.39774	3.46	0.0006
price_01	70.53271	9.308165	7.58	<.0001
price2_01	-12.0838	1.516086	-7.97	<.0001
pov185_01	-3.21627	6.486841	-0.5	0.62
agehh2529_01	6.49752	28.93322	0.22	0.8223
agehh3034_01	-14.2633	27.77668	-0.51	0.6076
agehh3544_01	-4.58302	27.20727	-0.17	0.8662
agehh4554_01	2.591666	27.24497	0.1	0.9242
agehh5564_01	0.499307	27.37444	0.02	0.9854
agehhgt64_01	13.1924	27.69354	0.48	0.6338
emphhpt_01	-30.096	6.419753	-4.69	<.0001
emphhft_01	-34.1345	5.635128	-6.06	<.0001
eduhhhs_01	9.891026	11.49489	0.86	0.3896
eduhhu_01	2.780122	11.1931	0.25	0.8039
eduhhpc_01	2.0626	12.72489	0.16	0.8712
reg_Central_01	38.49808	6.372043	6.04	<.0001
reg_South_01	13.15951	5.693868	2.31	0.0209
reg_West_01	11.03131	6.435031	1.71	0.0865
race_Black_01	-79.8937	6.459008	-12.37	<.0001
race_Oriental_01	-55.8508	13.88413	-4.02	<.0001
race_Other_01	-18.6492	13.06988	-1.43	0.1537
hisp_yes_01	-24.4041	9.653289	-2.53	0.0115
agepclt6_only_01	-8.61285	11.12997	-0.77	0.4391
agepc6_12only_01	-17.2234	8.710504	-1.98	0.0481
agepc13_17only_01	-7.32755	8.497862	-0.86	0.3886
agepclt6_6_12only_01	-32.5557	11.56146	-2.82	0.0049
agepclt6_13_17only_01	-10.7601	25.29436	-0.43	0.6706
agepc6_12and13_17only_01	-16.6813	10.82562	-1.54	0.1234
agepclt6_6_12and13_17_01	-33.6922	24.47256	-1.38	0.1686
fhonly_01	-2.82848	5.332496	-0.53	0.5958
mhonly_01	63.48453	7.282451	8.72	<.0001

SUR Results for Calcium System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	135.2692	31.17923	4.34	<.0001
price_02	38.46877	7.27488	5.29	<.0001
price2_02	-6.80642	1.116354	-6.1	<.0001
pov185_02	-2.5629	5.907218	-0.43	0.6644
agehh2529_02	24.32226	28.83534	0.84	0.399
agehh3034_02	4.791329	27.7574	0.17	0.863
agehh3544_02	-3.79709	27.35747	-0.14	0.8896
agehh4554_02	1.17437	27.37385	0.04	0.9658
agehh5564_02	4.582006	27.48477	0.17	0.8676
agehhgt64_02	10.42643	27.71071	0.38	0.7067
emphhpt_02	-21.9945	5.743496	-3.83	0.0001
emphhft_02	-25.0995	5.002135	-5.02	<.0001
eduhhhs_02	0.990944	10.0849	0.1	0.9217
eduhhu_02	-10.7826	9.831029	-1.1	0.2728
eduhhpc_02	-8.43837	11.22079	-0.75	0.4521
reg_Central_02	31.74677	5.749179	5.52	<.0001
reg_South_02	16.89372	5.041629	3.35	0.0008
reg_West_02	4.95822	5.728867	0.87	0.3868
race_Black_02	-76.2312	5.645544	-13.5	<.0001
race_Oriental_02	-51.5484	11.70176	-4.41	<.0001
race_Other_02	-21.4276	10.37904	-2.06	0.039
hisp_yes_02	-8.2497	9.432589	-0.87	0.3818
agepclt6_only_02	10.63711	11.19599	0.95	0.3421
agepc6_12only_02	-15.2157	7.779489	-1.96	0.0505
agepc13_17only_02	-1.08453	7.632269	-0.14	0.887
agepclt6_6_12only_02	-30.3126	10.72604	-2.83	0.0047
agepclt6_13_17only_02	-10.1757	27.48339	-0.37	0.7112
agepc6_12and13_17only_02	-15.7335	9.271403	-1.7	0.0898
agepclt6_6_12and13_17_02	-19.9273	18.97219	-1.05	0.2936
fhonly_02	3.146424	4.697581	0.67	0.503
mhonly_02	49.81978	6.4377	7.74	<.0001

SUR Results for Calcium System (Continued)

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	192.7397	37.67763	5.12	<.0001
price_03	5.994114	5.52218	1.09	0.2778
price2_03	-2.12154	0.716769	-2.96	0.0031
pov185_03	-9.91088	6.178555	-1.6	0.1088
agehh2529_03	0.265064	37.99741	0.01	0.9944
agehh3034_03	-7.61791	36.71298	-0.21	0.8356
agehh3544_03	-16.1921	36.1803	-0.45	0.6545
agehh4554_03	-22.5676	36.10119	-0.63	0.5319
agehh5564_03	-16.6288	36.15561	-0.46	0.6456
agehhgt64_03	-2.50804	36.35035	-0.07	0.945
emphhpt_03	-15.6992	6.070485	-2.59	0.0097
emphhft_03	-23.4526	5.219973	-4.49	<.0001
eduhhhs_03	4.639973	4.818853	0.96	0.3356
eduhhpc_03	-6.90025	6.454167	-1.07	0.2851
reg_Central_03	26.70889	6.253591	4.27	<.0001
reg_South_03	18.88726	5.308648	3.56	0.0004
reg_West_03	2.756	6.163664	0.45	0.6548
race_Black_03	-68.7593	6.03523	-11.39	<.0001
race_Oriental_03	-57.2853	11.82807	-4.84	<.0001
race_Other_03	-11.5668	10.01075	-1.16	0.248
hisp_yes_03	-8.34521	9.075068	-0.92	0.3578
agepclt6_only_03	1.660904	11.4026	0.15	0.8842
agepc6_12only_03	-19.9169	8.766636	-2.27	0.0231
agepc13_17only_03	4.466808	8.04648	0.56	0.5788
agepclt6_6_12only_03	-31.0678	12.49777	-2.49	0.013
agepclt6_13_17only_03	-28.6524	26.80217	-1.07	0.2851
agepc6_12and13_17only_03	-5.05838	10.18648	-0.5	0.6195
agepclt6_6_12and13_17_03	-9.99565	20.29305	-0.49	0.6223
fhonly_03	-1.67565	4.829361	-0.35	0.7286
mhonly_03	62.44333	6.990805	8.93	<.0001

VITA

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