

CONSEQUENCES OF COMMUTING PATTERNS AND THE STRUCTURE OF FOOD
RETAIL MARKETS FOR SNAP REDEMPTION: IMPLICATIONS FOR FOOD ACCESS

A Dissertation

by

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ABSTRACT

Persistent food insecurity and hunger increase the risk of illness, psychological dysfunction and lower educational achievement. Even though these burdens affect society at large, they are most acutely felt by the individuals and households living in poverty. To address the costs of hunger and food insecurity, policies have been designed, many by urban planners, to increase access to healthy food. Because low-income populations are assumed to shop at the nearest store that sells food, most policies have focused on opening new supermarkets in “food deserts.” However, there is little evidence that such assumptions are true or that nearby supermarkets make a difference.

This dissertation presents a 7-year panel model for 207 counties in Texas as a tool to test the consequences of commuting patterns and the structure of the retail grocery market on food dollars spent by people living in poverty. The model uses longitudinal data from the Supplemental Nutrition Assistance Program (SNAP). The model uses publicly available geocoded data on SNAP benefits and redemptions, retail locations, and commuting patterns. The model explicitly examines the consequences of commuting patterns and retail markets, both local and in surrounding counties, for SNAP redemption.

Results show that commuting patterns and the grocery retail market are important factors for predicting SNAP redemptions. Specifically, workers that commute out of a county have a negative effect on the amount of SNAP dollars redeemed in a county, and workers that commute into a county have the opposite effect. Large SNAP retailers, such as super stores or chain stores, have the largest positive effect. The number of supermarkets in a neighboring county does not affect the net SNAP dollars redeemed within a county, but the number of neighboring super stores or chain stores does. SNAP

redemptions decrease significantly when counties do not have large retailers and when counties have more outbound workers than inbound workers. The factors identified in this research that influence redemption patterns may have implications for policies that attempt to enhance SNAP redemptions. In the broader picture, such policies may have a significant impact on food access for people living in poverty.

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NOMENCLATURE

ARRA	American Reinvestment and Recovery Act
BEA	Bureau of Economic Analysis
BRD	USDA Benefit Redemption Division
FNS	Food and Nutrition Service
LAUS	BLS Local Area Unemployment Statistics
LEHD	Longitudinal Employer-Household Dynamics
LODES	LEHD Origin-Destination Employment Statistics
OPM	Official Poverty Measure
SAIPE	Census Small Area Income and Poverty Estimates
SNAP	Supplemental Nutrition Assistance Program
SPM	Supplemental Poverty Measure
TXHHS	Texas Health and Human Services Commission
TFP	Thrifty Food Plan
USDA	United States Department of Agriculture

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1. INTRODUCTION

1.1 The Ideal Family in Poverty

The ideal family in poverty has a food budget of around \$650 a month, for two adults (a man and a woman between the ages of 20-50) and two children (6-8 years old and 9-11 years old). No one in the family has health problems or special dietary needs. One adult has at least 20 hours a week to plan, purchase, and prepare all the families meals and snacks. The primary meal preparers know how to plan healthy meals that produce no waste, have the skills required to cook from scratch using the most basic ingredients, and know how to check to make sure everyone gets their required micro and macronutrients. They have access to all the equipment necessary to cook from scratch. The family must have dependable access to a productive vegetable garden. The family lives within walking distance of a price-sensitive food retailer. Its primary grocer provides fresh produce, meat and dairy items for a fair price. The family lives in a part of the country with a lower than average cost-of-living. If the family lives in a city, the city must consider food production to be an integral part of urban life and must protect the family's right to grow their own food.

With all of these things in place, a family of four would find it possible to eat healthy meals for less than \$2.00 per person per meal. All the same, the family would need to save part of its food budget for special occasions like birthdays or holidays, and it would need to expand its budget in the event of a pregnancy, natural disaster, or to meet special dietary needs. This ideal family has no margin for error, and any deviation from the ideal means that its food budget would not be adequate to meet their basic needs.

The image of the ideal family in poverty above—which outlines the assumed living

conditions and abilities of the 18 million American families that find themselves in poverty—is clearly out of sync with reality, primarily because society and the food system have radically changed over the past sixty years. The disconnect between policy and reality reinforces disparities in food access.

Within the past ten years policymakers have sought to better understand how issues of food access impact health, hunger and food insecurity. Historic measures of food insecurity looked strictly at a family's finances. Interventions to increase food security have largely focused on increasing family incomes through means-tested programs such as the Supplemental Nutrition Assistance Program (SNAP)—formerly called Food Stamps. If a family can prove that its income falls below the national poverty guideline and that its assets (car, bank accounts etc.) fall below designated levels, then the government will provide supplemental income. The current model for increasing food security does not take into consideration the availability of low-cost healthy food or other factors such as the time required to prepare an adequate diet on the prescribed budget. The most recent effort by the Federal Government to change the current model has been to designate low-income with low-food access as “Food Deserts,” with low-access to food measured by proximity to a grocery store with more than \$2 million in food sales a year. The “Food Desert” concept highlights neighborhoods that lack supermarkets, but it does not capture the true nature of the problem of access to healthy affordable food for people living in poverty. Living near a supermarket does not guarantee a family has the capability to buy, transport, store, and prepare a healthy diet on an unforgiving budget.

My dissertation examines the influence of commuting patterns and grocery retail markets on food assistance dollars spent by people living in poverty. The results of my dissertation show that mobility—specifically the home-work commute—and store type—specifically the large retailers—helps to predict the redemption of food assis-

tance dollars. Commuting patterns and the grocery retail market are therefore important for understanding the food shopping patterns of people living in poverty. Because food shopping patterns influence the adequacy of a family's food budget, access to large food retailers who market to price-sensitive consumers, may help families stretch their food assistance dollars and make a healthier diet possible for them. This dissertation reinforces the importance of mobility and access to larger food retailers for the food security of low-income families.

In this dissertation, I argue that food assistance redemption patterns provide insight into the shopping patterns of people living in poverty. A better understanding of these patterns will give urban planners insight into food access and food security issues.

1.2 The Significance of Poverty and Food Access

People living below or near poverty are the main focus of this dissertation. When basic needs exceed income, the building blocks for life are unavailable. Poverty, in America, means that the basic building blocks for well-being are out of reach. One in four Americans lives in or near poverty, and 75% of Americans will experience poverty during their lifetime (Rank, 2005).

Government agencies distribute trillions of dollars each year to prevent the costs to society caused by the failure to meet basic needs, which both contributes to and characterizes poverty. Unfortunately, policymakers define poverty using outdated assumptions. The current food-income definition of poverty assumes that low-income households have easy access to affordable healthy food; adequate food storage and prep facilities; and spend a minimum of 16 hours a week preparing and cooking healthy meals (Food Research and Action Center, 2012; Rose, 2007). These assumptions were originally made in the early 1960's, a time when less than 12% of mothers (the assumed homemakers) were in the workforce. Today, over 70% of mothers participate in the

labor force. Furthermore, the assumptions that connected food budgets with poverty were formulated at a time before national supermarkets dominated the food system and before large retailers transferred transportation and storage costs to the consumer. Operating under 60-year-old assumptions, low-income families have no margin for error. In this context, government programs set up an impressive facade that does not address the true costs of poverty.

Food insecurity is one of these costs. Households with monthly incomes below \$1,000 per person (185% percent of the 2015 poverty guidelines) are most likely to struggle with hunger because of limited access to nutritionally adequate, safe, and acceptable foods (Anderson, 1990; Coleman-Jensen et al., 2011). Hunger adds a tremendous social burden to America; in 2007—before the economic recession increased food insecurity—the minimum cost burden of hunger was estimated to be over \$90 billion a year. This figure included \$67 billion dollars caused by increased medical costs due to illness and psychological dysfunction and \$9 billion created by increased workforce absenteeism and school drop out rates (Brown et al., 2007). Even though these burdens affect society at large, they are most acutely felt by the individuals and households living in poverty.

1.3 The Significance of Urban Planners

Is it the role of urban planners to eliminate or at least ameliorate the costs related to poverty and food access? Despite the universal acceptance of the importance of healthy food as a basic resource for well-being, little is understood about the role urban planners may have in ensuring equitable food access, availability and affordability. Planners have long considered ensuring access to public goods such as clean air and clean water as part of their core responsibilities, but food is new territory.

Urban planning has had a significant role in ameliorating the maladies created by

rapid urbanization. The planning profession has developed the technical knowledge to serve the public interest for clean water, clean air, and adequate shelter. Over the past 100 years the planning profession has recognized and internalized its ethical obligation to communicate empowerment by demonstrating how clean water, clean air, and adequate shelter are distributed to a majority urban, dense, and heterogeneous society. Within the past 10 years the American Planning Association has started to encourage researchers and practitioners to recognize the ethical obligation to communicate how healthy food is distributed within cities (Kaufman, 2004). Planning professionals have been asked to focus on how food-system related policies can reduce diet-related illness and improve a community's quality of life (Kaufman, 2004). However, research on the disparities in food distribution in cities has not shown a correlation with negative well-being (Zenk et al., 2011). Understanding the relationship between the distribution of healthy food and well-being is a wicked problem that will require the planning profession to look beyond the knowledge needed to solve "simple" technical problems, and to look towards the complex skills needed to remove built-environment barriers to healthy food.

1.4 Overview of Dissertation

Chapter 2 provides background on how poverty is defined and how SNAP benefits are determined. This background shows that SNAP participants must be as efficient and thrifty as possible to make the most of the prescribed food budget. Chapter 2 also lays out the scholarly conversations that surround issues related to food access. Chapter 3 describes approaches to increasing food security and food access. Chapter 4 describes in detail the research design, the data science used to build the panel dataset and the models proposed for the study. Chapter 5 presents the results from the models. Chapter 6 discusses the results, the limitations of the study, and possible

future research. Appendix A provides the USDA definitions for different store types. Appendix B provides an example of how the USDA breaks down monthly food cost estimates. Appendix C presents various robustness checks for the models presented in Chapters 5. Finally, Appendix D provides the complete replication code from Stata. The code in Appendix D will allow future researchers to validate, replicate, and expand on the research laid out in this dissertation.

2. LITERATURE REVIEW

Inequalities in the food system exist. People living at or near poverty experience the greatest inequalities related to food access. One in five Americans struggles with food insecurity and suffers the intolerable consequences (Coleman-Jensen et al., 2011). The costs created by poverty and food access are too high. This chapter summarizes the conversations around the primary issues and provides direction towards potential solutions discussed in Chapter 3.

Within the relevant literature about the problems related to poverty and food access several gaps exist. First, the current definition of poverty is based on outdated assumptions. Second, food access research has not incorporated the importance of mobility and store type. Third, data from the SNAP program could be utilized to a greater extent to understand the shopping patterns of low-income households. These gaps help direct research into potential solutions and illuminate what is currently known and unknown. This dissertation will fill some of these gaps and make a significant contribution to the conversation about poverty, food access, and the role of urban planners.

2.1 Historic Background

Urban planning research depends heavily on the definition of poverty, but lacks a critical perspective on the way poverty is measured. Therefore, this section provides background on the way poverty is measured, and some historic background on the basis for poverty measures. The topics covered in this section reveal the complications and assumptions associated with defining poverty, issues that have proven intractable for more than 60 years.

2.1.1 *Defining Poverty*

In 2013 federal and state governments distributed \$2.4 trillion to individuals in the United States; a significant portion of these monies were distributed using the definition of poverty to determine eligibility and amount of need (Bureau of Economic Analysis, 2014). Therefore, the definition of poverty is “a major feature of the architecture of American social policy” (Fisher, 2008). In the United States poverty was officially defined in the early 1960’s. Prior to the 1960’s individual government programs determined eligibility without federal guidance. The Johnson Administration started “The War on Poverty”, which precipitated the need to quantify the number of Americans living in poverty. Original poverty levels recommended in 1964 to President Johnson were set at \$3,000 per year for families of all sizes and \$1,500 per year for unrelated individuals. No adjustments were made for family size. Mollie Orshansky, a statistician working at the Social Security Administration, convinced the government to use size of family, gender of head of household, farm and non-farm designations for the statistical measure of poverty (Fisher, 2008).

To provide scientific justification for defining poverty, Orshansky argued that a nutritious diet was the most basic need families should not go without. Orshansky recognized that other basic needs existed, but decided they were too difficult to define and quantify. Therefore, Orshansky used two sources to determine the minimum income needed to meet basic needs. First, Orshansky used the existing government food budgets as the basis for what an adequate diet should cost. The USDA’s economic food plan was considered the minimum budget a family could use to purchase an adequate diet. Second, Orshansky used the 1955 USDA Household Food Consumption Survey to determine how much the average family spent on food. The 1955 USDA Household Food Consumption Survey found that the average American household spent 30% of

their total income on food. Together, Orshansky defined poverty as any family that had a total income less than three times the economic food plan. In other words, two critical assumptions were made.

The first assumption set the food-income multiplier at three. Since the average household in 1955 spent one out of every three dollars on food, a family should be able to purchase a healthy diet with a third of their income and have enough money left over for the undefined needs.

The second assumption was that the USDA food plans would allow for an adequate diet. Orshansky developed poverty thresholds based on two food plans. The first group of poverty thresholds used the economy food plan, a very restrictive food budget, designed for extreme circumstances, such as the Great Depression and the catastrophic droughts of the 1930's. The second group of poverty thresholds used the low-cost food plan, a slightly less restrictive food budget. Orshansky preferred basing poverty on the low-cost food plan. The federal government chose to base poverty on the economy food plan, which significantly reduced the number of people designated as living in poverty (Fisher, 2008). The formula for defining poverty has not changed since the 1960s. The economy food plan, now called the Thrifty Food Plan (TFP), has been adjusted for inflation.

The Thrifty Food Plan has its roots in the science of nutrition and food plans that have been in use since 1894. The first food plans were based on recommendations for energy and protein needs of laborers to ensure they could do moderate muscular work (Cofer et al., 1962). The first food plan to focus specifically on people living in poverty was introduced in the 1930's for families distressed by drought and the Great Depression. The 1930 food plan was designed for families that had deviated from normal food habits. The families targeted by the food plans were rural families that normally had significant home-food production. Families on the 1930's plans were encouraged

to “to maintain a home garden, a flock of poultry, and one or more cows, and to produce their own meat supply” (Stiebeling, 1930, 2). The USDA also emphasized that to provide for low-cost diets local agencies would need to encourage home food production and conservation, and work with food dealers and business associations to make inexpensive and nutritious foods available (Stiebeling, 1930). The USDA made a clear distinction between normal times and the extreme situation caused by the drought and depression. However, the 1930’s food plan would become the model for future food plans.

A 1962 report by the Department of Agriculture provided insight into the thinking behind the low-cost and economic food plans, the 1962 descriptions are valuable because they were published before the food plans were tied to federal assistance, and the poverty thresholds. The USDA (1962) report described five food plans at four levels of cost. “They include a plan at liberal cost, one at moderate cost, two at low cost, and an economy plan for emergency use” (Cofer et al., 1962, 1). The current TFP is based on the economy food plan designed for emergency use, which was based on the 1930’s economy plan. The four food budgets allowed for different amounts of food waste. The USDA assumed 5-8% food waste on the low-cost food plan, 15% on the moderate, and 20% on the liberal food plan. The economy plan would tolerate 0% waste. The low-cost plan is described as “sufficient to allow for only a minimum of discard and plate waste beyond the normal loss of bone and inedible refuse. Menus based on the [low-cost] plans will not be elaborate. They will include foods that require a considerable amount of home preparation and call for skill in cooking to make varied and appetizing meals” (Cofer et al., 1962, 8). The economy food plan was 30% more restrictive than the low-cost plan. The USDA assumed that the moderate-cost plan would be suitable for the average US family. The moderate-cost plan allowed for higher-priced cuts of meat, a few out-of-season foods, and some partially prepared

foods. The liberal plan allowed for more expensive choices.

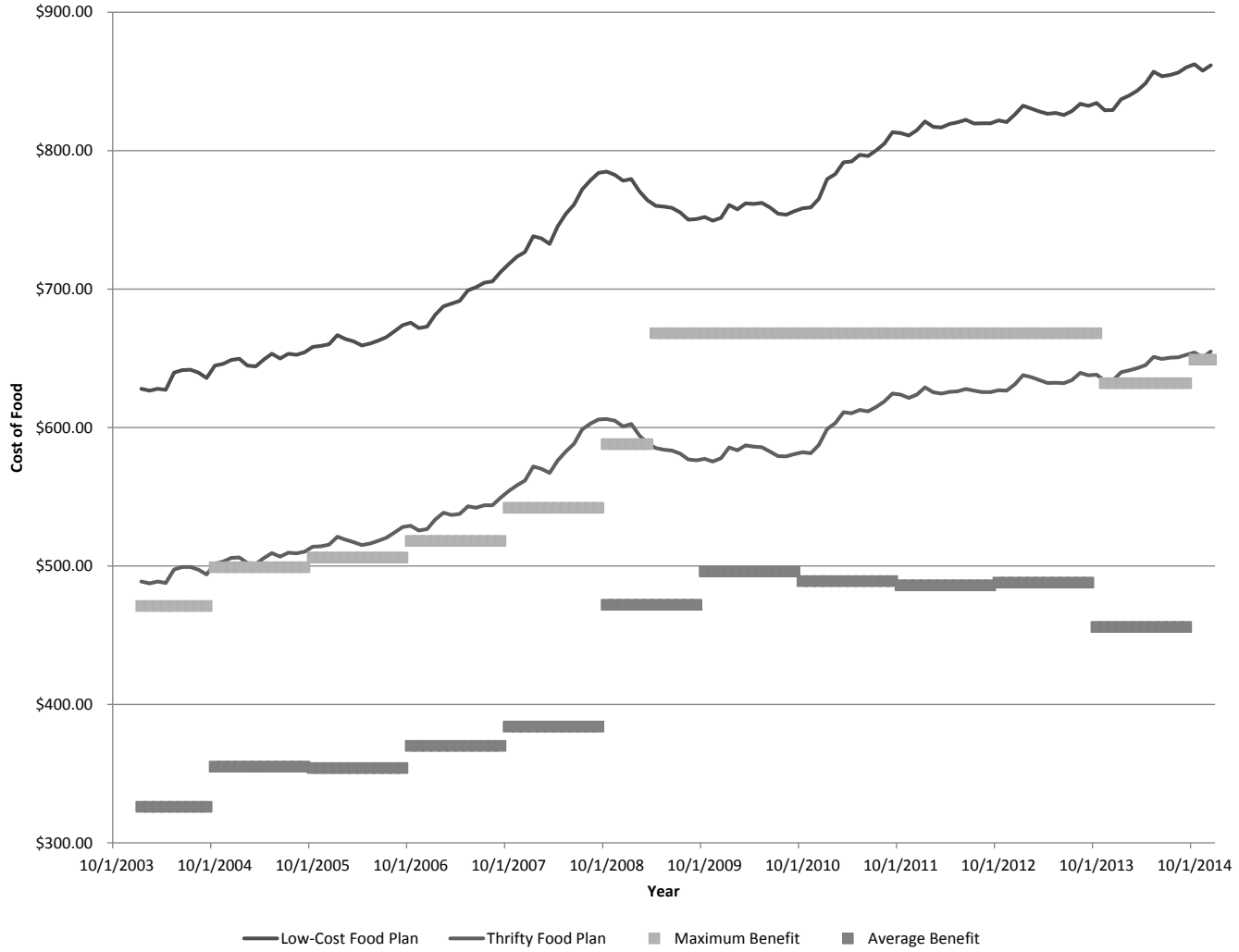
Families on the Economy Food Plan had to choose exactly the foods recommended to meet recommended nutritional goals. The plan assumed that a family had a dedicated “housewife” who “will be a careful shopper, a skillful cook, and a good manager who will prepare all the family’s meals at home. There is no additional allowance for snacks or higher cost of meals away from home or meals served to guests. Nor is there extra allowance for the ice-cream vendor or soda pop so often a part of our children’s daily diet” (Orshansky, 1963, 8).

The 1930’s food plan and the Economy Food Plan were both designed for short-term emergency use. Remember that the Thrifty Food Plan is based on the Economy Food Plan and in terms of dollar amounts has been adjusted for inflation. The Thrifty Food Plan determines the maximum food assistance benefit and sets the guidelines for food budgets that many must follow for years. In 2011 the average SNAP household received benefits for 12 months, households with elderly individuals received benefits for 20 months (Strayer et al., 2012). Once a person has experienced poverty there is a 78% chance they will experience it again and 51% of adults who have experienced poverty will do so for five or more years (Rank, 2005). Alarming 30% of Americans will experience five or more years living below the poverty line (Rank, 2005). The emergency use food plans were not designed for long-term use, but today millions of households are expected to make healthy adequate meals from the same budgets year after year.

Figure 2.1 shows how the relationship between the cost of USDA Food Plans and SNAP benefits between 2003 to 2014. The dollar amounts in Figure 2.1 are for a family of four with school-age children. The USDA sets maximum SNAP benefits for each Fiscal Year in October based on the cost of food from the previous June Thrifty Food Plan. The USDA updates their cost of food tables every month.

Figure 2.1: Relationship between the cost of USDA food plans, maximum, and average SNAP benefits 2003 to 2014. For a family of four with school-age children.

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As shown in Figure 2.1 the cost of food typically increases each month. Therefore the cost of food is typically greater than the maximum SNAP benefit. The American Recovery and Reinvestment Act of 2009 (ARRA) created an exception to the standard between April 2009 and October 2013 when the maximum SNAP benefit was based increased above the June 2008 TFP by an additional 13.6%. The ARRA effectively increased the average SNAP benefit by \$80 in April 2009, the average and maximum benefits then remained constant until November 2013, when they increase was removed and benefits were again determined by the June 2012 TFP. The average four-person household on SNAP receives around two-thirds of the maximum benefit. This means that for the family to eat an adequate diet they need to spend 30% of their remaining income on food. Appendix B provides more details on the USDA food plans and examples of the USDA's monthly reports from June 2004 and June 2009.

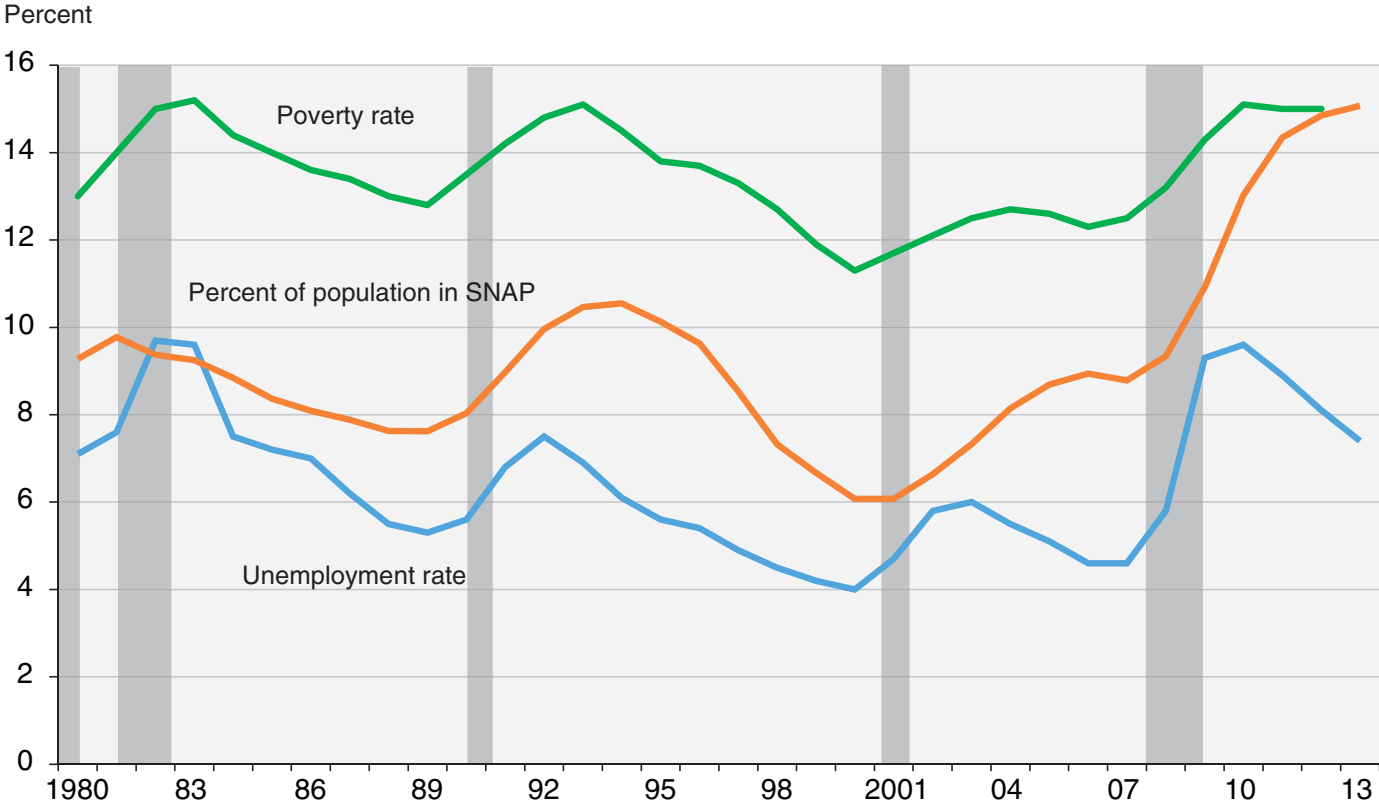
Today, the USDA uses the plan originally designed for rural families in emergency conditions to determine the maximum federal food assistance benefit. The Food Research and Action Center advocates for using the low-cost food plan as the basis for setting food assistance benefits (Food Research and Action Center, 2012). However, because the TFP is used to set the poverty threshold any change that increases the food budget would also increase the poverty level. The link between the poverty thresholds and the TFP makes it difficult to change the TFP, a change would lead to an unpopular increase in the number of people defined as living in poverty.

Federal food assistance programs have existed since the 1960's when they grew out of strategies first focused on addressing farm surpluses. In the 1970's the food stamp program showed a positive impact on food security, but policymakers began to cut the safety-net in the 1980's. In the 1990's Food Stamp participation grew rapidly after years of decline. The program reached a peak of 28.0 million in March 1994 and then the numbers declined until 2000. Politicians supported stricter limits on access

in the 1990's (Allen, 1999; Borjas, 2004; Ganong and Liebman, 2013). In 2008, the food stamp program was renamed the Supplemental Nutrition Assistance Program or SNAP. SNAP participation has grown and declined in correlation with increases and decreases in poverty. In 2005 the gap between the number of individuals living below poverty and the number of individuals on food assistance started to close; in 2012 the numbers reached near parity with 46.6 million individuals participating in SNAP and 47.1 million individuals living below poverty. According to USDA statistics 82% of people who participated in SNAP lived below the poverty line, with the remaining 18% living near the poverty line(Oliveira, 2014). Figure 2.2 illustrates the consistent correlation between the three measures, until 2005 when the gap between SNAP and poverty began to close. The point to take away from Figure 2.2 is that before 2008 the number of people participating in SNAP was well below the number of people eligible to participate. Over the past decade improvements in the SNAP program have made it easier to participate, and therefore participation rates have increased. The bottom line is that SNAP spending patterns now represent the spending patterns of people living in poverty. This means that the 46 million people living in poverty have almost no margin of error in their food shopping. The amount of money provided through the SNAP program falls well below what the average household spends on food. The Thrifty Food Plan, sets the maximum SNAP benefit and low-income households are expected to spend 1 out of every 3 dollars on food. The TFP is built on assumptions that families produce some of their own food and that local governments work to ensure the availability of inexpensive and nutritious foods. The TFP assumes that for a family to have a healthy diet, all meals and snacks will be prepared at home, no food will be wasted, and the lowest-priced items will be available (Food Research and Action Center, 2012). A family receiving the maximum SNAP benefit would need to spend 60% more on food to reach a subsistence diet.

Figure 2.2: Percentage of population in SNAP and selected economic indicators, 1980-2013 (Oliveira, 2014, 16).

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Note: Gray vertical bars indicate recession. SNAP = Supplemental Nutrition Assistance Program. Recessions: January 1980 to July 1980, July 1981 to November 1982, July 1990 to March 1991, March 2001 to November 2001, December 2007 to Jun3 2009.

Source: USDA, Food and Nutrition Service; U.S. Bureau of Labor Statistics; and U.S. Census Bureau.

2.1.2 *Efforts to Change the Definition of Poverty*

Orshansky recognized that no single poverty measure would be successful but that “it should be possible to assert with confidence how much, on an average, is too little” (Orshansky, 1965, 3). The arbitrary, but not unreasonable, standard for “too little” was based “on the amount of income remaining after allowance for an adequate diet at minimum cost” (Orshansky, 1965, 4). For people living below the arbitrary standard “everyday living implied choosing between an adequate diet of the most economical sort and some other necessity because there was not money enough to have both” (Orshansky, 1965, 4). Orshansky described people living below the arbitrary standard as the “undoubted poor.” In 1965, a family spending one out of every three dollars on food was the most certain and defensible definition of poverty.

With a few minor changes, Orshansky’s poverty thresholds were established as the official measure of poverty in 1969. In 1965 the poverty level for a family of four was \$60 a week. Converting the 1965 amounts into 2014 dollars, the average family of four would need \$1,963 a month to have an adequate diet and provide for all other items. The official federal poverty level in 2014 was just \$25 higher than the inflation adjusted amount determined by Orshansky in 1965 – \$1,988 for a family of four. Orshansky (1965) described a family of four living just above poverty as living “within the bleak circle of poverty” – a “less conservative but by no means generous” standard. In 1965, a family living near the bleak circle of poverty would have earned around \$77.00 a week in earnings; \$2,519 a month in 2014 dollars. The official federal 130% poverty level in 2014 was just \$65 higher than the inflation adjusted amount determined by Orshansky in 1965 – \$2,584 for a family of four. Orshansky’s standards for counting the “undoubted poor” have determined six decades of policy.

The basis for the poverty thresholds has been debated for years, and many alterna-

tives have been suggested, despite the debates the reference poverty thresholds today can be calculated by simply multiplying the TFP for a family of four by three. Orshansky (1965) was the first critic of her measure of poverty and saw the food-income relationship as an “interim guide.” Orshansky called for additional variables such as geographic variables of community size and region and further study of income-consumption patterns. Economist and policy researchers have debated about how to improve poverty measures. The debate has focused on what should be included as a minimum level of consumption and the multiplier that should be used to ensure that income levels are large enough to meet basic needs. The official poverty measure (OPM) includes food, as defined by the Thrifty Food Plan, multiplied by three to determine the minimum level of consumption. The OPM multiplier was considered out-of-date by 1969 when the OPM was adopted (Ruggles, 1990). Based on consumer expenditures, the multiplier should have been four in 1960-61, six by 1988, and 7 today (Ruggles, 1990).

The debate over how to improve poverty measures produced a major National Academies of Science panel report (Citro and Michael, 1995). The report discusses various ways to improve poverty measurements and laid the foundation for change. In 2011, the US Census Bureau recognized a few of the deficiencies in the poverty measure. The Census Bureau made several adjustments and provided statistics using a Supplemental Poverty Measure (SPM). The SPM allows for cost-of-living differences for metropolitan areas, uses food, clothing, shelter, and utilities expenditures, and includes government cash transfers as income. Together these changes highlight how anti-poverty programs help reduce overall poverty and provide for geographic variations in cost-of-living.

In conclusion, it is important to understand how poverty is defined and the assumptions that are associated with the definition. The primary assumptions relate directly to food access.

2.2 The Importance of Mobility for Food Access

The primary focus of studies of food spending patterns of poorer households has assumed that the neighborhood food environment has a significant effect on food purchases. This assumption has led to a focus on how the resources available near one's home affects well-being. However, findings that correlate disparities in the distribution of resources with negative well-being have been inconsistent (Zenk et al., 2011). For example, Raja et al. 2010 found that closer proximity to supermarkets relative to convenience stores was associated with lower BMI; however similar studies found that there was no correlation between proximity to food retail, diet quality, or weight gain (Boone-Heinonen et al., 2011; Lee, 2012; Cummins et al., 2014). One explanation for the inconsistency is a limited definition of activity space, the urban space where a person most frequently interacts with the built environment (Zenk et al., 2011). A person's activity space is typically defined using Census data based on residential address. An expanded definition of activity space has the potential to improve the understanding of the relationship between people and place (Cummins et al., 2007).¹ One factor that influences the geographic scope of activity space is mobility.

Blumenberg and Pierce 2012 measured mobility by automobile ownership and person-miles traveled and found that low-income households are quick to convert increases in income into increased mobility, primarily by increasing automobile ownership. Income was a primary predictor of automobile ownership and persons-miles traveled, with low-income individuals averaging 1,496 trips (83% by car) and higher-income individuals averaging 1,671 trips per year (91% by car). Automobile ownership was found to increase mobility, but low-income households were more likely to have

¹Cummins et al. 2007 suggest that for low-income households activity space may be defined by medical services, workplaces, training locations, day care and after-school care facilities, shopping centers, food outlets, religious institutions, the home locations of families and friends (i.e. their social support network), parks, libraries, WIC/Aid Food Coupons, and soup kitchens.

unreliable access to vehicles, either due to competition among household members or due to the need for frequent vehicle maintenance (Clifton, 2004; Blumenberg and Pierce, 2012). Blumenberg and Pierce 2012 found that households with workers had a higher rate of automobile ownership.

Despite restricted mobility, low-income households find ways to overcome limitations and increase shopping choice. Clifton 2004 interviewed low-income families living in Austin, Texas, and found that car-pooling was a frequent strategy to overcome limited mobility. In Detroit, LeDoux and Vojnovic 2013 found that even households with very limited mobility, such as the elderly and households without a car, bypassed local convenience stores and shopped at larger grocery stores.

Trip chaining, clustering multiple trips together, is another way households increase mobility. Households that live in areas of concentrated poverty and who live farther from food retail are more likely to trip chain and less likely to go directly to the store from home (Ver Ploeg, 2009). By combining non-work with work trips, drivers may be able to access food resources that would otherwise be too far from home. Recent research using local commute data has shown that households that live in areas with low food access may have greater access to supermarkets if they shop on the way home from work (Widener et al., 2013). Increased mobility allows low-income consumers to take advantage of sales, search for lower prices and to purchase bulk items (Clifton, 2004).

A 2009 report by the USDA found that distance to nearest supermarket and an areas income were the primary predictors of time spent traveling to grocery stores and shopping frequency. Households in low-income low-access areas² spend more time traveling to grocery stores and shop less frequently than households in higher income

²Areas where more than 40 percent of the population has income at or below 200 percent of Federal poverty thresholds and that are more than 1 mile from a supermarket or large grocery store.

areas with greater food access. When controlling for household income, low-income households spend more time traveling to grocery shopping (Ver Ploeg, 2009).

2.3 The Importance of Store Type for Food Access

Grocery retail targets specific segments of the socioeconomic spectrum, which is described as horizontal differentiation between value-conscious and price-insensitive consumers (Ellickson and Grieco, 2013). For example, the entry of a new Walmart Supercenter may have little impact on higher-end retailers such as Whole Foods but have a greater impact on firms such as Save-A-Lot. Horizontal differentiation is linked to household income, which has been shown to be the greatest predictor in the likelihood that a household will make important food purchases, like milk at a convenience store, a grocery store, supercenter, or a warehouse, with low-income households being most likely to shop at a convenience store (Dong and Stewart, 2012).

Market basket studies found that store prices varied considerably by store type. Bulk stores and some supermarkets were the only store types where the Market Basket Prices were below the Thrifty Food Plan (TFP), the food plan used to determine food assistance benefits. Research has found that the TFP is inadequate because food prices are too high at most stores (Breyer and Voss-Andreae, 2013; Horning and Fulkerson, 2015) and because the TFP makes difficult assumptions about food practices (You et al., 2009; Davis and You, 2010; Drewnowski, 2010). In areas with low-cost-of-living, families that invest time into planning their shopping may find that the TFP is adequate (Stewart et al 2011). In summary store type and shopping patterns are critical for making the TFP work.

SNAP redemption data reflects the importance of large stores specifically super stores and supermarkets. The USDA started to separate super stores from supermarkets in 2005, despite the fact that the format first appeared in 1988. Together super-

markets and super stores redeem over 82% of SNAP benefits. The definition of super stores is actually quite broad and includes any large store that sells food and general merchandise; supermarkets with a pharmacy are also considered super stores. The definition includes stores such as Target and Walmart Discount Stores which may have limited food options. The understanding of the importance of stores such as Walmart Supercenters is limited and apocryphal. There have been a few media reports based on off-hand comments by grocery executives that indicate that Walmart plays a significant role in the food stamp program (Clark, 2014; McMillan, 2014). The concerns about SNAP redemptions going mainly to a few retailers has led to a recent court decision to make SNAP retailer transaction data public, an issue that the USDA has sought public comment on because the USDA considers the information confidential (Federal Register, 2014; U.S. Department of Agriculture Office of Communications, 2014). Very little research has been conducted that shows the impact of super stores in relationship to supermarkets. The USDA conducted a study using their internal and confidential SNAP redemption data and found that after April 2009, when SNAP benefits increased significantly as part of federal economic recovery efforts, redemptions at super stores and supermarkets increased (Andrews et al., 2013). However, this study combined data from supermarkets and super stores/chain stores. Therefore, it is not empirically clear from the literature that supercenters have a greater impact on low-income food spending patterns when compared to supermarkets. It is clear from the literature that while many grocery retail outlets provide food access they may not provide food affordability, and for families using SNAP benefits lower food prices make the difference between food security and food insecurity.

2.4 Food Security and Food Access

Food access and affordability are persistent problems for many Americans; 9.1% of Americans live with low food security and 5.4% of Americans live with very low food security (Coleman-Jensen et al., 2011). Low food security is defined as “households that avoid substantial reductions or disruptions by relying on a few basic foods and reducing variety”. Very low food security is defined as conditions where “eating patterns of one or more household members were disrupted and their food intake reduced, at least some time during the year, because they couldn’t afford enough food” (Coleman-Jensen et al., 2011, 5). From 2010-2012, the states with the highest prevalence of food insecurity were Mississippi (20.9%), Arkansas (19.7%) and Texas (18.4%) (U.S. Department of Agriculture, 2013). Food insecure is defined as “access to adequate food is limited by a lack of money and other resources” and includes both low and very low food secure households (Coleman-Jensen et al., 2011, V).

The current standard for measuring food security at the national and state level is the Current Population Survey Food Security Supplement (CPS-FSS). The CPS-FSS includes 18 questions used to assess the food security of households, the relationship of the individuals within the household and the extent of their food security (low or very low). The 18-item scale focuses on the financial constraints associated with food security, by far the most significant indicator (Coleman-Jensen et al., 2011). The focus on financial constraints means that the current standard for recognizing disparities in the food spending patterns of poorer households ignores other possible barriers to security that are created by the built environment (Blumberg et al., 1999). Blumberg et al. 1999 state that additional measures are needed to properly capture food security caused by other involuntary limitations or restrictions besides financial constraints, such as low-food access.

Socioeconomic factors are the leading variables that predict food-insecure households. Significant characteristics include: households with incomes near or below poverty, non-Hispanic Black and Hispanic households, and single-parent households (Coleman-Jensen et al., 2011). Food-secure households spend 27% more on food than similar size food-insecure households (Coleman-Jensen et al., 2011). However, food expenditures make up a larger percentage of income among low-income households. Based on the 2010 Consumer Expenditure Survey the lowest 20% quintile of consumers spent 33% of their income on food while the average consumer spent less than 10% (U.S. Department of Labor and U.S. Bureau of Labor Statistics, 2012).

A significant body of research has established that low-income populations experience greater barriers to food access and isolation within neighborhoods with fewer resources (Block et al., 2012; Gittelsohn et al., 2008; Ohls et al., 1999). Studies looking at the built environment have used measures of food access based on the number, type, and quality of retail stores as well as distance between food retail and households (Raja et al., 2008; Ver Ploeg, 2009). Broader elements of the built environment include availability of land for food production, local land use policies, and transportation options (Cohen, 2002; Ver Ploeg, 2009). Research will improve the measurement tools available to local governments and play an important role in removing some of the barriers created by land use policies and limited mobility (Allen, 1999; Block et al., 2012; Pothukuchi and Kaufman, 1999).

The United States Department of Agriculture (USDA) defines low-food access for urban and rural populations. Low-income households within cities that do not have a grocery store within 1 mile of their residence and households in rural areas that do not have a grocery store within 10 miles of their residence are considered to be in food deserts. This measure is based on the assumption that healthy food is primarily available at supermarkets and large grocery stores with annual sales of more than \$2

million and all major food groups sold (Ver Ploeg et al., 2009). This assumption leaves out healthy food stores such as small fruit and vegetable market and small health foods stores. The measure also leaves out small convenience stores that may sell healthy food (Raja et al., 2008; Sharkey et al., 2009).

Shannon 2014 proposes looking at the difference between SNAP benefit and redemption patterns to understand the role that retail locations have on food spending. Earlier studies have found that at the state-level SNAP participants spend a significant portion of their benefits away from home. Castner and Henke (Castner and Henke, 2011) reported that the District of Columbia, Vermont, Rhode Island, West Virginia, South Dakota, Delaware, Tennessee, New Mexico and Idaho were the ten states with the lowest proportion of within-state spending. At the state-level the District of Columbia provides an interesting city-like case. In fiscal year 2009 over \$70 million, 44.3% of the SNAP dollars distributed to DC households, were redeemed out-of-state. Nationally only 5.3% of SNAP dollars are spent out-of-state. Vermont, Rhode Island, and West Virginia have significant out-of-state SNAP redemptions ranging from 22.6-16.7%. Clearly DC is a unique case that might shed light on other cities with significant out-flows of SNAP dollars and on the spatial disparity in food access experienced by poorer households.

2.5 Gaps to Focus On

This review of the background on how poverty is defined and the current literature that relates to poverty and food access highlights the need for urban planners to develop a better understanding of the food system and the complex way in which households decide where to shop. This chapter highlighted three significant gaps. The literature shows that poorer households experience barriers that influence their food shopping patterns. The historic background shows that the way poverty is defined has

important implications for how people participating in the SNAP program access food. Therefore research that focuses specifically on the SNAP program will fill a significant gap in understanding the relationship between food access and poverty. Second, food access research has not incorporated the importance of mobility and store type. The literature shows that mobility and types of grocery retail may influence shopping patterns. Increased mobility is expected to increase food options and the larger format stores, especially super stores, are associated with reducing barriers to food. While several qualitative studies (Clifton, 2004; Raja et al., 2008; LeDoux and Vojnovic, 2013), a few cross-sectional studies (Castner and Henke, 2011; Shannon and Harvey, 2012), and one theoretical study (Widener et al., 2013) have found evidence that suggest mobility and store type are important factors longitudinal studies are missing. One longitudinal study has been conducted using county level SNAP data (Andrews et al., 2013), however this study did not look at differences between super stores and supermarkets, and the study did not consider mobility. Chapter 3 will discuss current policy and planning efforts to increase food security and food access. Chapter 3 will conclude by setting the research question and rationale for the dissertation.

3. APPROACHES TO INCREASING FOOD SECURITY AND FOOD ACCESS

In chapter 1, I laid out the problems and cost associated with poverty, food access and the role of urban planners to address inequalities in the food system. In chapter 2, I presented how the main academic conversations surrounding these key issues address the importance of mobility and the retail grocery market to food access, within the context of how poverty is defined. Chapter 3 discusses current approaches to increase food access and food security. The framework laid out in the following pages links the academic conversations described in Chapter 2 with the research design laid out in Chapter 4.

3.1 Urban Planners and the Food System

Planners have long considered access to air, water and shelter as part of their core responsibilities but food is new territory. In 2004 the American Planning Association first encouraged planners to expand their scope to include how healthy food is distributed within cities (Kaufman, 2004). Planners influence the food environment by crafting policies that effect economic development and land use. Economic development policies impact the food retail environment. Land use policies impact the production of local food. Studies, that evaluate the efforts of planners are mostly cross-sectional, such studies imply causation (Lytle, 2009). Longitudinal studies are needed to provide more compelling evidence of causation.

3.2 The Food System as a Linear Food Supply Chain

The food supply chain describes all that lies between the seed and the consumer (Pullman and Wu, 2011; Carolan, 2012). The modern food system has become a linear supply chain. Theories for a rationalized society dominate the linear food system,

driving the system towards greater efficiency, calculability, predictability, and control (Ritzer, 2012). These four factors have led the food supply chain to consolidate the number of businesses involved. As the marketplace consolidates, the food system takes on the shape of an hourglass, where a few food manufactures, processors, wholesalers, distributors and retailers control the chain (Carolan, 2012).

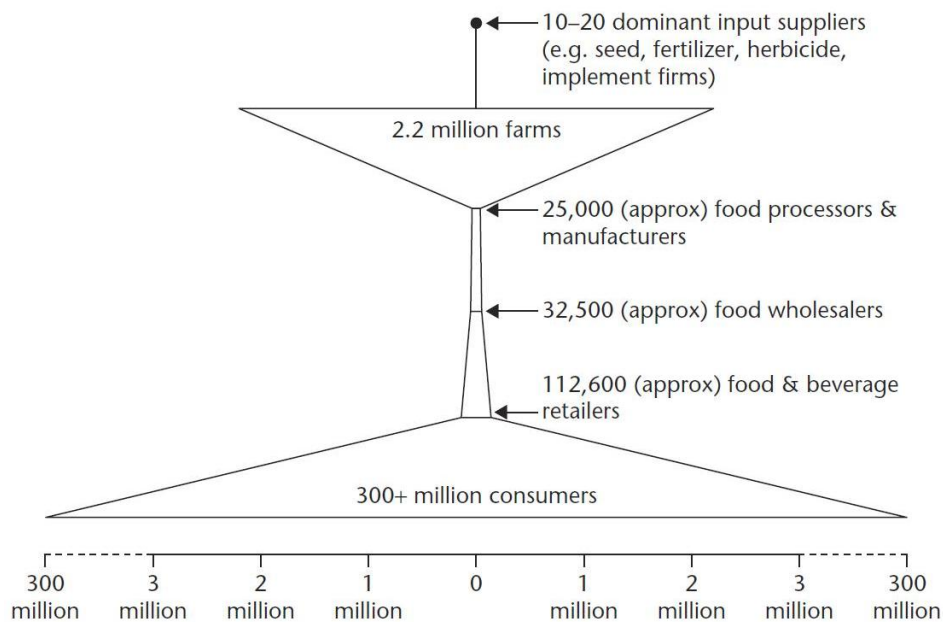


Figure 3.1: US food system “hourglass” (hanging by a thread) (Carolan, 2012).

Figure 3.1 provides a conceptual view of the supply chain and illustrates the limited number of businesses in the system. At the start of the supply chain, ten to twenty companies control all of the inputs to the food system (Carolan, 2012), leaving the entire system hanging by a thread. Next in the supply chain are the food producers. Intense market concentration has left farmers with very few sellers, a monopsony. The perishable nature of food reduces the farmers power to negotiate, giving buyers the

power to dictate price. At the bottom of the hourglass millions of consumers depend on a few retailers for food.

The linear food supply chain defines cities as consumers and leaves the control of the food system in the hands of a shrinking number of global companies. The perspective created by a rationalized food system limits the types of policies and interventions possible. If a few companies control the food supply, then global and international policies would be required to effect change. If food is merely an efficiently produced standardized resource to be consumed, then local policy needs to apply technical tools that ensure equal distribution, similar to policies that clean and pipe water across a city.

To ensure equal distribution and increase access to healthy food planners have implemented policies that alter the food retail environment. Cities can provide economic incentives to encourage new supermarkets to open in low-income “food deserts”. These incentives can include tax breaks, low-cost or free land, the issuance of tax-exempt bonds, training funds, the construction of roads, and other infrastructure investments. The state of Pennsylvania started the Fresh Food Financing Initiative in 2004 to help urban and rural communities attract new supermarkets. The program helped 88 projects with \$73.2 million in loans and \$12.1 million in grants (The Reinvestment Fund, 2010). The Pennsylvania initiative was the model for the federal Healthy Food Financing Initiative (HFFI) which started in 2011 (The Reinvestment Fund, 2010).

Evidence that links new supermarkets with improving public welfare has been mixed. New grocery stores have been shown to positively affect property values, especially in areas where home values were in decline (Greenstone and Moretti, Greenstone and Moretti; The Reinvestment Fund, 2006; Song and Sohn, 2007). Traditional methods for measuring economic impact compares the number of jobs gained versus the cost of the tax breaks awarded to firms (Greenstone and Moretti, Greenstone and Moretti).

Since grocery stores offer mostly entry level jobs with low wages, planners leave them out of economic development plans (Pothukuchi, 2005). Fiscal impacts do not capture changes in access to healthy food that improve health or lower transportation costs. Research has not found a connection between new supermarkets in low-income areas to improved health outcomes (Boone-Heinonen et al., 2011; Cummins et al., 2014).

3.3 The Local Food Movement

Policies have also been implemented that support the local food movement and reject the global control of the food supply. The local food movement could be seen as a negative response to global-linear supply chain (Born and Purcell, 2006). Local food advocates claim that local food systems are more ecological, healthy, or democratic than regional, state, national or global systems. Within the local food movement, the Community Food Sovereignty (CFS) movement desires a total transformation of the food system, from international and global to something that recognizes the rights of local communities to define their own food system. The CFS movement sees the current food system driven by an industry that leads to chaotic and negative effects (Allen, 1999). The CFS movement wants to put the consumer first (Goodman and DuPuis, 2002)

Cities have attempted to use local regulations to keep grocery store sizes below a technical threshold (Dunkley, Helling, and Sawicki, 2004). Restrictions are typically designed to mitigate negative externalities such as noise, traffic and environmental quality caused by large supermarkets, supercenters, or warehouse format stores. Most cities in Vermont have zoning policies that limit big-box stores, which has led to the state having the fewest number of Walmarts per capita. The governor of Vermont's support was critical for the first Walmart Supercenter which opened in 2014, before then Vermont was the only state that did not have a Walmart Supercenter (Norman,

2013). The Institute for Local Self-Reliance provides information on strategies to limit the size of retailers providing model ordinances for cities to adopt (Institute for Local Self-Reliance, 2013).

An alternative approach to influence the food environment is to increase direct-marketing between food producers and consumers. Farmers markets are an example of direct-marketing. Farmers markets are sensitive to clustering, seasonal changes, and the need for increased interaction between vendors, farms, other markets and existing concentrations of consumers (Beckie et al., 2012). Studies have found that farmers markets struggle to help low-income households. The economic needs of farmers often trump the moral desire to provide increased food access to low-income households. Local producers find demand from buyers willing to pay higher prices and some producers find that perishable crops, such as soft fruits and vegetables, are not as profitable as commodity crops, such as cotton or corn (Bloom and Hinrichs, 2010; Giombolini et al., 2010). Because buying directly from the producer involves interactions with inherent power, privilege, race and class elements; several studies have found that local efforts produce misunderstandings or lack of interest in among low-income customers (DeLind, 1993; Hinrichs, 2000; Alkon, 2008; Block et al., 2012).

Many food system planning efforts have sought to find out what the local supply and demand models reveal about the local food system (Colasanti and Hamm, 2010; Giombolini et al., 2010). These studies find that the acreage farmed would need to increase if everyone ate the recommended minimum servings of fruits and vegetables. (Young and Kantor, 1999; Buzby et al., 2006). Examples from Cuba and developing countries support the argument that increases in local food production increase food security for people living in poverty by increasing the supply of perishable produce (Koont, 2008; Wodon and Zaman, 2010; Febles-González et al., 2011; Aubry et al., 2012). However, programs that have found success in reaching low-income house-

holds are primarily run by the low-income community and build on a foundation of environmental justice and empowerment (Block et al., 2012).

The local food movement falls into a trap by focusing strictly on local solutions. All scales—local, region, state, national, global—are nested within each other and therefore one scale cannot be isolated from the other (Zhu et al., 2011). Born and Purcell (2006) provide a clear warning that “local solutions” are not inherently the best solution. Trying to force localization creates problems of definition of the scale within a fluid environment of social movement. Critical analysis must ask if interventions to the food system provide a strategy that is unique because it is local (Born and Purcell, 2006). Urban planners and policymakers should ask who will be empowered by a local-scale intervention.

3.4 Conclusion

Urban planners have created the tools necessary to influence the food environment (Pothukuchi et al., 2007; Raja et al., 2008). Unfortunately these local efforts often benefit middle-income and upper-income households (Alkon, 2008; Bloom and Hinrichs, 2010). Therefore, planners must not assume that “local” interventions will be inherently “good” (Born and Purcell, 2006). Findings that correlate disparities in the distribution of food with negative well-being have been inconsistent (Zenk et al., 2011). Longitudinal studies are needed to show causation. However, longitudinal studies have issues with how the health of the population, environment characteristics, and neighborhood characteristics change over time and are not independent (Lytle, 2009). This dissertation provides an example of how a longitudinal study provides improved ways to measure how changes in the grocery retail market influence the shopping patterns of people living in poverty, while considering mobility and store type.

4. RESEARCH DESIGN

This chapter outlines the research question, research design, variable creation, and data analysis that will be used to study the consequences of mobility and store type with respect to food access for people living in poverty. The goal of this chapter is to ensure that the results of this dissertation will be robust. The first section provides justification for studying Texas counties between 2005 and 2011. The second section describes the construction of a balanced panel dataset with net SNAP redemptions as the dependent variable; mobility and store type as the independent variables and control variables that include unemployment, poverty, and adjacent county stores. The third section describes why a fixed effects panel model was selected and the statistical tests that will be used to test the significance of mobility and store type.

4.1 Research Question and Hypotheses

Research question: How do commute patterns and differences in food retailers influence the food shopping patterns of people living in poverty?

The following three hypotheses are drawn from the research question:

- Hypothesis 1: The commute patterns of a county's low-income populations will have a significant effect on the net of SNAP dollars redeemed within a county. Specifically, outbound workers will have a negative effect and inbound workers will have a positive effect.
- Hypothesis 2: The number and type of SNAP retailers within a county will have a positive effect on the amount of SNAP dollars redeemed within a county.
- Hypothesis 3: The number of SNAP retailers in nearby counties will have a negative effect on the net SNAP dollars redeemed within a county.

4.2 Geographic Coverage

Texas counties provide an excellent area to study the significance of mobility and store type. From 2010-2012, 18.4% of Texas households experienced food insecurity. Texas ranked just behind Arkansas (19.7%) and Mississippi (20.9%) as the states with the worst food security (U.S. Department of Agriculture, 2013). Between 2005 and 2011 around 40% of Texas SNAP households had earned income (Barrett, 2006; Strayer et al., 2012). The 2011 American Community Survey (U.S. Census Bureau, 2012) estimated that 82% of Texas households who participated in SNAP in the past 12 months had at least one person that worked during the year. In 2009 less than 2% of Texas SNAP households shopped out-of-state, compared to between 4.6% - 9.5% of households in neighboring states (Castner and Henke, 2011). Texas has 254 counties and 25 metropolitan statistical areas. In summary, Texas provides a large geographic area with a significant population living with food insecurity. Based on assumptions associated with earned income and mobility presented in Chapter 2, the commute patterns for low-income jobs may represent the mobility patterns of SNAP participants in Texas.

4.3 Dependent Variable

The units of observation for this study are Texas counties. The dependent variable is county net SNAP redemptions y_{it}

$$y_{it} = r_{it} - b_{it}, t = 1, 2, \dots, 7 \quad (4.1)$$

where r_{it} represents the SNAP dollars redeemed within a county and b_{it} represents the benefits distributed to county residents for county i and in year t (each year from 2005 to 2011). Hence, non-zero values imply that SNAP dollars are being spent out-

side their home county. Positive values imply that non-county residents are redeeming SNAP dollars in the county, while negative values indicate that county residents are not shopping at local retailers. Texas has 254 counties, however not all of the counties can be included in the sample. For each year between 39 and 21 counties are redacted because there are fewer than four SNAP retail stores in the county. The redaction protects individual store redemption figures that are considered proprietary information by the USDA. In Texas there are 8 counties that do not have SNAP retailers and therefore have no within-county SNAP redemptions. The missing counties account for less than 1% of SNAP dollars redeemed within Texas. The final sample will consist of data on 207 counties based on data availability. Table 4.1 provides a summary of the redemption differences between 2005 and 2011 for the 207 Texas counties.

Table 4.1: Summary of Texas net SNAP redemptions by year (in dollars).

T	Year	N	Minimum	Maximum	Mean	Median	Std Dev
1	2005	207	-8,305,607	43,359,888	85,088	-218,710	3,381,856
2	2006	207	-4,473,360	24,203,736	133,934	-139,067	2,289,820
3	2007	207	-7,051,900	18,814,038	36,528	-148,301	2,046,699
4	2008	207	-15,667,412	72,852,128	38,320	-225,018	5,516,854
5	2009	207	-15,075,016	41,292,196	35,050	-329,696	3,814,135
6	2010	207	-15,116,615	49,890,392	325,806	-375,784	5,068,784
7	2011	207	-19,156,730	61,958,508	651,648	-273,226	5,980,104

Sources: Author calculations using USDA Food and Nutrition Service (FNS) Benefit Redemption Division and Bureau of Economic Analysis (BEA) data.

Across all seven years the mean is greater than zero, and the median is less than zero. More than half of the counties lose some SNAP dollars, and fewer counties attract significant dollars, which skews the distribution towards counties with larger positive values. Table 4.1 suggests that on average SNAP participants are shopping outside their home county.

Mapping the dependent variable helps to illustrate how the spending patterns are spatially distributed. Figure 4.1 shows how the dependent variable varies across counties between 2005 and 2012.¹ The missing counties are concentrated in rural West Texas. Counties with positive net SNAP redemptions tend to be surrounded by counties with negative SNAP redemptions, which suggests that neighboring county grocery retail markets may influence the dependent variable. Most of the large metropolitan counties in Texas had net SNAP gains of more than \$10 million between 2005 and 2012. Harris County (Houston) attracted more than \$349 million.² Bexar County (San Antonio) lost more than \$49 million, the most of any large Texas metro county.

Figure 4.1 highlights the fact that non-Texas residents are free to redeem their benefits in Texas. El Paso, a large metropolitan city, borders New Mexico and had net SNAP gains greater than \$100 million, while the neighboring county in New Mexico had net SNAP losses greater than \$100 million. The analysis controls for this by including out-of-state residents who work in Texas counties.

¹USDA provided data for 2005 to 2012. Future models use data from 2005-2011 due to lack of commuting data for 2012.

²A portion of dollars redeemed in Harris County come from SNAP participants from Louisiana who were relocated to Houston after Hurricane Katrina in 2005 and from Disaster SNAP dollars distributed after Hurricane Ike in 2008.

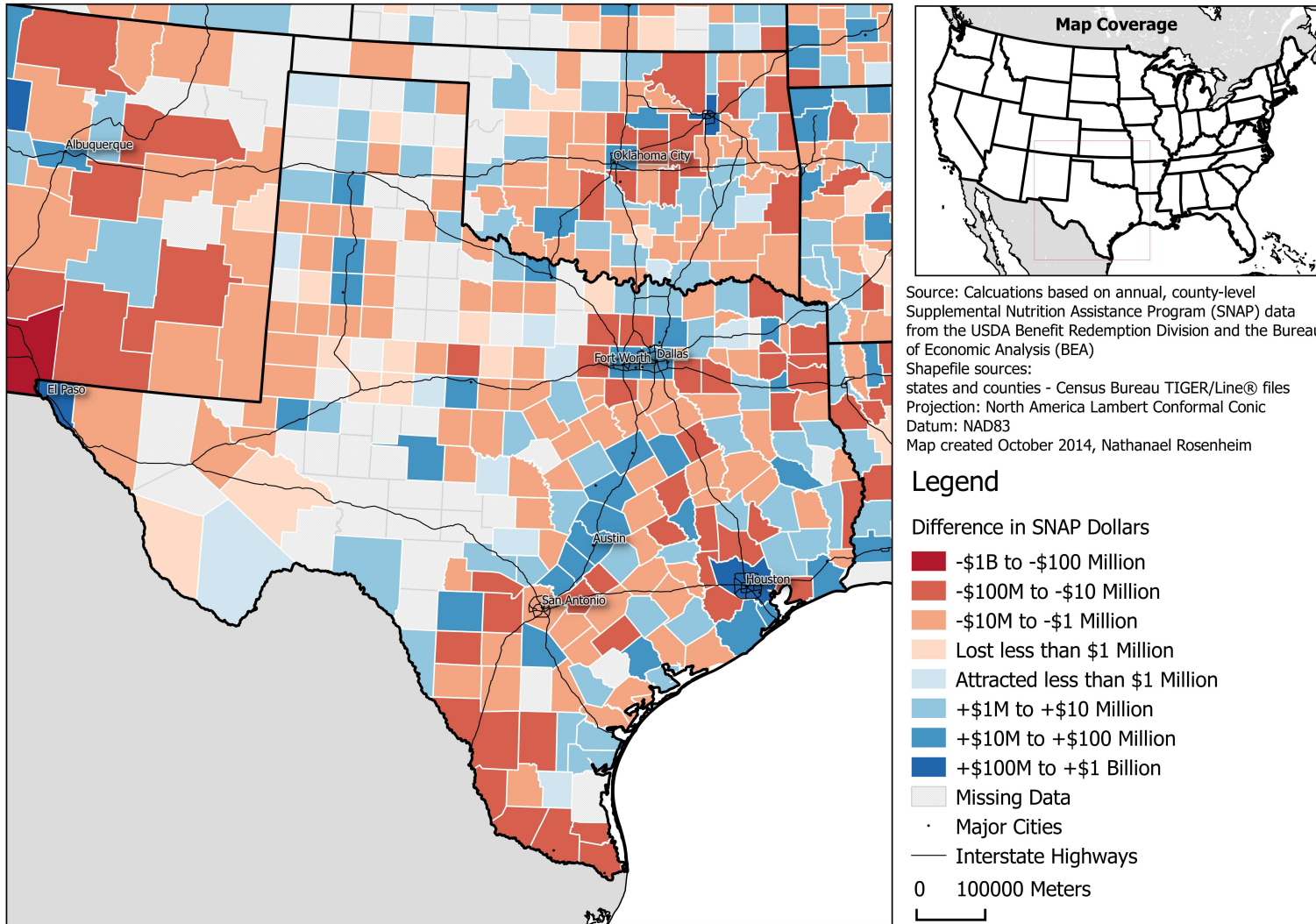


Figure 4.1: Map of total SNAP dollars lost or attracted within counties between 2005-2012.

4.4 Principal Data Sources and Data Management

To construct the dependent variable, SNAP redemption and benefit data was obtained. The data come from several sources with different formatting. The following sections describe how the data was obtained and modified to allow for the construction of the dependent variable.

To prepare the panel dataset the six input datasets were obtained and prepared so that each dataset included two common merge variables. The first merge variable was year (2005-2011). The second merge variable was a county identification. A county identification variable was made by using the Federal Information Processing Standard (FIPS) code for states and counties. A five digit county identification code included the two-digit state code first and the three-digit county code second. All input datasets were modified so that each had one observation per county per year.

Table 4.2 provides a summary of the dependent and independent variables used for this study. All observations are reported for calendar year. Except for the commute data all of the source measurements were reported at the county level.

4.4.1 SNAP Redemption Data

USDA redemption data was originally supplied in Excel files with one observation for each county in the United States for calendar years 2005 through 2012. Redemption data were provided through correspondence with the SNAP, Retailer Policy and Management Division, Food and Nutrition Service, U.S. Department of Agriculture. Redemption data for each county and year represents the aggregated amount of SNAP dollars redeemed at all retailers within a county between January 1 and December 31 for each year. The data are based on Electronic Benefit Transfer (EBT) transactions made by individual SNAP participants at individual stores using a government issued EBT card, similar to a credit card, that requires a four-digit personal identifica-

Table 4.2: Measurement table.

Construct	Dependent Variables	Measurement
Net SNAP Dollars Redeemed within county	Dollar amount of benefits allocated to county residents	Bureau of Economic Analysis (BEA)
	Dollar amount redeemed at SNAP retailers within county	USDA Benefit Redemption Division (BRD)
Independent Variables		
Mobility of Low-Income Population within county	Outbound and Inbound Low-income workers	LODES Format Version 7.0 2005-2011
	Persons unemployed	BLS Local Area Unemployment Statistics (LAUS)
	People of all ages in poverty	Census Small Area Income and Poverty Estimates (SAIPE)
Number of SNAP retailers within counties by store type	Structure of food retail market	USDA BRD Store type counts by county

tion code. The transaction data are collected by state contractors and administratively reported to the USDA. To prepare the original data file for merging, a common county code was added. The original data file included the two-letter state abbreviation and the numeric three-digit county FIPS code without leading zeros. Two-digit state FIPS codes were added by merging a dataset with both the state abbreviation and the state FIPS codes. The three-digit county codes were created by adding leading zeros to the numeric FIPS codes and converting the results to a string value. The two-digit state FIPS codes and three-digit county codes were then concatenated to create a five-digit county code.

The original data file included a column with both dollar amounts for redemptions and the word “REDACTED” for counties with fewer than four SNAP retailers. The USDA

redacts redemption data for counties to protect individual store redemption figures that are considered proprietary information, and cannot be released. the redemption dollar amounts did not have a consistent format, some counties included a decimal and others had whole dollar amounts. To clean the redemption information, a variable for the redacted data was generated and a variable that checked for a decimal was created. Together these variables were used to reformat the county redemption data into a consistent dollar amount. The redemption values were set to missing for all counties with redacted values. The variable RedactedFlag was retained to confirm counties with missing data were in the original dataset.

4.4.2 *SNAP Benefits Data*

SNAP benefits data makes up the second part of the dependent variable. The U.S. Department of Commerce Bureau of Economic Analysis (BEA) regional economic accounts describe county-level distribution of U.S. economic activity and growth. Data are reported annually based on calendar year. Data are reported on place of residence. Dollar estimates are in current dollars (not adjusted for inflation). Dollar amounts are reported in thousands of dollars. BEA data are based on information provided by state agencies, when data are not available BEA imputes, interpolates or extrapolates to provide data for all years. BEA does not flag imputed data, however, 75% of the county-level data are derived from direct measures (BEA 2013). Food assistance benefit data from 1969 to 2012 are included in the Personal Current Transfer Receipts Accounts (CA35).

The original data file was formatted as a comma separated text file, with one file for each state. The original files included a five-digit county FIPS code, based on state and county FIPS codes. The original files included one observation for multiple government transfer programs. Each observation included data for years 1969 to 2012. Data for

the SNAP program was retained creating one observation per county, with all years.

The data was then transposed on the year variables, creating a dataset with one observation for each county for each year, with a variable that represents the amount of SNAP dollars distributed to the county. The variable for SNAP dollars distributed included both dollar amounts in thousands and text codes for missing or redacted data. A new variable was created to store the reason for the missing or redacted values. Observations with missing or redacted codes were replaced with missing values. Observations with dollar amounts in thousands available were multiplied by 1,000 to convert the amounts into whole dollars.

The above operations were completed for all state level files and each state was then appended into one file.

4.4.3 USDA ERS SNAP Benefits Data

To confirm the consistency of the BEA data and to add the number of SNAP program participants, data from the USDA Economic Research Service (ERS) was obtained. The USDA ERS provides county level SNAP benefits data for calendar years between 1969 to 2012. The ERS data combines BEA and Census data into an Excel file with one observation for each county. Data was transposed and merged to create a long dataset with one observation for each county and year with the dollar amount distributed to the county and the number of program participants. Missing or redacted data was flagged in the original Excel file. Two new variables were generated to preserve the program benefit and program number flags. Both variables were replaced with missing values if the data was flagged in the original file. The source file had program benefit amounts in thousands of dollars; therefore each value for county benefits was multiplied by 1,000. The original Excel file included a five-digit FIPS county code and a two-digit state FIPS code.

4.4.4 Comparing Benefit and Redemption Data

The USDA monitors where SNAP redemptions are used and provides annual reports on the characteristics of SNAP redemptions. Table 4.3 shows that the vast majority of SNAP dollars are redeemed at supercenters and supermarkets (see Appendix A for a list of store type definitions). Table 4.3 also shows that the total number of stores that accept SNAP has increased between 2005 and 2011, with increases in all categories except supermarkets, medium and small grocery stores. The decrease in the number of grocery stores represents consolidation within the industry and a shift towards the supercenter format. By 2011 the supercenter had become the dominant location for SNAP redemptions. During this time period redemptions increased at convenience store and combination stores, which may be an indication of limited access to supermarkets or grocery stores. In 2009 the average SNAP household made 9.3 transactions a month at four different retailers and spent \$29.48 per transaction (Castner and Henke, 2011). By the end of each month 97.3% of all benefits distributed are re-

Table 4.3: Characteristics of SNAP redemptions by store type.

Store Type	FY 2005		FY 2011	
	Stores	Redemptions (%)	Stores	Redemptions (%)
Supercenters	140	0.03	17,937	48.35
Supermarkets	35,663	86.41	18,696	34.21
Medium or Small Grocery Store	34,610	6.57	27,498	3.87
Convenience Store	31,982	1.86	87,857	4.58
Combination Grocery/Other	38,074	1.95	55,205	5.06
Farmer's Market	371	0.01	2,445	0.02
Other Retail	16,815	3.38	17,552	3.91
Total	157,655	100.00	227,190	100.00

Sources: USDA Benefit Redemption Division Annual Report (2006, 2012).

deemed. Any unspent benefits can be carried over and expire after one year (Castner and Henke, 2011).

Table 4.4: National level reported SNAP redemptions and benefits by fiscal year.

Fiscal Year	Average Participation	Redemptions	Benefits	Proportion
	Thousands	Millions of Dollars		
2005	25,628	\$28,358.41	\$28,567.88	100.74%
2006	26,549	\$30,242.11	\$30,187.35	99.82%
2007	26,316	\$30,339.74	\$30,373.27	100.11%
2008	28,223	\$34,407.15	\$34,608.40	100.58%
2009	33,490	\$49,956.72	\$50,359.92	100.81%
2010	40,302	\$64,443.52	\$64,702.16	100.40%
2011	44,709	\$71,614.26	\$71,810.92	100.27%
2012	46,609	\$74,584.91	\$74,619.34	100.05%

Sources: USDA Food and Nutrition Service (FNS) Benefit Redemption Division Annual Reports and SNAP Participation and Costs National Level Annual Summary.

Comparing Tables 4.4 and 4.5 confirms that the data used for this dissertation are similar to the data published by the USDA. In most years the amount of SNAP dollars distributed as benefits is slightly greater than the amount of dollars redeemed. For the United States the SNAP program represents a closed system with virtually all of the dollars distributed redeemed. Table 4.6 shows that Texas is similar to the United States, but Texas has more dollars redeemed than distributed to state residents. The slightly larger amount of dollars redeemed at stores in Texas is an indication that some residents from neighboring states shop in Texas.

4.4.5 *Commuting Pattern Data*

Data based on unemployment insurance forms will be used to capture the commute patterns of low-income households. The LEHD (Longitudinal Employer-Household Dy-

Table 4.5: National level SNAP redemptions and benefits by calendar year.

Calendar Year	Average Participation	Redemptions	Benefits	Proportion
	Thousands	Millions of Dollars		
2005	26,008	\$29,255.67	\$29,490.72	100.80%
2006	26,242	\$29,444.71	\$29,388.55	99.81%
2007	27,547	\$30,842.94	\$30,919.80	100.25%
2008	31,624	\$36,784.84	\$37,032.83	100.67%
2009	38,701	\$54,152.71	\$54,760.95	101.12%
2010	43,718	\$66,213.87	\$66,514.10	100.45%
2011	46,139	\$72,513.43	\$72,729.22	100.30%
2012	47,396	\$74,610.83	\$74,859.48	100.33%

Sources: USDA FNS BRD Shared Data and BEA.

Table 4.6: Texas SNAP redemptions and benefits by calendar year.

Calendar Year	Average Participation	Redemptions	Benefits	Proportion
	Thousands	Millions of Dollars		
2005	2,468	\$2,814.44	\$2,806.59	99.72%
2006	2,411	\$2,797.92	\$2,778.47	99.30%
2007	2,456	\$2,771.37	\$2,773.91	100.09%
2008	2,863	\$3,401.15	\$3,403.94	100.08%
2009	3,361	\$4,594.49	\$4,602.30	100.17%
2010	3,901	\$5,690.58	\$5,638.52	99.09%
2011	4,067	\$6,108.64	\$5,988.82	98.04%
2012	4,038	\$6,046.08	\$5,996.87	99.18%

Sources: USDA FNS BRD Shared Data and BEA.

namics) Origin-Destination Employment Statistics (LODES) Format Version 7.0, provides detailed information about the residence and workplace locations for workers in the United States between 2002-2011 (Center for Economic Studies, 2015). LODES utilizes administrative records of workers and employers covered by state unemployment insurance. Spear (2011) found that LODES improved existing county commute

pattern data because it provided annual reports and more detailed geographic information. For each Origin-Destination pair LODES data provides count data broken down by all jobs and primary jobs by income. Income is broken down into jobs earning \$1,250/month or less, between \$1,251/month and \$3,333/month, and greater than \$3,333/month. For this study commute patterns of SNAP households are assumed to be similar to the patterns of primary jobs earning less than \$1,250 a month. A primary job is the highest paying job for an individual worker, a job that pays less than \$1,250/month would pay less than \$15,000 per year. A job is counted if it has positive earnings between April to June and between January and March, therefore LODES may underreport very short term jobs (Graham et al., 2014).

The LEHD program geocodes home and work addresses as they are reported on unemployment insurance forms. Because this data is considered confidential most of the information is coarsened. Coarsening is used to aggregate multiple groups with low numbers of cases into smaller groups to increase the number of cases. All of the data is initially aggregated to the Census Block level, the smallest Census geographic entity. The origin-destination data is then coarsened based on the number of workers in a pair and the distance between the origin and destination. For origin destination pairs that are less than the average commute distance the data are coarsened to the Census Tract. Residential and work pairs that are farther apart are coarsened to areas with a minimum of 100,000 people and pairs that are very far apart (greater than 500 miles) are coarsened to areas with a minimum of 400,000 people. Therefore the Block level data will highlight areas with high concentrations of workers, Census Tract data provides accurate home-work pairs for the majority of workers, and county-level data will be similar to the administrative data. In the end, 90% of residential locations are coarsened below the Census Tract level and 97% of job locations have subcounty precision (Graham et al., 2014). Therefore, the LODES block level counts were aggregated

to the county level which should have the effect of removing the synthetic nature of the data.

Jobs that pay less than \$1,250/month will be used to capture low-income commute patterns, and more specifically the commute patterns of households that potentially participate in the food stamp program. To qualify for SNAP a family must have earnings less than the poverty guidelines (U.S. Department of Health and Human Services, 2015). In FY 2002 the monthly earning poverty guidelines for one person was \$738 and for a family of four it was \$1,508. In FY 2011 the monthly earning poverty guidelines for one person was \$908 and for a family of four it was \$1,863. Thus, primary jobs paying less than \$1,250/month may represent families that would qualify for SNAP. The data most likely includes many households that do not qualify for SNAP, because the data does not link multiple jobs to one person or to one household. A family of four may have multiple workers who have multiple jobs giving the family a total income well above the poverty guidelines. It is not possible to determine from the LODES data if a person or a household has more than one job.

For the purposes of this research commute patterns of low-income earners is the focus. More specifically, do low-income workers commute patterns influence SNAP redemption patterns within a county. Will net SNAP redemptions be lowered in counties that have a large outflow of low-income workers, or increase in counties that have a large influx of low-income workers? As the commute patterns change over time will SNAP redemption patterns also change? Determining the general pattern of commuting will help to define the general mobility of low-income households.

4.4.6 Store Type

The USDA divides authorized SNAP retailers into 17 store types. The store types relate to the type of food sold and the size of the retailer. Appendix A provides a de-

tailed summary of the 17 definitions. The table on page 41 provides summary data on redemptions by store type from the USDA Benefit Redemption Division for fiscal years 2005 and 2011. Based on the data summarized in the table on page 41 supercenters and supermarkets are the most important store types because they attract over 85 % of SNAP redemptions. Within the store type data supermarkets are coded as SM and supercenters, super stores and chain stores are coded as SS. Supercenters actually include a wide range of stores and chain stores. For example, the SS code may refer to any Walmart Supercenter, Walmart Discount Store, Kroger Store, Target or any large national grocery retail chain. Therefore, the store type data provides limited detail on the actual type of supermarket or supercenter. However by 2011 a significant number of supermarkets have been converted into supercenters, because they include a pharmacy, bank and general merchandise. The table on page 41 shows that in 2005 the USDA classified 140 stores as supercenters and 35,663 as supermarkets. In 2011 the number of supermarkets dropped to 18,696 and the number of supercenters had increased to 17,937. The shift in store types was due mostly to the USDA updating their store type definition and to major grocery chains converting existing grocery stores.

Overall the number of SNAP retailers increased significantly from 2005 to 2011. The majority of the increase was in the number of convenience stores and combination stores that started accepting SNAP benefits. During the study period stores were required to carry at least three varieties of qualifying food in each of the four staple food groups, with perishable foods in at least two categories (meat, poultry, fish; bread or cereal; vegetables or fruits; dairy products). At a minimum a convenience store that stocked 12 food items (for example canned vegetables, canned meat, cereal boxes, milk and some fresh fruit) could be an authorized SNAP retailer. Combination stores include dollar stores and drug stores. National chains such as Family Dollar, Dollar General, Walgreens and CVS started including some food sales and increased the number of

outlets between 2005 and 2011.

Store type data was provided through correspondence with the SNAP, Retailer Policy and Management Division, Food and Nutrition Service (FNS), U.S. Department of Agriculture. Excel files with monthly counts of authorized stores by store type, county, and year were provided by the USDA. Each file was imported into SAS. Each observation included the state and county FIPS codes, store type code, and the number of stores within each store type category for each month. The state and county FIPS codes were combined to create a five-digit FIPS county id. The average number of stores by type was calculated for each county. The dataset was then transformed from long to wide, with each county having one observation with 17 store type variables. The same steps were used for each year and all annual files were appended together to create one panel dataset with one observation per county per year.

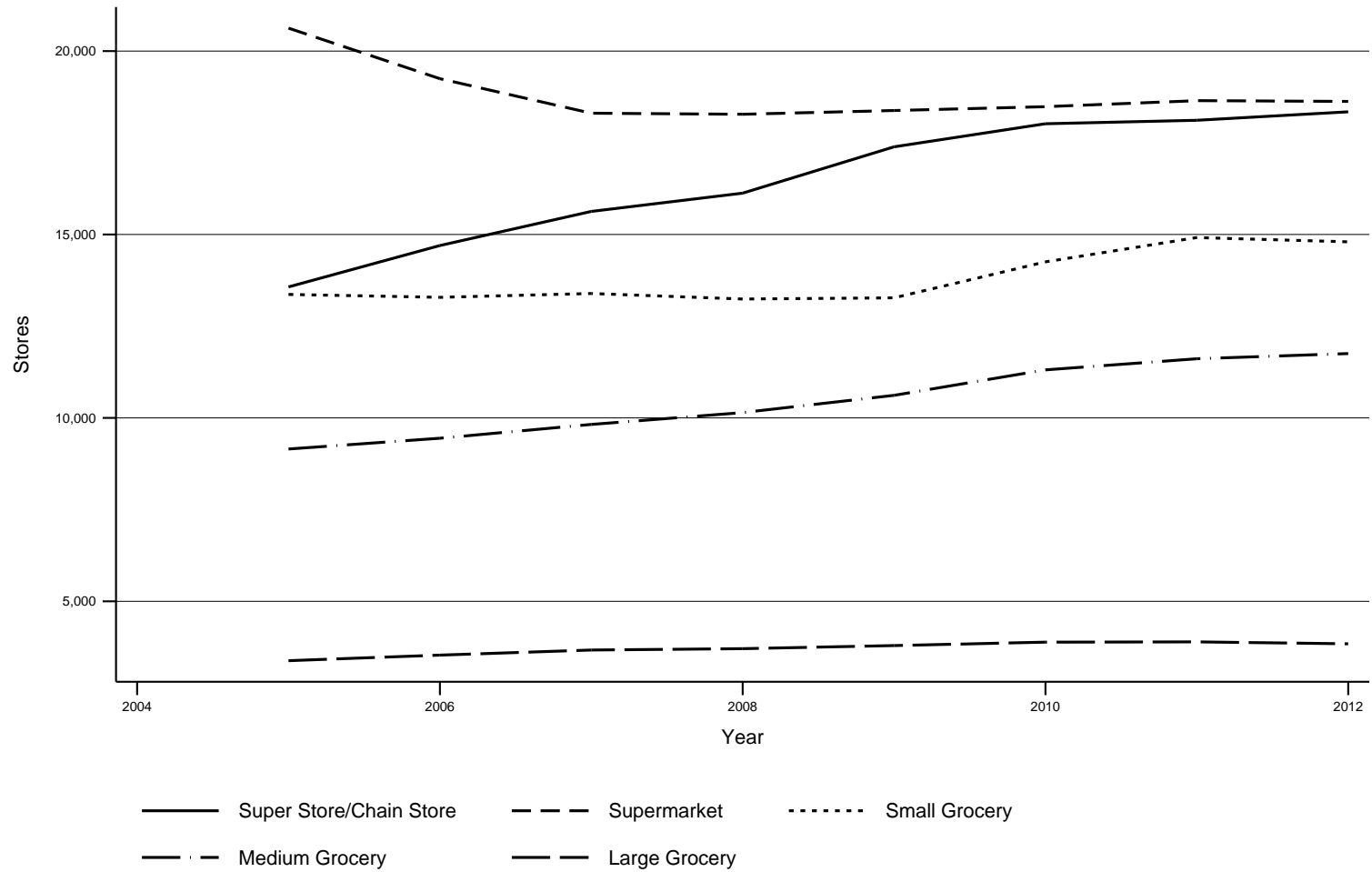


Figure 4.2: Change in number of supercenters, supermarkets and grocery stores between 2005-2012 across the United States.

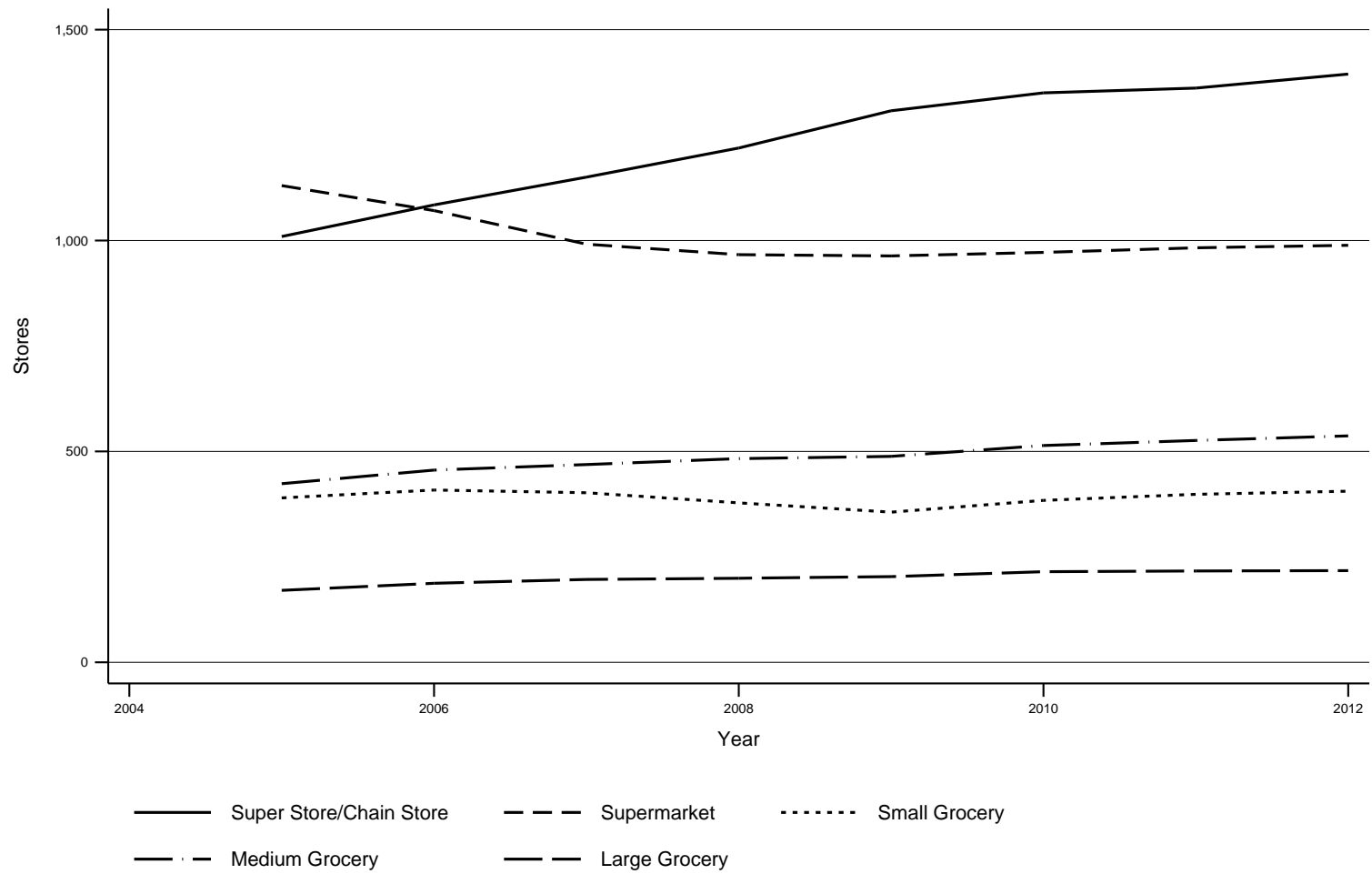


Figure 4.3: Change in number of supercenters, supermarkets and grocery stores between 2005-2012 in Texas.

Figures 4.2 and 4.3 compare the number of supercenters, supermarkets and grocery stores in the store type data provided by the USDA across the United States and Texas between 2005 and 2012. The total numbers for the US are comparable to the numbers from the annual reports shown in Table 4.3. However, the numbers are different significantly because the USDA has updated their definition of supercenter. In the FY 2005 Annual Report the USDA only reported 140 supercenters while the USDA store type data reported 13,572 supercenters in CY 2005. The difference can be attributed to the changes in grocery retail and the emergence of the supercenter as the dominant store type. Figure 4.3 shows that Texas has more supercenters than supermarkets and fewer small, medium and large grocery stores when compared to the rest of the United States.

Figures 4.4 and 4.5 compare the number of convenience stores, combination stores and supercenters in the store type data provided by the USDA across the United States and Texas between 2005 and 2012. The United States and Texas saw similar increases in the number of convenience stores and combination stores during the study period. The number of large format stores (supercenters, supermarkets and grocery stores) was relatively flat when compared to the sharp increase in smaller format stores.

Data was provided for all counties, regardless of the number of stores in the county. Therefore the data covered the entire United States. The contiguous coverage provides information the number and type of stores in a neighboring county.

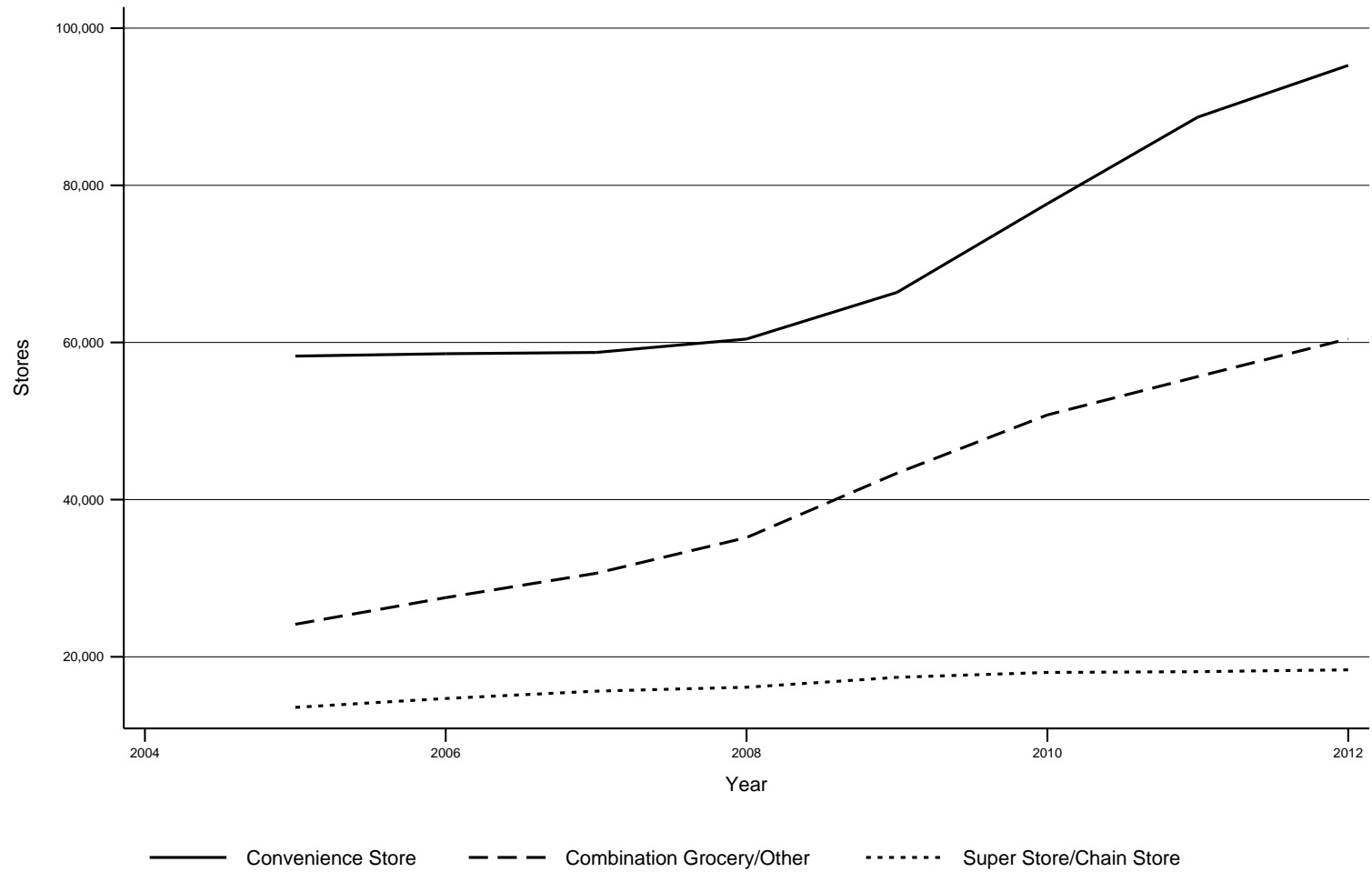


Figure 4.4: Change in number of convenience stores, combination stores and supercenters between 2005-2012 across the United States.

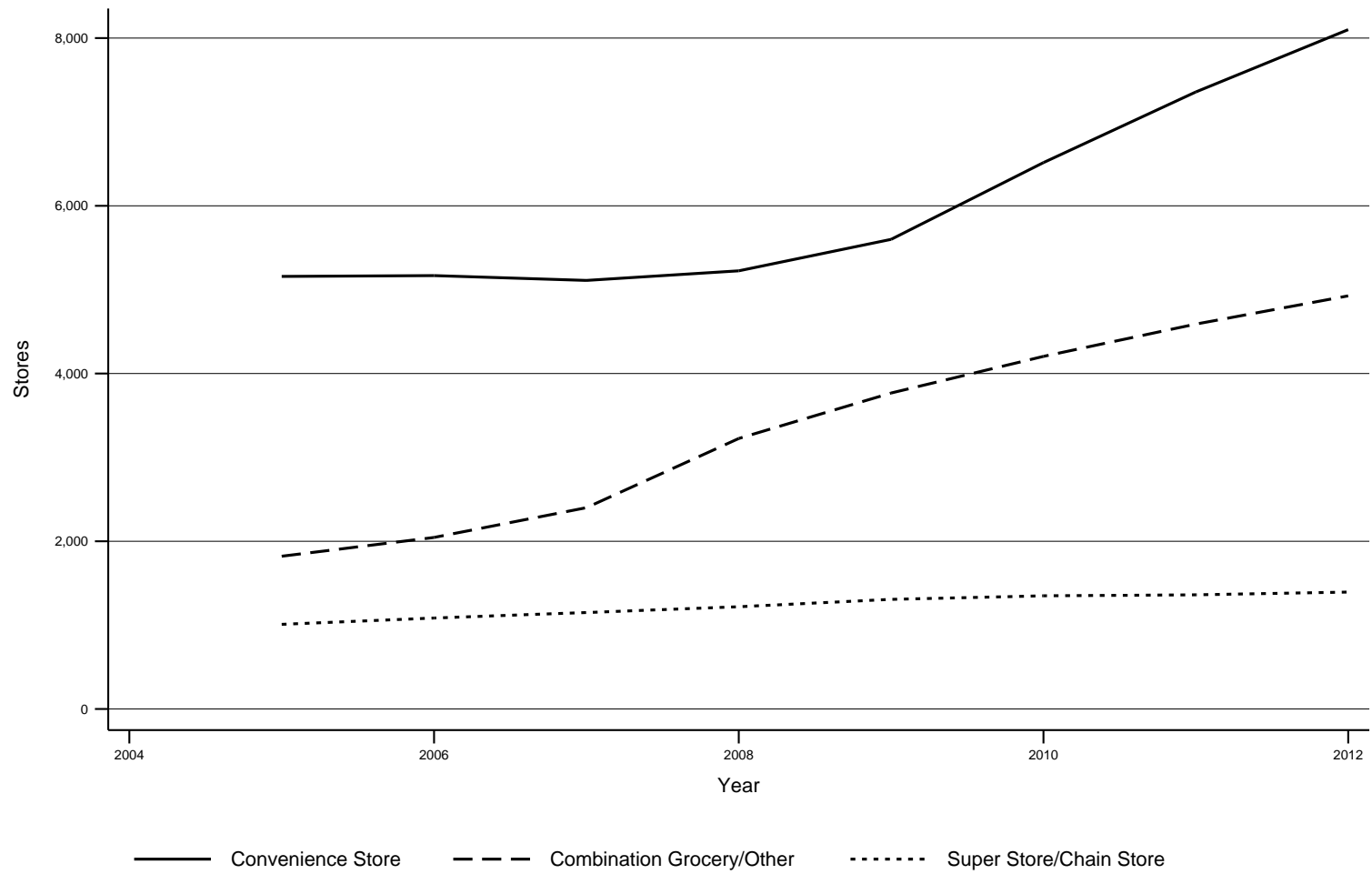


Figure 4.5: Change in number of convenience stores, combination stores and supercenters between 2005-2012 in Texas.

4.4.7 *Unemployment Data*

Annual estimates of county unemployment rate were retrieved from the Bureau of Labor Statistics (BLS) Local Area Unemployment database. The BLS reports the annual average labor force, employed, unemployment and unemployment rate for all counties in the United States starting in 1990.

BLS data are provided for each year in an Excel file format. The data for each year was imported into SAS. Each observation in the original files included the state and county FIPS codes, which were combined to create a five-digit FIPS county id. Each year file was appended together to create one panel dataset with one observation for each county and each year.

4.4.8 *Poverty Data*

Estimates of poverty were provided by the US Census Small Area Income and Poverty Estimates (SAIPE). The SAIPE program combines data from administrative records, decennial census, and the American Community Survey (ACS) to estimate the number of people living in poverty within a county. The estimates also include estimates for people age 0-17 in poverty. The methodology for estimating the number of people living in poverty was changed in 2006 to incorporate data from the ACS.

SAIPE data are provided for each year in an Excel file format. The data for each year was imported into SAS. Each observation in the original files included the state and county FIPS codes, which were combined to create a five-digit FIPS county id. Each year file was appended to create one panel dataset with one observation for each county for each year.

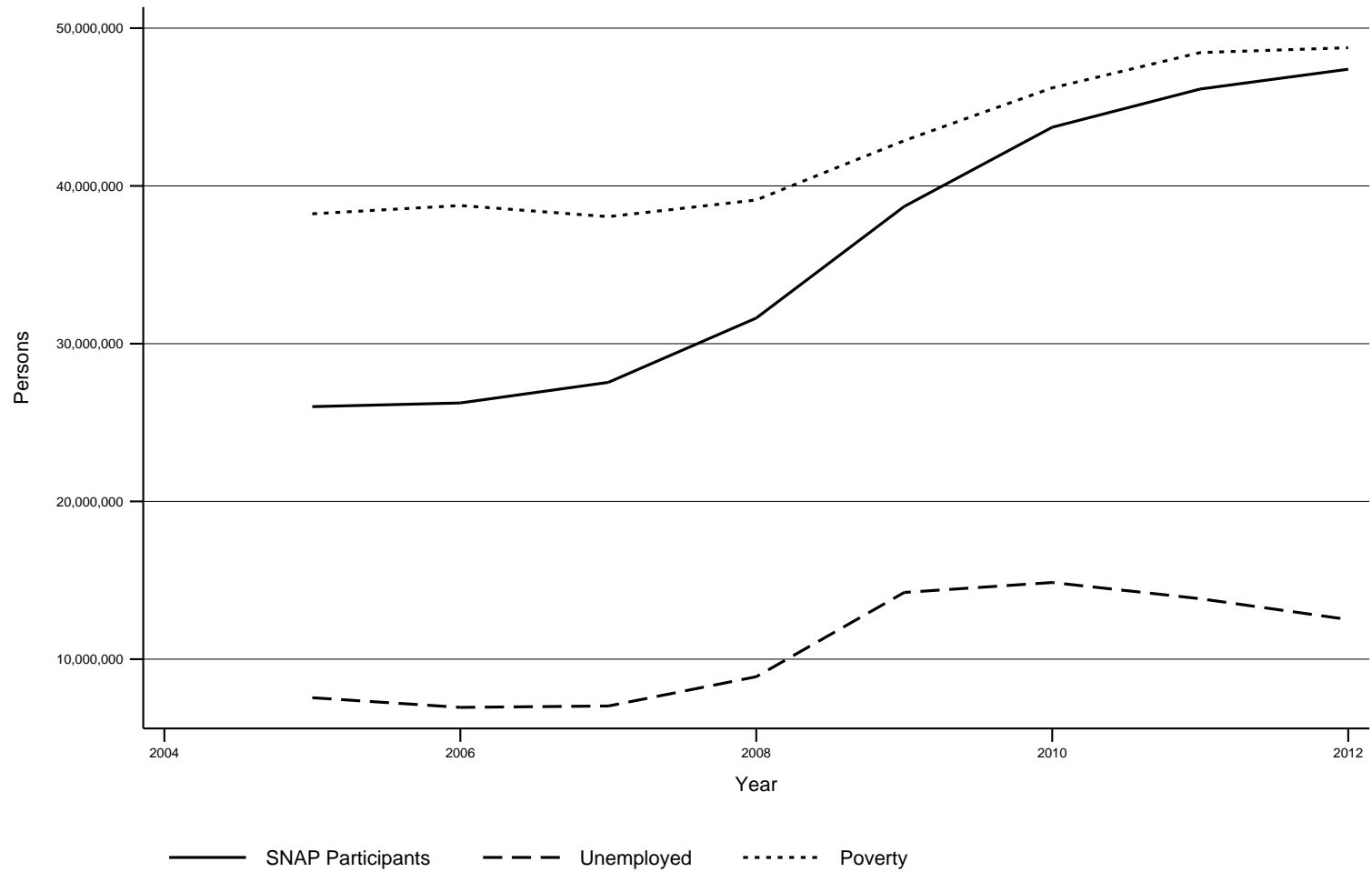


Figure 4.6: Relationship between persons participating in SNAP, people living below the poverty line and unemployment between 2005-2012 across the United States.

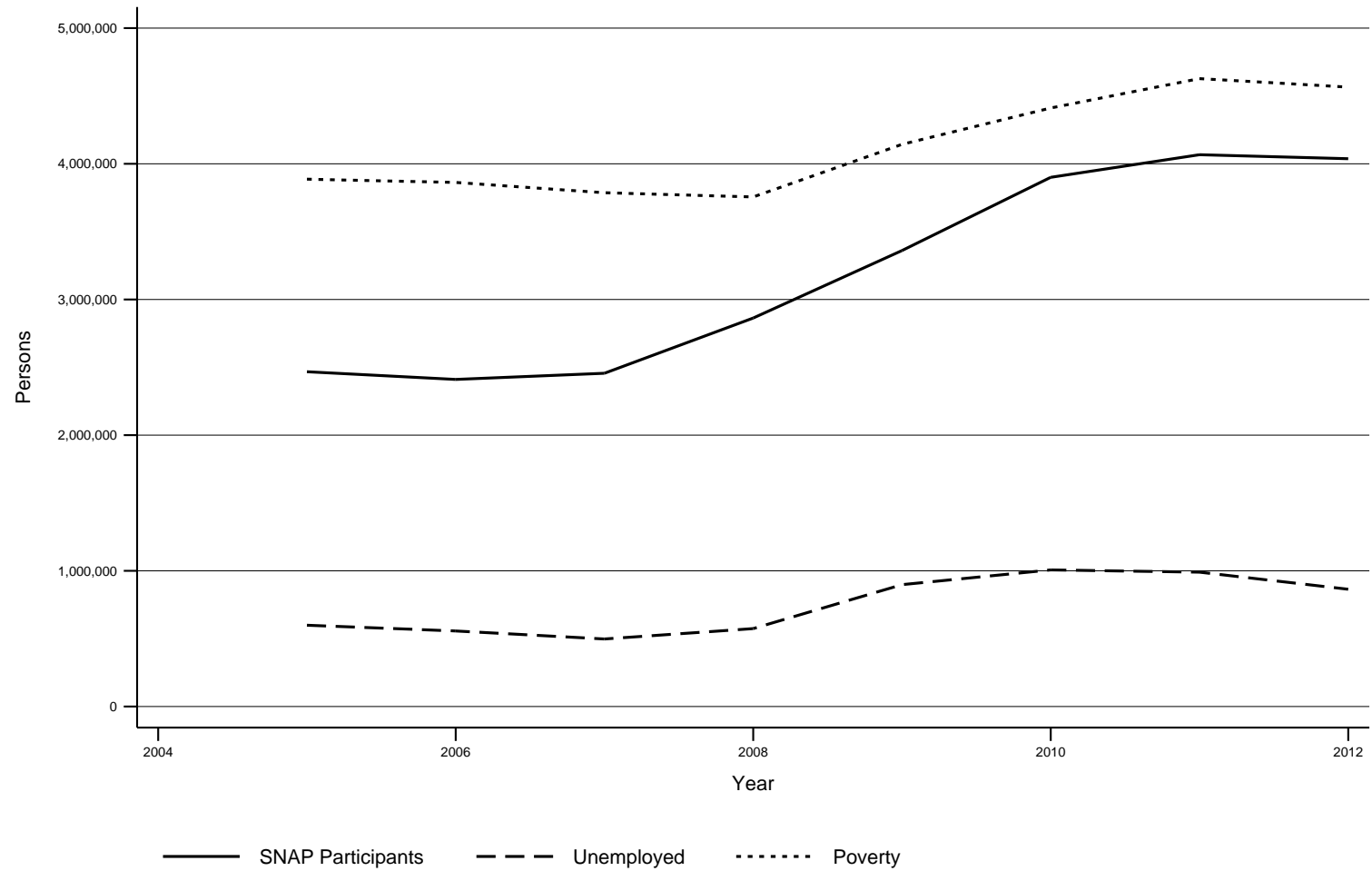


Figure 4.7: Relationship between persons participating in SNAP, people living below the poverty line and unemployment between 2005-2012 in Texas.

4.4.9 Comparing Unemployment, Poverty and SNAP Participation

Figures 4.6 and 4.7 compare the relationship between persons participating in SNAP, people living below the poverty line and unemployment between 2005-2012 across the United States and Texas. These figures show how poverty and unemployment increased significantly during the economic recession which started in 2008. SNAP participation also increased during this same time period and grew at a faster rate than increases in poverty and unemployment. Texas experienced trends similar to the United States, however as Figure 4.7 shows the gap between the number of people in poverty and the number of people participating in SNAP is greater in Texas than it is in the United States. This difference reflects the fact that Texas has a lower than average SNAP participation rate. Texas ranked in the bottom 10 states with a SNAP participation rate of around 46% of eligible working-poor households in 2008 (Cunnyngham et al., 2013).

Overall, poverty and unemployment are important factors that drive changes in the SNAP participation.

4.4.10 Summary of Data by Year

Tables 4.7, 4.8, and 4.9 detail the variables that compose the dependent variable and the explanatory variables for Texas for each year between 2005 and 2011. During the time period the population of Texas increased by 2.85 million people or by 12.6%. The state also experienced increases in the number of people living in poverty and the number of people who were unemployed, as illustrated by Figure 4.7. SNAP dollars distributed and redeemed increased significantly. In 2005 2.5 million Texas residents participated in SNAP and received \$2.8 billion. In 2011 4.0 million Texas residents participated in SNAP and received \$6.0 billion. The increase in SNAP participation and dollars distributed experienced in Texas was similar to trends across the United States.

In 2005 Texas SNAP retailers redeemed nearly 100% of the dollars distributed with Net SNAP redemptions of \$17 million. net SNAP redemptions remained somewhat constant from 2007 to 2009, with the state attracting an additional \$7 million each year. In 2011 Texas SNAP retailers redeemed an additional \$134 million from other states.

For mobility data the number of outbound and inbound workers is roughly equal each year. This is because a person that is an outbound worker for one county is an inbound worker for another county. There are slightly more inbound workers than outbound workers for Texas counties, this is because the number of low-income workers that come from other states exceeds the number of low-income workers that live in Texas but work in other states. The number of unemployed persons decreased slightly in 2007 and then increased sharply in 2009. The number of people living in poverty also increased significantly in 2009.

The variables chosen to represent mobility are a mix of variables that are exclusive and overlapping. An outbound worker for one county cannot be an inbound worker for the same county. A person that is unemployed should not be counted as an outbound worker for the same county. However, a person living in poverty may be an outbound worker or an unemployed person. The number of people living in poverty is significantly larger than the number of workers and the number of people unemployed. Therefore, while there may be some overlap, the number of people living in poverty also captures many non-workers such as children, elderly, and individuals not participating in the labor market.

4.4.11 Explanation of Demeaned Values

Fixed-effects panel models transform the dependent and explanatory variables by demeaning the values for each county. The Stata 12 (StataCorp, 2011) command

Table 4.7: Sum of SNAP and mobility related variables for Texas counties 2005-2007.

	2005	2006	2007
Total Population, (persons)	22,621,357	23,208,210	23,680,688
Redeemed, (\$)	2,812,303,131	2,795,510,281	2,770,260,366
Distributed, (\$)	2,794,690,000	2,767,786,000	2,762,699,000
Net Difference, (dollars)	17,613,131	27,724,281	7,561,366
<i>Mobility</i>			
Outbound workers, (jobs)	730,510	739,171	799,013
Inbound workers, (jobs)	730,992	738,358	799,258
Unemployed, (persons)	595,901	553,779	495,091
Poverty, (persons)	3,862,963	3,839,299	3,764,985
<i>Retail Grocery Market</i>			
Super Store/Chain Store	1,005	1,080	1,145
Supermarket	1,114	1,056	976
Convenience Store	5,115	5,127	5,073
<i>Neighboring Market</i>			
Super Store/Chain Store	5,903	6,301	6,625
Supermarket	6,272	5,957	5,537
Convenience Store	27,515	27,633	27,435

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table 4.8: Sum of SNAP and mobility related variables for Texas counties 2007-2009.

	2007	2008	2009
Total Population, (persons)	23,680,688	24,157,895	24,649,871
Redeemed, (\$)	2,770,260,366	3,398,290,265	4,590,338,252
Distributed, (\$)	2,762,699,000	3,390,358,000	4,583,083,000
Net Difference, (dollars)	7,561,366	7,932,267	7,255,251
<i>Mobility</i>			
Outbound workers, (jobs)	799,013	807,250	821,659
Inbound workers, (jobs)	799,258	819,503	830,534
Unemployed, (persons)	495,091	571,558	893,338
Poverty, (persons)	3,764,985	3,734,193	4,120,585
<i>Retail Grocery Market</i>			
Super Store/Chain Store	1,145	1,214	1,303
Supermarket	976	953	950
Convenience Store	5,073	5,187	5,562
<i>Neighboring Market</i>			
Super Store/Chain Store	6,625	7,025	7,530
Supermarket	5,537	5,430	5,432
Convenience Store	27,435	28,141	30,346

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table 4.9: Sum of SNAP and mobility related variables for Texas counties 2009-2011.

	2009	2010	2011
Total Population, (persons)	24,649,871	25,090,350	25,479,879
Redeemed, (\$)	4,590,338,252	5,682,522,827	6,100,163,147
Distributed, (\$)	4,583,083,000	5,615,081,000	5,965,272,000
Net Difference, (dollars)	7,255,251	67,441,826	134,891,146
<i>Mobility</i>			
Outbound workers, (jobs)	821,659	801,559	861,515
Inbound workers, (jobs)	830,534	809,617	869,691
Unemployed, (persons)	893,338	1,001,930	985,445
Poverty, (persons)	4,120,585	4,388,205	4,604,220
<i>Retail Grocery Market</i>			
Super Store/Chain Store	1,303	1,345	1,357
Supermarket	950	960	973
Convenience Store	5,562	6,468	7,299
<i>Neighboring Market</i>			
Super Store/Chain Store	7,530	7,775	7,852
Supermarket	5,432	5,510	5,600
Convenience Store	30,346	35,705	40,727

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

XTREG transforms the dependent and explanatory variables. The Stata 12 (StataCorp, 2011) command XTREG also places the constraint on the model that the sum of all fixed-effect intercepts α_i is equal to zero. Therefore, XTREG reports an intercept which is the average value of the fixed-effects.

Therefore, the dependent variable for the analysis is actually the demeaned net SNAP difference \tilde{y}_{it}

$$\tilde{y}_{it} = y_{it} - \bar{y}_i + \bar{y}, t = 1, 2, \dots, 7 \quad (4.2)$$

where y_{it} represents the net SNAP dollars redeemed within a county in year t , \bar{y}_i represents mean net SNAP dollars redeemed within a county, and \bar{y} represents the grand mean net SNAP dollars redeemed. By including the grand mean the Stata 12 (StataCorp, 2011) command XTREG is able to report an intercept that is the average of all intercepts and ensures that transformed variables have the same mean values as the untransformed variables (Gould, 2013). Hence, the demeaned values represent the difference from the mean. A negative value suggests that the county's SNAP retailers are redeeming less SNAP dollars than the county's average. A positive value suggests that the county's SNAP retailers are redeeming more SNAP dollars than the county's average.

Tables 4.10 and 4.11 compare the untransformed and transformed dependent variable. The mean values for the transformed variables are the same as the untransformed variables shown in Table 4.10.

The median values for demeaned net redemptions are all positive, in contrast to net redemptions which have negative median values. The difference in median values shows that while the majority of counties have negative net redemptions between 2005 and 2011 the majority of counties saw an increase when compared to their mean. The increasing redemption values reflect the increasing number of SNAP participants and

Table 4.10: Summary of net SNAP difference (in dollars).

Year	N	Min	Max	Median	Mean	SD
2005	207	-8,305,607	43,359,888	-218,710	85,088	3,381,856
2006	207	-4,473,360	24,203,736	-139,067	133,934	2,289,820
2007	207	-7,051,900	18,814,038	-148,301	36,528	2,046,699
2008	207	-15,667,412	72,852,128	-225,018	38,320	5,516,854
2009	207	-15,075,016	41,292,196	-329,696	35,050	3,814,135
2010	207	-15,116,615	49,890,392	-375,784	325,806	5,068,784
2011	207	-19,156,730	61,958,508	-273,226	651,648	5,980,104
Total	1,449	-19,156,730	72,852,128	-223,960	186,625	4,261,047

Table 4.11: Summary of demeaned net SNAP difference (in dollars).

Year	N	Min	Max	Median	Mean	SD
2005	207	-10,055,616	6,641,186	216,818	85,088	1,396,652
2006	207	-20,234,052	9,141,486	279,078	133,934	1,817,795
2007	207	-25,623,750	5,037,795	262,903	36,528	2,029,528
2008	207	-17,427,626	28,414,340	191,369	38,320	2,628,926
2009	207	-3,474,204	3,346,777	96,398	35,050	835,978
2010	207	-3,026,920	15,974,559	60,034	325,806	1,756,597
2011	207	-7,067,035	21,686,642	125,382	651,648	2,663,822
Total	1,449	-25,623,750	28,414,340	178,444	186,625	1,977,355

the increase in per capita SNAP benefits during the study period.

Tables 4.12 and 4.13 provide descriptive statistics for the explanatory variables used to model net redemptions. Table 4.12 provides the descriptive statistics for the untransformed variables and Table 4.13 provides descriptive statistics for the demeaned variables. The mean values for each variable are the same in both tables. The median values do change with the median values in the transformed variables roughly equaling the mean values. The maximum values for the demeaned variables are significantly less than the maximum values for the untransformed variables. The smaller maximum values illustrate how counties with larger populations have smaller increases from their mean values during the study period.

Table 4.12: Basic descriptive statistics for SNAP and mobility related variables for Texas counties 2005-2011.

Variable	N	Min	Max	Median	Mean	SD
<i>Mobility</i>						
Outbound workers, (jobs)	1,449	46	74,115	1,234	3,838	8,858
Inbound workers, (jobs)	1,449	32	117,253	704	3,863	12,188
Unemployed, (persons)	1,449	48	171,899	671	3,518	12,125
Poverty, (persons)	1,449	354	803,895	4,092	19,541	65,659
<i>Retail Grocery Market</i>						
Super Store/Chain Store	1,449	0	264	1	6	22
Supermarket	1,449	0	128	2	5	13
Convenience Store	1,449	0	1,079	7	27	84
<i>Neighboring Market</i>						
Super Store/Chain Store	1,449	0	381	11	34	65
Supermarket	1,449	0	253	14	27	38
Convenience Store	1,449	1	1,297	69	150	208

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table 4.13: Basic descriptive statistics for SNAP and mobility related demeaned variables for Texas counties 2005-2011.

Demeaned Variable	N	Min	Max	Median	Mean	SD
<i>Mobility</i>						
Outbound workers, (jobs)	1,449	-6,730	11,603	3,831	3,838	628
Inbound workers, (jobs)	1,449	-8,946	17,265	3,865	3,863	802
Unemployed, (persons)	1,449	-38,078	52,374	3,483	3,518	3,447
Poverty, (persons)	1,449	-58,106	142,684	19,527	19,541	6,660
<i>Retail Grocery Market</i>						
Super Store/Chain Store	1,449	-25	29	6	6	2
Supermarket	1,449	-5	20	5	5	1
Convenience Store	1,449	-72	317	27	27	15
<i>Neighboring Market</i>						
Super Store/Chain Store	1,449	-23	87	34	34	7
Supermarket	1,449	13	62	27	27	3
Convenience Store	1,449	-7	530	148	150	46

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

For example, the maximum number of people living in poverty was 803,895, but the maximum demeaned value was 142,684. The minimum values for the demeaned variables are all negative, while the untransformed variables all had minimum values near zero. The negative demeaned minimum values demonstrate how the transformed variables represent differences from the counties mean during the study period.

Demeaned variables are less correlated with one another than the untransformed variables. For example, among the retail grocery market variables shown in Table 4.12 all of the untransformed variables are highly correlated (counties with large numbers of supermarkets also have large numbers of convenience stores). However, the cor-

relations among the transformed variables in Table 4.13 are much lower. The correlation between super stores/chain stores and supermarkets is $r = 0.93$. The correlation between the demeaned values for super stores/chain stores and supermarkets is $r = -0.40$. The reduction in correlation helps to improve the performance of the model.

The fixed-effects model uses the transformed variables described to predict the within-county demeaned net difference. Therefore, while the XTREG command is used to calculate the coefficients and standard errors for the models using the untransformed variables, the same results can be obtained using the standard ordinary least squares command REGRESSION with the transformed variables.

Tables 4.14 and 4.15 compare the means of model variables across quintiles for the dependent variable. The first quintile shows that some large counties have a large net difference between the benefits distributed and the benefits redeemed. The lowest quintile counties have retail opportunities; on average there are 6 super store/chain stores and 5 supermarkets in counties that have the largest net difference in SNAP benefits. The lowest quintile counties also have the largest number of super store/chain stores and supermarkets in their neighboring counties. The highest quintile counties however have a larger proportion of super stores. The first four quintiles have more outbound workers than inbound workers. The highest quintile counties have the largest populations, more retail opportunities and more inbound workers than outbound workers. The values from Tables 4.14 and 4.15 suggest that counties with a greater number of outbound workers than inbound workers are also counties that lose SNAP dollars. These are not necessarily rural counties, or counties that do not have places to shop. The models described in the next section will help to confirm the correlations suggested in the data.

Table 4.14: Quintiles of net SNAP difference: Mean of SNAP and mobility related variables.

	1	2	3	4	5	Total
Total Population, (persons)	139,370	29,653	24,013	51,118	339,390	116,555
	(318,556)	(63,152)	(52,611)	(107,103)	(714,555)	(373,557)
Redeemed, (\$)	25,017,378	3,467,288	3,154,256	7,629,776	57,998,152	19,426,769
	(64,819,969)	(6,380,121)	(8,872,876)	(13,006,205)	(130,601,620)	(68,729,926)
Distributed, (\$)	27,445,779	4,158,179	3,385,641	7,390,197	53,940,581	19,240,144
	(66,325,999)	(6,392,266)	(8,861,062)	(12,959,599)	(124,019,747)	(66,123,881)
Net Difference, (dollars)	-2,428,401	-690,892	-231,386	239,580	4,057,570	186,625
	(2,195,027)	(160,398)	(115,232)	(197,536)	(7,968,533)	(4,261,047)
<i>Mobility</i>						
Outbound workers, (jobs)	4,902	1,525	1,110	2,101	9,570	3,838
	(8,965)	(3,189)	(2,254)	(3,782)	(15,301)	(8,858)
Inbound workers, (jobs)	3,912	925	775	1,775	11,958	3,863
	(9,966)	(2,176)	(1,757)	(3,780)	(23,163)	(12,188)
Unemployed, (persons)	4,235	865	611	1,339	10,563	3,518
	(9,429)	(2,034)	(1,324)	(2,878)	(23,771)	(12,125)
Poverty, (persons)	25,793	4,401	3,879	8,207	55,549	19,541
	(61,740)	(6,490)	(10,233)	(15,444)	(124,562)	(65,659)
<i>Retail Grocery Market</i>						
Super Store/Chain Store	6	2	1	3	18	6
	(15)	(3)	(2)	(6)	(45)	(22)
Supermarket	5	1	1	3	13	5
	(12)	(2)	(3)	(6)	(25)	(13)
Convenience Store	40	7	7	12	72	27
	(98)	(8)	(20)	(21)	(147)	(84)

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Note: Standard deviation values in parentheses

Table 4.15: Quintiles of net SNAP difference: Mean of neighboring market variables.

	1	2	3	4	5	Total
<i>Neighboring Market</i>						
Super Store/Chain Store	59 (86)	28 (57)	16 (39)	20 (42)	46 (76)	34 (65)
Supermarket	43 (45)	25 (36)	17 (31)	19 (26)	33 (43)	27 (38)
Convenience Store	265 (267)	130 (165)	71 (107)	100 (163)	184 (239)	150 (208)
Year	2,009 (2)	2,008 (2)	2,008 (2)	2,008 (2)	2,008 (2)	2,008 (2)

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

Note: Standard deviation values in parentheses

4.5 Research Design

As described in the previous section, a balanced panel dataset was constructed from publicly available administrative SNAP data on benefits distributed to a county, benefits redeemed at county retailers, commuting patterns, and retail locations. Commute data has not yet been released for 2012, therefore the panel dataset covers the period from 2005 to 2011 (7 years). Data for Texas counties with redemption data for all years ($N = 207$) were used for the study. The models presented below seek to establish the causal relationship between changes in the explanatory variables and changes in SNAP spending patterns. Since the explanatory variables vary over the time period, a fixed-effects model was used.

Fixed-effects models reduce omitted variable bias by purging the model of unobserved variables and time-invariant factors. The unobserved variable a_i captures time-constant factors that affect y_{it} . An unobserved county effect or a county fixed effect represents all factors affecting within-county SNAP spending that do not change over time. Geographic features, such as the county's location in Texas, are included in a_i . Many other factors may not be exactly constant, but they might be roughly constant over the seven-year period. These might include certain demographic features of the population (age, race, and education). The Stata 12 (StataCorp, 2011) command XTREG will be used to determine the fixed-effects parameters and intercepts.

4.6 Model Descriptions

The following models are designed to tell the story about how SNAP spending patterns are influenced by commuting patterns and the grocery retail market. The models are simple enough to be understood easily yet have enough substance to provide some insights about the food system. Specific insights include how the mobility of people living in poverty influences spending behavior, how different types of retail influence

spending behavior and how neighboring retail influences spending.

4.7 Model 1-Basic Mobility Model

Model One focuses on how low-income mobility patterns shapes net SNAP spending patterns:

$$y_{it} = \alpha_i + \beta_1 occ_{it} + \beta_2 icc_{it} + z_{it}\lambda + u_{it}, t = 1, 2, \dots, 7 \quad (4.3)$$

where y_{it} represents the net difference between SNAP benefits redeemed within a county and the benefits distributed to county residents for county i and in year t (each year from 2005 to 2011). Model One is a fixed-effects model with an intercept α_i for each county across all years. The explanatory variables represent county commuting patterns and a set of controls. The first explanatory variable occ_{it} represents the number of low-income primary jobs outside the county that are held by workers³ who live in the county for each county i and in year t . The second explanatory variable icc_{it} is the number of low-income primary jobs inside the county that are held by workers who live in another county for each county i and in year t . The final explanatory variables are the number of county residents who are considered unemployed and the number of residents estimated to be living in poverty. These county characteristics are represented by the vector z_{it} and are included because they are theoretically associated with reduced mobility.

The coefficients of interest are β_1 and β_2 . It is expected that $\beta_1 < 0$, that is, a higher number of low-income jobs that commute out-of-county will decrease the dollars redeemed within the county. It is expected that $\beta_2 > 0$, that is, a higher number of low-income jobs that commute into the county will be associated with an increase in the dollars redeemed within the county. With respect to the λ 's, it is expected that unem-

³ A low-income primary job is defined as a primary job (the job that a worker holds which earns him/her the greatest income) that earns less than \$1,250 a month.

ployment and poverty will have positive coefficients, since as each increases, mobility would be expected to decrease, leading to an increase in within-county redemptions.

4.8 Model 2-Retail Market Plus Mobility

Mobility may not be the only explanation for differences in net SNAP spending. Value-conscious consumers may bypass local retail opportunities to find lower prices and better selection. To control for the influence of retail opportunities Model Two will incorporate county level store type data:

$$y_{it} = \alpha_i + \beta_1 occ_{it} + \beta_2 icc_{it} + \beta_3 sc_{it} + \beta_4 sm_{it} + \beta_5 cs_{it} + z_{it}\lambda + u_{it}, t = 1, 2, \dots, 7 \quad (4.4)$$

where store types include the number of super stores/chain stores sc_{it} , supermarkets sm_{it} , and convenience stores cs_{it} in county i in year t . Equation 4.4 includes three out of the 17 types of retail. The 14 excluded retail types account for less than 10% of SNAP redemptions. Combined stores were excluded because, as shown on page 52, the increase in combination stores is highly correlated with the increase in convenience stores. In addition to the retail measures, Equation 4.4 includes the explanatory variables from Equation 4.3. It is expected that retail stores will reduce the effects of inbound commute patterns because counties with large numbers of inbound commuters are more likely to have greater retail options. Conversely, it is expected that including retail opportunities will increase the effect of outbound commuters, since counties with large numbers of outbound workers are more likely to be rural counties with fewer stores. It is expected that $\beta_3 > \beta_4 > \beta_5$, that is, while all store types will have positive effects on redemptions; the effects of store type will vary. Super stores/chain stores will have the greatest positive effect followed in order by supermarkets, and convenience stores, with the latter having the smallest positive effect. Research suggests that supercenters, which are included in the super store/chain store counts, are the

only store type where a family can purchase the Thrifty Food Plan market basket for a price at or below the maximum SNAP benefit (Breyer and Voss-Andreae, 2013; Horning and Fulkerson, 2015). Research also suggests that low-income households travel specifically to larger chain stores, bypassing smaller retailers (Clifton, 2004; LeDoux and Vojnovic, 2013). The magnitude of β_3 will help to confirm the importance of super stores/chain stores within the food system for low-income consumers. The difference between β_1 and β_2 between Models One and Two will reinforce previous qualitative findings that suggest that low-income consumers are willing to travel greater distances even when the local retail market has retail options.

4.9 Model 3-Placing the County in Context with Neighboring Markets

The final model presents a more refined approach that places each county within a spatial context. The spatial context will be based on neighboring counties. Model 3 will include the number of stores in neighboring counties.

$$y_{it} = \alpha_i + \beta_1 occ_{it} + \beta_2 icc_{it} + \beta_3 sc_{it} + \beta_4 sm_{it} + \beta_5 cs_{it} + \beta_6 nsc_{it} + \beta_7 nsm_{it} + \beta_8 ncs_{it} + z_{it}\lambda + u_{it}, t = 1, 2, \dots, 7 \quad (4.5)$$

where $\beta_3 - \beta_5$ are the local retail market that were determined to be significant from Model 2 (number of super stores, supermarkets, or convenience stores) and $\beta_6 - \beta_8$ are the number of store types in a neighboring county i in year t .⁴ Model 3 will look at the influence of different store types in neighboring counties. It is expected that β_6 for super store/chain stores will have a significant and negative value. It is also expected that β_7 and β_8 will not be significant, suggesting that the number of supermarkets and convenience stores in a neighboring county will not influence the SNAP redemptions in

⁴Neighboring county is defined as counties that have a shared border or vertex. The neighboring counties included counties in neighboring states.

a county. By including neighboring retail market it is expected that the difference between β_3 and β_4 will become larger, providing further support that super stores/chain stores have a greater influence on SNAP spending than supermarkets.

4.10 Summary

This chapter summarized the data sources and steps taken to create a panel dataset. The three models proposed for this research are specified to test the three hypotheses proposed. If the three models provide statistically significant parameters the null hypotheses will be rejected. The next chapter presents the results. The results will help urban planners and policymakers determine the influence of mobility and store type on the shopping patterns of poorer households.

5. RESULTS

The tables on pages 75, 79, and 83 present the parameter estimates for the three models described in the previous chapter. The models predict the net difference in county SNAP redemptions for 207 Texas counties between 2005 and 2011. Model One represents a base model including commute measures and the two control measures, while Model Two includes additional measures assessing not only the consequences of commuting patterns, but also the county's retail environment for net redemptions. Model Three includes the neighboring county retail market. All three models are statistically significant, with the first accounting for 6.0% of the within-observation variance, while the second model accounts for 24.7%, and the third model accounts for 25.5% of within-county variance. As anticipated, the increased within-observation variance accounted for by the second model is statistically significant. The results for each model are supportive of the expectations, that low-income mobility patterns and county retail environments have significant consequences for net SNAP county redemptions.

5.1 Model One Results

Model One, Table 5.1, captures the effects of low-income commuting patterns on net SNAP spending within counties. The effect of outbound low-income workers is both significant and negative as expected. Specifically, a county resident that has a low-income primary job outside the county decreases net SNAP redemptions by \$434. A worker commuting into a county increases net redemptions significantly by \$606. Statistically the absolute values of the coefficients are same, which may be interpreted to mean that the effect of workers may cancel out if the number of outbound workers were to equal the number of inbound workers. The table on page 64 shows that indeed the average and median county have equal numbers of inbound and outbound workers.

However, the first four quintiles shown in the table on page 66 have greater numbers of outbound workers. Model One also includes two control variables, the number of persons unemployed and the number of persons living in poverty. The coefficient on unemployed persons is significant and positive, suggesting that unemployed persons increase SNAP spending within a county. The second control variable is persons living in poverty. The coefficient on persons living in poverty is not significant; this suggests that changes in the number of people living in poverty has no effect on changes in the net difference in SNAP redemptions in a county. During the study period the number of people living in poverty increased dramatically from 3.9 million to 4.6 million. The coefficient on persons living in poverty was expected to be positive because people living in poverty are assumed to have lower mobility and therefore an increase in poverty would increase within-county spending. However, Model One suggests that increases in poverty do not change SNAP spending patterns.

5.2 Model Two Results

Model Two, Table 5.1, provides a more complete picture of the potential effects of low-income commute patterns after also controlling for a county's retail grocery market. Before discussing the consequences for mobility effects, let us focus on the effects of food retail establishments. As mentioned above, controlling for in-county SNAP retail environment improves the overall model performance. In general, increased food retail opportunities increases net SNAP redemptions for a county significantly, and the effects are as anticipated.

Table 5.1: Parameter estimates from Models 1 and 2 of net SNAP difference.

	Model 1	Model 2v1	Model 2v2
	Net Difference, (dollars)	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>			
Outbound workers, (jobs)	-434.20*** (116.32)		-501.16*** (109.46)
Inbound workers, (jobs)	606.95*** (94.48)		312.04*** (86.75)
Unemployed, (persons)	222.31*** (30.74)		-7.88 (33.77)
Poverty, (persons)	-14.14 (15.79)		-162.48*** (18.32)
<i>Retail Grocery Market, (stores)</i>			
Super Store/Chain Store		261,469.28*** (37,702.10)	372,495.75*** (48,471.71)
Supermarket		251,716.71*** (54,244.15)	343,731.41*** (55,845.30)
Convenience Store		35,370.76*** (5,719.93)	89,759.13*** (7,666.89)
Constant	-997,551.62** (373,564.06)	-3,522,937.51*** (339,572.52)	-2,188,209.33*** (487,624.29)
Observations	1449	1449	1449
Adjusted R^2	0.060	0.159	0.247

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

The effect of an additional super store/chain store or supermarket is as expected; when a county in Texas added a new super store/chain store between 2005 and 2011 the county's net difference in SNAP dollars redeemed increased by \$372,496. An additional supermarket had a similar effect. The effect of an additional convenience store was significant with each new convenience store increasing the net difference by \$89,759 for a county. The effect of combined stores is not included in the model because it had the largest variance inflation factor, with only 5.5% of the variance in combination stores not explained by the other predictors. When combination stores was tested it was not significant and had very little influence on the other coefficients.

5.2.1 *Comparing Model One to Model Two*

With retail opportunities included in the model, the coefficients for outbound workers and inbound workers change. The coefficient for outbound workers increases as expected; the increase, however, is not statistically significant. The coefficient for inbound workers decreases significantly from \$606 to \$312 ($F(1, 1235) = 11.56, p > 0.001$). The insignificant change in the coefficient for outbound workers suggests that outbound workers are less impacted by changes in the retail market within their county. The significant shift in the coefficient for inbound workers suggests that inbound workers are more impacted by changes in the retail markets where they work. Since an inbound worker in one county is an outbound worker for another county, the results from Model Two clarify the influence of retail markets on net SNAP redemptions in a county.

In Model One, unemployment has a positive and significant effect on spending within the county. An increase in unemployment increases spending within a county. Model Two refines the interpretation. If the in-county SNAP retail opportunities are controlled for, changes in unemployment do not affect spending patterns. The effect of

poverty on SNAP spending is not significant in Model One. In Model Two an increase in the number of persons in poverty has an unexpected a negative effect on net SNAP dollars. The shift in the coefficients and the negative effect of poverty may be an issue of multicollinearity. The correlation between the transformed values of poverty and unemployment is $r = 0.88$. Unemployment has a variance inflation factor of 9.53, with 10.5% of the variance in unemployment not explained by the other predictors. Therefore the unexpected negative coefficient on poverty is difficult to explain, the result however does suggest that poverty and unemployment are not clear controls for low mobility.

Table 5.1 compares two versions of Model Two, version 1 without the mobility predictors and version 2 with the mobility predictors. Without mobility factors the model accounts for 15.9% of the within-observation variance, a significant drop from the combined model. The coefficients on all three store types drop significantly when mobility factors are not included. When mobility factors are considered the retail market has a greater impact on the net difference in SNAP redemptions.

5.3 Model Three Results

Table 5.2 compares two versions of Model Three. In version 1 three predictor variables were included to determine the consequences of the county's neighboring retail grocery market. Together none of the predictors were significant. However, the first version of the third model reduces the coefficient for supermarkets from \$343,731 to \$272,937 ($F(1, 1232) = 1.45, p > 0.23$) and only reduces the coefficient for super store/chain store from \$372,496 to \$360,702 ($F(1, 1232) = 0.06, p > 0.81$). The reduction of the supermarket coefficient indicates that there is a larger difference between supermarkets and super stores/chain stores. A second version of Model Three includes the number of neighboring super store/chain stores and the number of neigh-

boring supermarkets. In the second version of Model Three only the number of super stores/chain stores in the neighboring counties is significant. The number of neighboring super stores/chain stores has a significant and negative effect on a county's net SNAP redemptions. The number of supermarkets in a neighboring county was not found to have a significant effect. Comparing the first and second versions of Model 3 reveals issues with multicollinearity. The $r = 0.774$ between the number of super store/chain stores and convenience stores in neighboring counties indicates that the two values are strongly related. The $r = -0.516$ between the number of super store/chain stores and supermarkets in neighboring counties indicates that the two values have a strong negative relationship. The negative relationship between super store/chain stores and supermarkets helps explain the positive coefficient on supermarkets, and the trend during the time period for supermarkets to exit and for super store/chain stores to enter the market. Removing neighboring convenience stores from the model removes the strongest correlation. Without neighboring convenience stores in the model neighboring super stores/chain stores becomes significant and the coefficient on super stores/chain stores decreases from -9,545.45 to -22,221.27 ($F(1, 1233) = 2.57, p > 0.109$). Of the three types of neighboring retail grocery market store types considered only super store/chain stores has a significant effect on net SNAP redemptions. Therefore, the final version of Model Three shown on page 79 includes only the number of super stores/chain stores in a neighboring county.¹ All three versions of Model Three have similar coefficients for the mobility, super store/chain store, and convenience store predictors.

¹The author fully recognizes that simply dropping the potentially offending variable does not "solve" the problem of multi-colinearity because specification issues are now introduced. However, given the fact that this dissertation is exploring the issue of utilizing unique public data to address food security issues, this does allow for a short term solution that can be better remedied by undertaking a more elaborate gathering of larger data to address this issue in the future.

Table 5.2: Parameter estimates from Model 3 of net SNAP difference.

	Model 3 v1	Model 3 v2
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−438.77*** (111.15)	−446.39*** (110.91)
Inbound workers, (jobs)	284.46** (86.78)	284.15** (86.78)
Unemployed, (persons)	9.27 (34.55)	11.70 (34.47)
Poverty, (persons)	−166.45*** (18.44)	−166.63*** (18.44)
<i>Retail Grocery Market, (stores)</i>		
Super Store/Chain Store	360,702.01*** (49,033.88)	366,341.57*** (48,730.07)
Supermarket	272,936.84*** (58,795.02)	276,546.36*** (58,692.59)
Convenience Store	94,032.45*** (7,900.14)	92,324.28*** (7,725.21)
<i>Neighboring Market, (stores)</i>		
Super Store/Chain Store	−9,545.45 (14,603.32)	−22,221.27** (7,909.79)
Supermarket	27,262.13 (19,883.79)	15,386.23 (16,220.45)
Convenience Store	−2,075.62 (2,010.12)	
Constant	−2,124,581.36* (892,148.42)	−1,659,696.24* (770,238.51)
Observations	1449	1449
Adjusted R ²	0.255	0.255

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

5.3.1 *Comparing Model One to Model Three*

Model One and Model Three have similar coefficients for outbound workers. The fact that the coefficient on outbound workers remains statistically constant across all three models suggests the number of outbound workers is strongly associated with negative net SNAP redemptions.

The results for inbound workers shift significantly between Model One and Model Three. In Model One an inbound worker increases net SNAP redemptions by \$607, while in Model Three an inbound worker increases net SNAP redemptions by \$282. The difference between the models may be explained by the inclusion of local retail opportunities. A county without a super store/chain store or supermarket would have less of an increase in net SNAP redemptions than a county that had larger stores for inbound workers to shop at. Unemployment and poverty do not change significantly between Models Two and Three.

5.4 Summary

Across all three models the results support rejecting the null hypotheses and provided support for the hypotheses presented at the start of chapter 4.

- Hypothesis 1: The commute patterns of a county's low-income populations will have a significant effect on the net of SNAP dollars redeemed within a county. Specifically, outbound workers will have a negative effect and inbound workers will have a positive effect.
- Hypothesis 2: The number and type of SNAP retailers within a county will have a positive effect on the amount of SNAP dollars redeemed within a county.
- Hypothesis 3: The number of SNAP retailers in nearby counties will have a negative effect on the net SNAP dollars redeemed within a county.

For hypothesis one all three models show that commute patterns of a county's low-income population do have an effect on the net of SNAP dollars redeemed within a county. Specifically, persons that commute out of a county have a significant and negative effect on the amount of SNAP dollars redeemed in a county. Person that commute into a county have a significant and positive effect on the amount of SNAP dollars redeemed in a county.

For hypothesis two, Models Two and Three show that the number and type of SNAP retailers within a county has a positive effect on the amount of SNAP dollars redeemed within a county. In Model Two the type of SNAP retailers is significant when comparing convenience stores with larger supermarkets and super store/chain stores. In Model Two super store/chain store have a larger coefficient but it is not statistically different from supermarkets, with a difference between store types at a 90% confidence interval of -\$42,051-\$99,579. Model Three decreases the coefficient for supermarkets by controlling for neighboring super stores/chain stores. In Model Three super stores/chain stores have a larger coefficient that is statistically different from supermarkets, with a difference between store types at a 90% confidence interval of \$1,228-\$148,360.

For hypothesis three Model Three shows that the number of SNAP retailers in neighboring counties has a negative effect on the net SNAP dollars redeemed within a county. Model Three clarifies that the type of SNAP retailers in a neighboring county is also significant. Specifically, the number of supermarkets in a neighboring county does not affect the net SNAP dollars redeemed within a county, but, the number of super store/chain stores does.

The changes in coefficients on unemployment and poverty suggest that issues of multicollinearity may be confounding the model results. While the measures of poverty and unemployment were expected to control for persons with lower mobility the results from the models do not support the original assumptions. Chapter 6 will discuss these

limitations and options for improving future research.

The key results are the indication that super stores/chain stores have a significantly larger consequence for net SNAP redemptions and the indication that commute patterns have a significant impact on net SNAP redemptions. Comparing the mean values for each quintile shown on page 66 provides context when comparing the coefficients in Table 5.3. Adding one super store/chain store would have a comparable effect to adding 1,000 inbound workers.

All of the models provide insight into the dynamics of the food system. Several robustness checks were used to test the model, and none of them changed the decision to reject all three null hypotheses. The fixed-effects model was compared to pooled OLS and random-effect models using the same variables. The full sample models ($N = 1,449$) were also compared to models without bad leverage points ($N = 1,388$). Appendix C summarizes the robustness checks and discusses the minor differences between models. Chapter 6 will discuss the limitations of the final model and suggests future research that may improve on the significant findings presented in this chapter.

Table 5.3: Parameter estimates from Models of net SNAP difference.

	Model 1	Model 2	Model 3
	Net Difference, (dollars)	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>			
Outbound workers, (jobs)	-434.20*** (116.32)	-501.16*** (109.46)	-436.50*** (110.41)
Inbound workers, (jobs)	606.95*** (94.48)	312.04*** (86.75)	281.95** (86.74)
Unemployed, (persons)	222.31*** (30.74)	-7.88 (33.77)	15.49 (34.23)
Poverty, (persons)	-14.14 (15.79)	-162.48*** (18.32)	-168.64*** (18.31)
<i>Retail Grocery Market, (stores)</i>			
Super Store/Chain Store		372,495.75*** (48,471.71)	360,618.02*** (48,353.10)
Supermarket		343,731.41*** (55,845.30)	285,823.70*** (57,869.62)
Convenience Store		89,759.13*** (7,666.89)	93,063.52*** (7,685.49)
<i>Neighboring Market, (stores)</i>			
Super Store/Chain Store			-25,518.11*** (7,104.99)
Constant	-997,551.62** (373,564.06)	-2,188,209.33*** (487,624.29)	-1,161,365.26* (563,248.69)
Observations	1449	1449	1449
Adjusted R ²	0.060	0.247	0.255

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

6. CONCLUSIONS

The models presented in Chapter 5 support the hypotheses related how commuting patterns and the grocery retail market shape the spending patterns of poorer households. The methodology used in this paper establishes the importance of knowing where SNAP dollars are distributed and where SNAP dollars are redeemed to determine the net difference of SNAP redemptions. The net difference of SNAP dollars redeemed provides important insight into the workings of the food system. Publicly available data makes it possible to see that low-income households shop outside their home counties and suggests that super stores are an important factor in predicting net SNAP redemptions. Furthermore, the findings of this dissertation illustrate how employment locations influence where people living in poverty spend their food dollars.

The findings presented in this dissertation apply to Texas counties between 2005-2011. Future research will need to explore how generalizable the results are to other parts of the country and to smaller areas.

6.1 Limitations and Future Research

While the findings presented in this dissertation are statistically valid and scientifically replicable, there are several important limitations that must be discussed. One of the strengths of the methodology presented is the use of publicly available data that is reported on an annual basis. The fact that the data are publicly available for most of the United States means that other states and regions can be studied. The use of annual data provides the opportunity to use longitudinal models that strength the case for causal relationships. However, with each strength there are several weaknesses.

First, the use of publicly available commuting pattern data comes with many limitations. Commuting pattern data may not include all SNAP participants who have jobs

and they definitely include many non-SNAP participants. The noise in the commuting pattern data means that while the coefficients on outbound and inbound workers are significant, the magnitude of the values may not relate to actual SNAP participants. The correlation between low-income workers and SNAP workers is not known and therefore the assumptions need further exploration. Future research could use the lower level geography, such as Census Tracts, available in the LODES data to refine the way outbound and inbound workers are counted. Future research could compare commuting patterns for low-income workers in high poverty tracts to workers in more affluent areas to see if there is a significant difference.

A second limitation or weakness of the models presented in this dissertation is that the fixed-effects model can only consider time-variant predictors. Therefore, the models do not include factors that are time invariant, or predictors that are not measured on an annual basis. For example, car ownership may be an important factor that influences mobility. Unfortunately, car ownership for SNAP households is unknown. The US Census Bureau includes measures of car ownership by household poverty status but these measures are only available from the multi-year American Community Survey (ACS) and therefore do not work in a panel model with annual data. Future research could explore other predictors in the ACS using a pooled OLS or a panel model with averages of 3 or 5 years worth of data per observation. By pooling the annual data, ACS variables that provide estimates for SNAP households could expand our understanding of the relationship between mobility and SNAP spending.

A third limitation for the interpretation of the results is the multicollinearity between variables. Multicollinearity between variables can impact the estimation of coefficients. For the three models presented, the coefficients on poverty and unemployment are the only ones that change radically between the three models. This issue with the coefficients may be due to the close relationship between poverty and unemployment.

During the period between 2005-2011 poverty and unemployment both increased in Texas. Because the increases are related (higher unemployment leads to increased poverty), the coefficients in the model are difficult to interpret. Within the full sample models described in Chapter 5 unemployment had a positive effect in Model 1 and no significant effect on net SNAP redemptions in Models 2 and 3. Poverty however had no significant effect in Model 1 and a negative effect in Models 2 and 3. Several robustness checks that are described in Appendix C show that the coefficients on poverty and unemployment are inconsistent. Further research would be required to replace the variables used with ones that are not overlapping. For example, unemployment could be replaced if it was possible to determine SNAP participants who are in households with and without workers. The poverty variable could be refined if it was possible to determine SNAP households that are in extreme poverty versus households that are near poverty.

Despite these limitations, the models extend the current understanding of how commuting patterns and the grocery retail market influence net SNAP redemptions. Current assumptions about the food shopping patterns of people living in poverty do not consider home-work commuting patterns, primarily because it is often assumed that people living in poverty do not work. The results from this dissertation suggest that commuting patterns are important for fully understanding SNAP redemptions. Current research has looked at food access for people in low-income populations, but generally considers supermarkets and super stores to be one category. The results from this dissertation suggest that within the grocery retail market, supermarkets and super stores have different effects, with super stores having a larger effect on SNAP redemptions. Future research could explore the generalizability of the models to other regions, and at scales smaller than counties. Future research could also improve the way constructs such as mobility and the grocery retail market are measured. The findings of this dis-

sertation never the less help to fill some of the gaps related to understanding food access.

6.2 Implications for Food Access

The importance of larger grocery stores in determining SNAP redemptions may have a significant implication for how food access is defined. Larger grocery stores often have lower food prices. Basker and Noel (2009) found that new Wal-Mart Supercenters had a 10% price advantage over existing retail stores. For existing stores to remain competitive they either cut prices or target higher-income shoppers. As large national chains have gained competitive advantages over smaller “mom-and-pop” retailers, the grocery retail market has consolidated (Basker and Noel, 2009; Foster et al., 2006; Haltiwanger et al., 2010). Consolidation has reduced the number of stores available to price-sensitive consumers, but has helped to lower prices at some stores. Much of the in-store cost savings for consumers, however, can be attributed to households assuming the cost of food storage and transportation. To make the most of lower prices, families must have the capability to buy in bulk and travel longer distances (Ellickson and Grieco, 2013). The changes in the food system have altered how households access food, but these changes are not reflected in how food assistance benefits are determined for people living in poverty. Urban planners and policymakers need to realize the gap between reality and how poverty and food benefits are determined. The reality is that SNAP dollars are only adequate when households have access to dependable transportation to larger food stores and the capability to store bulk food.

The definitions of poverty and food benefits minimize the true costs of food shopping. Food shopping is hard work, demands time and resources, and determines the food available in homes, which is a primary factor in the consumption of healthy foods (Ding et al., 2012). However, the time, energy, and expertise required for food shop-

ping is often overlooked. Food shopping requires large investments of time and energy and takes place in battle-ground type environments (Koch, 2012). SNAP participants spend significantly more time shopping for food and shop at more stores than the average shopper (Hamrick et al., 2011; Ver Ploeg, 2009). Families that participate in SNAP may need to shop at larger format stores to find a dependable source of low-cost food and reduce the amount of time and energy required to shop.

The findings of this dissertation suggest that grocery retail markets with more super stores and chain stores redeem more SNAP dollars than counties with only supermarkets and that low-income families travel to neighboring counties to redeem their SNAP benefits when neighboring counties have more super stores. Current research has focused on how new supermarkets in low-income areas influence diet quality. While limited, the research has not found that low-income shoppers eat a healthier diet when a new supermarket opens closer to their homes (Cummins et al., 2014). However, based on the results from this dissertation, future research could look at households in counties with significant negative net SNAP redemptions to see if driving long distances increases purchases of more shelf-stable foods and decreases purchases of more perishable items such as fresh produce.

SNAP spending may also provide insight into the food spending patterns, and food access, of non-participants. If households with the least amount of income are not shopping within the local grocery market are there problems with the local grocery market that are experienced by all consumers? Furthermore, do negative net SNAP redemptions mean that shoppers without mobility, both SNAP participants and non-participants, are stuck in a bad food environment—which may increase negative health outcomes. Future research could use the data presented in this dissertation to explore in greater detail food environments that have some food access but lose SNAP dollars.

While the findings from this dissertation suggest that super stores and chain stores

increase SNAP redemptions it is not clear that they increase food access by making food more affordable. It may be that super stores and chain stores, especially supercenters, reduce the amount of time it takes to complete household errands. The time savings associated with shopping in one large store—one that has general merchandise, a pharmacy, a bank, or even auto maintenance, along with a full service supermarket— may be a stronger driver of store choice than the financial savings offered by supercenters. In addition to time savings, SNAP participants may be influenced by issues related to social exclusion. When shopping at stores that market to higher income shoppers, such as Whole Foods, low-income shoppers may internalize a sense that the store is not welcoming to price-sensitive shoppers. Large super stores and chain stores that market to price-sensitive shoppers may produce a culture that is more inviting and welcoming to people living in poverty. Future qualitative research could focus on the effects of supercenters to determine why they have a larger effect on SNAP spending, when other store options are closer. If supercenters have the largest effect, an implication for food access would be that instead of defining food access by distance to a grocery store with more than \$2 million in sales, high food access may mean access to a supercenter. Food access could be clarified into areas such as food deserts, with no food access, areas with some food access, and areas with high food access. Areas with some food access may include a mix of supermarkets and chain stores, or super stores that focus on higher income consumers. Areas with high food access may include a mix of supercenters and super stores that are more attractive to price-sensitive consumers.

Assumptions about poverty directly impact the shopping patterns of poorer households. The food-income poverty model assumes that one out of every three dollars of income goes towards food, and SNAP benefits decrease according to this assumption. The Thrifty Food Plan, which is used to define poverty and SNAP benefits, assumes a household that produces no food waste and includes an expert food preparer, with

excellent menu planning and food shopping skills. The historic foundations of the TFP stressed the need for home food production, health education, and local networks that ensure the affordability of healthy food. These historic foundations are largely overlooked, despite the fact that they create the structure for how poverty and food assistance are defined. The assumptions behind the definition of poverty provide no margin of error for families that do not have the time or resources to make all their meals from scratch. SNAP participants are expected to have affordable healthy food nearby, but as the findings from this dissertation suggest, SNAP participants are spending more at distant super stores or chain stores, even when the nearby grocery retail market has other options such as supermarkets and convenience stores. These findings may suggest that the margin of error is even smaller for families that do not have access to larger grocery stores.

6.3 Conclusion

Urban planners consider research related to food access as a new frontier and have yet to integrate food systems planning into the profession. Current efforts within the profession to increase food access have focused on building new supermarkets in low-income neighborhoods. However, issues related to food access are more complex than these limited efforts imply. Planners and policymakers who attempt to increase food access need to consider commuting patterns, the grocery retail market, and the types of stores nearby. Low-income populations may be more willing to travel within the grocery retail market than previously anticipated. Also, food affordability may determine the influence of store type, but future research will need to clarify why super stores are having a larger effect on SNAP redemptions than any other retail type.

To reduce food insecurity and hunger for low-income populations, urban planners need to understand the way poverty is defined and how food assistance programs such

as SNAP function. Specifically, urban planners need to increase their sensitivity to how little margin of error federal programs provide people living in poverty. While it may be technically possible to eat a healthy diet on SNAP benefits, very few families live in the ideal conditions or have the capability to make it happen. Policymakers who consider the consequences of commuting patterns and the structure of food retail markets for SNAP redemptions, will have greater insight into the food system and may improve food access for people living in poverty.

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APPENDIX A

STORE TYPE DEFINITIONS

The following store type definitions include the store type name, two letter code, and a general description of how the store operates its business.

- Convenience Store: (CS)

Self-service stores that offer a limited line of convenience items and are typically open long hours to provide easy access for customers. Primarily engaged in retail sale of a variety of canned goods, dairy products, pre-packaged meats and other grocery items in limited amounts. Usually sell a large variety of ineligible products; such as hot coffee, alcohol, or tobacco products.

- Combination Grocery/Other: (CO)

Primary business is sale of general merchandise but also sell a variety of food products. Such stores include independent drug stores, dollar stores, and general stores.

- Direct Marketing Farmer (DF)

Designation applies to direct marketing farmers; these are individual producers of agricultural products, particularly fresh fruit and vegetables, as well as meat, fish, dairy, and/or grains that are sold to the general public through a direct marketing venue such as a roadside farm stand, pick-your own operation, and/or market stall within a farmers' market. This store type differs from fruit/vegetable, meat, fish,

and bread specialty firms in that the products are sold directly by the producer (farmer) rather than a retailer selling produce, meat, dairy, and/or grains purchased from a wholesale or other entity (i.e. a third party selling products purchased from or on behalf of a farmer/producer is not a direct marketing farmer).

- Delivery Route: (DR)

A store that does not have a permanent store location, this includes delivery routes that deliver food at set locations and times, as well as rolling routes. Routes typically sell milk, bread, produce or other staple foods and are most common in rural areas.

- Farmers' Market: (FM)

A single or multi-stall market that sells agricultural products, particularly fresh fruit and vegetables, to the general public at a single or multiple locations. This designation applies to any organization that operates a farmers' market location.

- Large Grocery Store: (LG)

A store that carries a wide selection of all four staple food categories. They may sell ineligible items as well, but their primary stock is food items.

- Medium Grocery Store: (MG)

A store that carries a moderate selection of all four staple food categories. They may sell ineligible items as well, but their primary stock is food items.

- Military Commissary: (MC)

Designation applies to all retail food entities, located on military installations that sell food and non-food products. Only authorized shoppers may shop at these entities and they must show proper military ID to use the commissary or Base Exchange.

- Non-Profit Food Buying Cooperative: (BC)

Any store that operates as a “cooperative”.

- Small Grocery Store: (SG)

A store that carries a small selection of all four staple food categories. They may sell ineligible items as well, but their primary stock is food items.

- Specialty Food Store - Bakery/Bread: (BB)

Food stores specializing in the sale of bread/cereal products. May also carry non-food items or other food items, but such stock is incidental to the primary specialty food stock.

- Specialty Food Store - Fruits/Vegetables: (FV)

Food stores specializing in the sale of fruits and/or vegetables that operates in a fixed or semi-permanent location. This includes any permanent store whose primary business is the sale of fruits/vegetables, such as a produce market; as well as any produce stand that does not qualify as a Direct Marketing farmer or is not affiliated with a farmers’ market. Seasonal produce stands qualify under this category. May also

carry non-food items or other food items, but such stock is incidental to the primary specialty food stock.

- Specialty Food Store - Meat/Poultry Products: (ME)

Food stores specializing in the sale of meat products. May also carry non-food items or other food items, but such stock is incidental to the primary specialty food stock.

- Specialty Food Store - Seafood Products: (SE)

Food stores specializing in the sale of seafood products. May also carry non-food items or other food items, but such stock is incidental to the primary specialty food stock.

- Supermarket: (SM)

Establishments commonly known as supermarkets, food stores, grocery stores and food warehouses primarily engaged in the retail sale of an extensive variety of grocery and other store merchandise. This store typically has ten or more checkout lanes with registers, bar code scanners, and conveyor belts.

- Super store/Chain Store: (SS)

Very large supermarkets, “big box” stores, super stores and food warehouses primarily engaged in the retail sale of a wide variety of grocery and other store merchandise. Includes stores that are large food/drug combo stores and mass merchandisers under a single roof, and membership retail/wholesale hybrids offering a limited variety of products in warehouse-type environment.

- Wholesaler: (WH)

Statutory/regulatory definition: an establishment that sells eligible food to meal services for resale to households.

Wholesale firms which have a retail operation and qualify under the co-located retailer/wholesaler provisions of the regulations shall be assigned a type consistent with their operations. These firms shall not be assigned a Wholesaler type.

APPENDIX B

USDA EXAMPLES OF MONTHLY COST OF FOOD

This appendix provides examples of how the USDA breaks down monthly food cost estimates. The June 2004 Thrifty Food Plan determined the FY 2005 maximum SNAP benefits. FY 2006- April 2009 had maximum monthly SNAP benefits set by the preceding June's Thrifty Food Plan (U.S. Department of Agriculture, 2004). The June 2008, plus 13.6% per the ARRA, determined the April 2009 through October 2013 maximum SNAP benefit (U.S. Department of Agriculture, 2008).

The USDA determines the monthly costs of food for individuals and families. The USDA plans provide the cost of eating at home. For individuals the USDA determines the cost of food for fifteen age groups—five age groups for children, five for males, and five for females. The cost of food is calculated on a weekly and monthly basis. The weekly and monthly costs are calculated for four plans. The Thrifty Food Plan is considered the least amount of money a person needs to spend to have an adequate diet. The Low-Cost Plan costs around 30% more than the Thrifty Food Plan. Bankruptcy courts use the Low-Cost Plan to determine food expenses. The Moderate-Cost Plan is considered the amount of money the average person or household spends on food. The Moderate-Cost Plan costs around 60% more than the Thrifty Food Plan. The highest cost plan is the Liberal Plan, which costs around 95% more than the Thrifty Food Plan. The Department of Defense uses the Moderate and Liberal Food Plans to determine allowances for food (Carlson et al., 2003).

Figure B.1: Official USDA food plans, June 2004 (U.S. Department of Agriculture, 2004).



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**Official USDA Food Plans: Cost of Food at Home at Four Levels,
U.S. Average, June 2004¹**

AGE-GENDER GROUPS	WEEKLY COST ²				MONTHLY COST ²			
	Thrifty plan	Low-cost plan	Moderate-cost plan	Liberal plan	Thrifty plan	Low-cost plan	Moderate-cost plan	Liberal plan
INDIVIDUALS³								
CHILD:								
1 year	18.00	22.50	26.30	31.80	78.20	97.60	114.10	137.60
2 years	17.90	22.10	26.30	31.90	77.40	95.70	113.90	138.00
3-5 years	19.60	24.30	30.00	36.00	84.70	105.10	130.00	156.10
6-8 years	24.30	32.40	39.90	46.80	105.40	140.50	173.10	202.80
9-11 years	28.50	36.50	46.70	54.20	123.60	158.30	202.20	235.00
MALE:								
12-14 years	29.80	41.40	51.30	60.10	129.20	179.30	222.20	260.60
15-19 years	30.70	42.50	53.10	61.60	132.90	184.10	230.00	267.00
20-50 years	32.70	42.30	52.60	64.20	141.60	183.10	227.80	278.30
51 years and over	29.70	40.20	49.60	59.40	128.50	174.30	214.90	257.50
FEMALE:								
12-19 years	29.80	35.70	43.40	52.10	129.20	154.50	187.90	226.00
20-50 years	29.70	36.80	45.00	58.00	128.70	159.50	195.00	251.50
51 years and over	29.10	35.80	44.60	53.40	126.10	155.20	193.30	231.20
FAMILIES:								
FAMILY OF 2⁴:								
20-50 years	68.60	87.00	107.30	134.50	297.30	376.90	465.10	582.80
51 years and over	64.60	83.60	103.60	124.10	280.00	362.40	449.00	537.60
FAMILY OF 4:								
Couple, 20-50 years and children—								
2 and 3-5 years	99.80	125.40	153.90	190.10	432.40	543.40	666.70	823.90
6-8 and 9-11 years	115.20	148.00	184.20	223.30	499.20	641.40	798.20	967.70

¹Basis is that all meals and snacks are purchased at stores and prepared at home. For specific foods and quantities of foods in the Thrifty Food Plan, see *Family Economics and Nutrition Review*, Vol. 13, No.1 (2001), pp. 50-64; for specific foods and quantities of foods in the Low-Cost, Moderate-Cost, and Liberal Plans, see *The Low-Cost, Moderate-Cost, and Liberal Food Plans, 2003 Administrative Report (2003)*. All four Food Plans are based on 1989-91 data and are updated to current dollars using the Consumer Price Index for specific food items.

²All costs are rounded to nearest 10 cents.

³The costs given are for individuals in 4-person families. For individuals in other size families, the following adjustments are suggested: 1-person—add 20 percent; 2-person—add 10 percent; 3-person—add 5 percent; 4-person—no adjustment; 5- or 6-person—subtract 5 percent; 7- (or more) person—subtract 10 percent. To calculate overall household food costs, (1) adjust food costs for each person in household and then (2) sum these adjusted food costs.

⁴Ten percent added for family size adjustment.

Figure B.2: Official USDA food plans, June 2008 (U.S. Department of Agriculture, 2008).



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Department of
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**Official USDA Food Plans: Cost of Food at Home at Four Levels,
U.S. Average, June 2008¹**

Age-gender groups	Weekly cost ²				Monthly cost ²			
	Thrifty plan	Low-cost plan	Moderate-cost plan	Liberal plan	Thrifty plan	Low-cost plan	Moderate-cost plan	Liberal plan
Individuals³								
Child:								
1 year	20.40	26.80	30.80	37.40	88.30	116.30	133.30	162.00
2-3 years	21.60	27.20	33.00	39.90	93.70	117.90	142.80	173.00
4-5 years	22.60	28.50	35.10	42.90	97.90	123.70	152.20	186.00
6-8 years	28.60	38.40	47.40	56.00	124.10	166.40	205.50	242.60
9-11 years	33.20	43.40	55.20	64.90	143.80	188.20	239.20	281.20
Male:								
12-13 years	35.10	49.00	60.70	71.70	151.90	212.10	263.10	310.80
14-18 years	36.50	50.60	62.80	73.00	158.00	219.40	272.20	316.10
19-50 years	39.10	50.10	62.50	76.00	169.30	216.90	270.70	329.40
51-70 years	35.80	47.60	58.10	70.40	155.20	206.30	251.60	305.10
71+ years	35.80	47.10	58.30	71.00	155.30	204.10	252.60	307.80
Female:								
12-13 years	35.30	42.80	51.40	62.30	152.90	185.60	222.50	270.00
14-18 years	35.00	43.00	51.60	63.40	151.80	186.10	223.50	274.70
19-50 years	34.90	43.70	53.50	68.80	151.20	189.60	231.60	298.30
51-70 years	34.50	42.60	52.90	63.20	149.50	184.80	229.10	273.80
71+ years	33.90	42.40	52.90	63.50	146.90	183.70	229.10	275.30
Families								
Family of 2:⁴								
19-50 years	81.30	103.20	127.50	159.30	352.50	447.10	552.60	690.40
51-70 years	77.30	99.30	122.00	147.00	335.10	430.10	528.70	636.80
Family of 4:								
Couple, 19-50 years and children—								
2-3 and 4-5 years	118.20	149.60	184.00	227.70	512.00	648.10	797.30	986.60
6-8 and 9-11 years	135.80	175.60	218.60	265.70	588.30	761.00	947.00	1151.40

¹The Food Plans represent a nutritious diet at four different cost levels. The nutritional bases of the Food Plans are the 1997-2005 Dietary Reference Intakes, 2005 Dietary Guidelines for Americans, and 2005 MyPyramid food intake recommendations. In addition to cost, differences among plans are in specific foods and quantities of foods. Another basis of the Food Plans is that all meals and snacks are prepared at home. For specific foods and quantities of foods in the Food Plans, see *Thrifty Food Plan, 2006* (2007) and *The Low-Cost, Moderate-Cost, and Liberal Food Plans, 2007* (2007). All four Food Plans are based on 2001-02 data and updated to current dollars by using the Consumer Price Index for specific food items.

²All costs are rounded to nearest 10 cents.

³The costs given are for individuals in 4-person families. For individuals in other size families, the following adjustments are suggested: 1-person—add 20 percent; 2-person—add 10 percent; 3-person—add 5 percent; 4-person—no adjustment; 5- or 6-person—subtract 5 percent; 7- (or more) person—subtract 10 percent. To calculate overall household food costs, (1) adjust food costs for each person in household and then (2) sum these adjusted food costs.

⁴Ten percent added for family size adjustment.

APPENDIX C

MODEL ROBUSTNESS CHECKS

This appendix compares the three models with and without bad leverage points. This appendix also compares pooled OLS and Random Effects models with the chosen Fixed-Effects models. Observations with standardized residuals greater than or less than four and predicted leverage values greater than four divided by the sample size were considered to have a bad leverage effect on the model (Sheather, 2009). Tests for leverage points were completed seven times with bad leverage points removed with each iteration until there were zero observations with a bad leverage effect.

In total 61 observations were removed from the model. Most of these were observations from large urban cities. This is due to the fact that counties with large populations had larger absolute values of net SNAP redemptions and therefore larger residual values.

Tables C.1 and C.2 compare the descriptive statistics for the full sample of 1,449 counties with the sample without the bad leverage points with 1,388 counties. Both samples have the same minimum and maximum values for the predictor values. However, removing the bad leverage points reduces the range of the dependent variable, net SNAP redemptions. The sample without the bad leverage points has slightly smaller mean and median values.

The tables on pages 116 to 118 compare the fixed-effects models presented in Chapter 5 with and without the bad leverage points. In all three comparisons the overall results described in Chapter 5 and the conclusions discussed in Chapter 6 remain the same. If anything the robustness checks confirm the importance of super stores and chain stores over supermarkets and convenience stores.

The tables on pages 119 to 122 compare the fixed-effects models presented in Chapter 5 with both pooled OLS and random effects models. The first two comparisons on pages 119 and 120 compare the models with the full sample. The second two comparisons on pages 121 and 122 compare the models without the bad leverage points. All four comparisons support the use of the fixed-effects model with the full sample and confirm that the results presented in Chapter 5 are robust.

Table C.1: Basic descriptive statistics for SNAP and mobility related variables for Texas counties 2005-2011, full sample.

Variable	N	Min	Max	Median	Mean	SD
Net Difference, (dollars)	1,449	-19,156,730	72,852,128	-223,960	186,625	4,261,047
<i>Mobility</i>						
Outbound workers, (jobs)	1,449	46	74,115	1,234	3,838	8,858
Inbound workers, (jobs)	1,449	32	117,253	704	3,863	12,188
Unemployed, (persons)	1,449	48	171,899	671	3,518	12,125
Poverty, (persons)	1,449	354	803,895	4,092	19,541	65,659
<i>Retail Grocery Market</i>						
Super Store/Chain Store	1,449	0	264	1	6	22
Supermarket	1,449	0	128	2	5	13
Convenience Store	1,449	0	1,079	7	27	84
<i>Neighboring Market</i>						
Super Store/Chain Store	1,449	0	381	11	34	65

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

Table C.2: Basic descriptive statistics for SNAP and mobility related variables for Texas counties 2005-2011, without bad leverage points.

Variable	N	Min	Max	Median	Mean	SD
Net Difference, (dollars)	1,388	-7,255,689	61,958,508	-230,589	-53,187	2,950,590
<i>Mobility</i>						
Outbound workers, (jobs)	1,388	46	74,115	1,165	3,101	7,249
Inbound workers, (jobs)	1,388	32	117,253	648	2,821	9,163
Unemployed, (persons)	1,388	48	171,899	637	2,453	9,645
Poverty, (persons)	1,388	354	803,895	3,768	12,530	45,250
<i>Retail Grocery Market</i>						
Super Store/Chain Store	1,388	0	264	1	4	16
Supermarket	1,388	0	128	1	4	10
Convenience Store	1,388	0	1,079	6	18	55
<i>Neighboring Market</i>						
Super Store/Chain Store	1,388	0	381	11	32	62

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

Table C.3: Parameter estimates from Model 1 of net SNAP difference with and without leverage points.

	Full Sample	Without Bad Leverage
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−434.20*** (116.32)	−234.85*** (54.66)
Inbound workers, (jobs)	606.95*** (94.48)	335.95*** (49.70)
Unemployed, (persons)	222.31*** (30.74)	−189.93*** (17.66)
Poverty, (persons)	−14.14 (15.79)	159.43*** (8.16)
Constant	−997,551.62** (373,564.06)	−1,804,539.49*** (174,354.14)
Observations	1449	1388
Adjusted R^2	0.060	0.233

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODES 7

Table C.4: Parameter estimates from Model 2 of net SNAP difference with and without leverage points.

	Full Sample	Without Bad Leverage
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	-501.16*** (109.46)	-394.14*** (53.00)
Inbound workers, (jobs)	312.04*** (86.75)	238.89*** (46.89)
Unemployed, (persons)	-7.88 (33.77)	-322.51*** (21.08)
Poverty, (persons)	-162.48*** (18.32)	83.44*** (11.99)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	372,495.75*** (48,471.71)	397,317.08*** (30,213.75)
Supermarket	343,731.41*** (55,845.30)	269,021.60*** (27,351.66)
Convenience Store	89,759.13*** (7,666.89)	27,746.53*** (4,356.96)
Constant	-2,188,209.33*** (487,624.29)	-2,804,915.16*** (221,052.42)
Observations	1449	1388
Adjusted R^2	0.247	0.355

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table C.5: Parameter estimates from Model 3 of net SNAP difference with and without leverage points.

	Full Sample	Without Bad Leverage
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−436.50*** (110.41)	−274.77*** (55.43)
Inbound workers, (jobs)	281.95** (86.74)	246.67*** (46.15)
Unemployed, (persons)	15.49 (34.23)	−278.01*** (21.89)
Poverty, (persons)	−168.64*** (18.31)	69.74*** (11.99)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	360,618.02*** (48,353.10)	393,994.97*** (29,728.33)
Supermarket	285,823.70*** (57,869.62)	231,123.94*** (27,564.51)
Convenience Store	93,063.52*** (7,685.49)	30,272.87*** (4,304.79)
<i>Neighboring Market</i>		
Super Store/Chain Store	−25,518.11*** (7,104.99)	−20,691.18*** (3,264.92)
Constant	−1,161,365.26* (563,248.69)	−2,371,813.81*** (227,952.52)
Observations	1449	1388
Adjusted R^2	0.255	0.376

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table C.6: Comparing parameter estimates from Models of net SNAP difference, pooled OLS and fixed-effects.

	Pooled OLS	Fixed-Effects
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−457.92*** (37.45)	−436.50*** (110.41)
Inbound workers, (jobs)	90.48** (32.79)	281.95** (86.74)
Unemployed, (persons)	284.58*** (29.47)	15.49 (34.23)
Poverty, (persons)	−82.94*** (9.83)	−168.64*** (18.31)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	217,195.41*** (17,493.38)	360,618.02*** (48,353.10)
Supermarket	105,216.53*** (30,452.39)	285,823.70*** (57,869.62)
Convenience Store	16,884.88*** (4,957.47)	93,063.52*** (7,685.49)
<i>Neighboring Market</i>		
Super Store/Chain Store	−3,669.07* (1,596.02)	−25,518.11*** (7,104.99)
Constant	100,676.02 (89,021.14)	−1,161,365.26* (563,248.69)
Observations	1449	1449
Adjusted R^2	0.569	0.255

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table C.7: Comparing parameter estimates from Models of net SNAP difference, fixed-effects and random-effects.

	Fixed-Effects	Random-Effects
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−436.50*** (110.41)	−518.33*** (57.51)
Inbound workers, (jobs)	281.95** (86.74)	174.38*** (50.36)
Unemployed, (persons)	15.49 (34.23)	126.07*** (22.08)
Poverty, (persons)	−168.64*** (18.31)	−164.21*** (11.67)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	360,618.02*** (48,353.10)	319,851.17*** (23,011.73)
Supermarket	285,823.70*** (57,869.62)	154,382.73*** (32,668.23)
Convenience Store	93,063.52*** (7,685.49)	66,688.79*** (5,452.14)
<i>Neighboring Market</i>		
Super Store/Chain Store	−25,518.11*** (7,104.99)	−4,238.46 (2,794.40)
Constant	−1,161,365.26* (563,248.69)	−30,988.70 (172,590.82)
Observations	1449	1449
Adjusted R^2	0.255	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table C.8: Comparing parameter estimates from Models of net SNAP difference, pooled OLS and fixed-effects, without bad leverage points.

	Pooled OLS	Fixed-Effects
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−335.54*** (26.01)	−274.77*** (55.43)
Inbound workers, (jobs)	268.78*** (26.34)	246.67*** (46.15)
Unemployed, (persons)	466.05*** (26.57)	−278.01*** (21.89)
Poverty, (persons)	−42.39*** (8.20)	69.74*** (11.99)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	−55,769.71*** (15,746.52)	393,994.97*** (29,728.33)
Supermarket	−28,712.66 (22,178.16)	231,123.94*** (27,564.51)
Convenience Store	13,269.04*** (3,787.42)	30,272.87*** (4,304.79)
<i>Neighboring Market</i>		
Super Store/Chain Store	−6,521.34*** (1,002.68)	−20,691.18*** (3,264.92)
Constant	−85,125.08 (55,193.82)	−2,371,813.81*** (227,952.52)
Observations	1388	1388
Adjusted R^2	0.683	0.376

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

Table C.9: Comparing parameter estimates from Models of net SNAP difference, fixed-effects and random-effects, without bad leverage points.

	Fixed-Effects	Random-Effects
	Net Difference, (dollars)	Net Difference, (dollars)
<i>Mobility</i>		
Outbound workers, (jobs)	−274.77*** (55.43)	−203.24*** (38.51)
Inbound workers, (jobs)	246.67*** (46.15)	46.06 (33.79)
Unemployed, (persons)	−278.01*** (21.89)	−53.38** (19.43)
Poverty, (persons)	69.74*** (11.99)	−19.81 (10.22)
<i>Retail Grocery Market</i>		
Super Store/Chain Store	393,994.97*** (29,728.33)	114,341.09*** (20,422.06)
Supermarket	231,123.94*** (27,564.51)	27,186.06 (22,081.64)
Convenience Store	30,272.87*** (4,304.79)	50,431.46*** (3,971.94)
<i>Neighboring Market</i>		
Super Store/Chain Store	−20,691.18*** (3,264.92)	−9,547.12*** (1,932.34)
Constant	−2,371,813.81*** (227,952.52)	−317,183.82** (119,657.73)
Observations	1388	1388
Adjusted R^2	0.376	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Author Calculations, USDA, SAIPES, BLS, BEA, LODS 7

APPENDIX D

REPLICATION CODE

D.1 Main STATA Program Code

D.1.1 Scrubbing SAS Data for Stata Analysis

```
1 clear all          // Clear existing data files
2 macro drop _all    // Drop macros from memory
3 log using work/NPRSNAP_Data_Model3, replace text
4 /*-----*/
5 /* Control Stata                                     */
6 /*-----*/
7 * Generic do file that sets up stata environment
8 clear all          // Clear existing data files
9 macro drop _all    // Drop macros from memory
10 version 12.1       // Set Version
11 set more off       // Tell Stata to not pause for --more-- messages
12 set varabbrev off  // Turn off variable abbreviations
13 set linesize 80   // Set Line Size - 80 Characters for Readability
14 set matsize 5000   // Set Matrix Size
15
16 /*****
17 /* Description of Program                                     */
18 /*****
19 // program:          NPRSNAP_Data_Model3.do
20 // task:             Setup Data for Model 3
21 // project:          Rosenheim 2015 Dissertation
22 // author:           Nathanael Rosenheim \ March 13 2015
23
24 /*****
25 /* Obtain Data                                             */
26 /*****
27 * Data produced by SAS program:
28 * /Posted/DataClean/SAS/Rosenheim2015Model2_26Sept.sas
29 local st = "TX"
30 local state = "Texas"
31 local fyear = "2005"
32 local lyear = "2011"
33 local tyears = 7
34 // Where is the data stored?
35 local datadir = "Posted/DataClean/Stata/"
36 //use 'datadir'Sept26Model2v9'st_'fyear_'lyear'.dta, clear
37
38 * Data from Oct 18 includes number of program participants
39 use 'datadir'Oct18Model2v9'st_'fyear_'lyear'.dta, clear
40
41 /*-----*/
```

```

42 /* Setting panel data */
43 /*-----*/
44 * In this case §countyŒ represents the entities or panels (i)
45 * §yearŒ Represents the time variable (t).
46 * Panel variables need to be real not string
47
48 generate panel = real(fips_county)
49 sort panel year
50
51 xtset panel year
52 * Save first and last year for future programs
53 local yrmin = r(tmin)
54 local yrmax = r(tmax)
55
56 /*****/
57 /* Scrub Data */
58 /*****/
59 /*-----*/
60 /* Create Year Dummies */
61 /*-----*/
62 /* Generates dummy variable for each year */
63 tabulate year, generate(dyear)
64
65 /*-----*/
66 /* Make a balanced panel */
67 /*-----*/
68 /* Drop variables with missing redemption data */
69 drop if redamt == .
70 bysort fips_county: gen nfips=[_N]
71
72 keep if nfips=='tyears'
73
74 *How many counties are in the panel?
75 bysort fips_county: gen nvals = _n == 1
76 quietly count if nvals
77 local cnty_cnt = r(N)
78
79 /*-----*/
80 /* Create Dependent Variable */
81 /*-----*/
82 label variable redamt "Redeemed, (\\$)"
83 label variable bea_snap "Distributed, (\\$)"
84
85 /* Round 1 - dependent variable */
86 gen Diff_SNAP_bea = redamt - bea_snap
87 label variable Diff_SNAP_bea "Net Difference, (dollars)"
88
89 local dep_var Diff_SNAP_bea
90
91 /*-----*/
92 /* Create Explanatory Variable - Mobility of Workers */
93 /*-----*/
94 /*
95 OCC represents the number of low-income jobs that

```

```

96 commute out-of-county in county i and in year t
97 These low-income workers have a home-work activity space that is larger than
   their
98 home county.
99
100 ICC is the number of low-income jobs that commute into county i
101 and in year
102 These low-income workers have a home-work activity space that is larger than
   their
103 home county.
104 */
105 /*
106 Data generated using LODES 7 Primary Jobs
107 SE01 = Workers Earning $1,250 per month or less
108 Out of County Commuters (OCC) is equivalent to
109 Living in the County but Employed Outside = Living in the County - Living &
   Employed in the County
110 */
111 gen occse01 = httotal_se01 - sum_se01
112 label variable occse01 "Outbound workers, (jobs)"
113
114 /*
115 Data generated using LODES 7 Primary Jobs
116 SE01 = Workers Earning $1,250 per month or less
117 Into County Commuter (ICC) is equivalent to
118 Employed in the Selection Area but Living Outside = Living in the County -
   Living & Employed in the County
119 */
120 gen iccse01 = wttotal_se01 - sum_se01
121 label variable iccse01 "Inbound workers, (jobs)"
122
123 label variable t_pop "Total Population, (persons)"
124 label variable unemployed "Unemployed, (persons)"
125 label variable eall "Poverty, (persons)"
126
127 saveold "Work/NPRSNAP_Model1_Model2_2015-3-11.dta", replace
128
129 /*-----*/
130 /* Add Model 3 Spatial Lag Variables */
131 /*-----*/
132 use "Work/NPRSNAP_Model1_Model2_2015-3-11.dta", clear
133 sort fips_county year
134
135 merge fips_county year using "Posted_2/NPRSNAP_StoreTypeLag_TX_2005_2011.dta"
136 drop if _merge == 2
137
138 saveold "Work/NPRSNAP_Model1_3_2015-3-13.dta", replace
139
140 /*-----*/
141 /* MODEL 1 */
142 /*-----*/
143 local modell_expvars occse01 iccse01 unemployed eall
144
145 /*-----*/

```



```

146 /* MODEL 2 */
147 /*-----*/
148 local model2_expvars meanss meansm meansc meanco
149
150 /*-----*/
151 /* MODEL 3 */
152 /*-----*/
153 local model3_expvars lag_meanss lag_meansm lag_meansc lag_meanco
154
155
156 /*-----*/
157 /* Demean Explanatory Variables */
158 /*-----*/
159
160 // For bacground on the code below see:
161 // program: /NPRSNAP/Work/Scratch/UnderstandingXtreg.do
162
163 gen one=1
164 local idvar panel
165 local fixedvars 'dep_var' 'model1_expvars' 'model2_expvars' 'model3_expvars'
166 foreach var of varlist 'fixedvars' {
167     * Build mean value of var by id
168     bys 'idvar': gen double sum_'var'i = sum('var')
169     bys 'idvar': gen double count_'var'i = sum(one)
170     bys 'idvar': gen double buildmeani_'var' = sum_'var'i/count_'var'i
171     * summarize to save overall mean value
172     summarize 'var'
173     bys 'idvar': gen mean_'var' = r(mean)
174
175     * find centered values for var by id
176     bys 'idvar': gen mean_'var'i = buildmeani_'var'[_N]
177     bys 'idvar': gen center_'var'i = 'var' - mean_'var'i
178     bys 'idvar': gen dm_'var' = center_'var'i + mean_'var'
179
180     * label demeaned variables
181     local l'var' : variable label 'var'
182     label variable dm_'var' "Demeaned 'l'var'"
183 }
184
185 * Create Local for model 1 and model 2 demeaned values
186 forvalues i = 1/3 {
187     foreach var of varlist 'model'i'_expvars' {
188         local demeaned_m'i' 'demeaned_m'i'' dm_'var'
189     }
190 }
191 saveold "Work/NPRSNAP_Data_Model3_2015-3-13.dta", replace
192
193 /*****
194 /* End Log */
195 /*****
196
197 log close
198 * Exit Program
199 exit

```

D.1.2 Tables and Figures for Chapter 4

```
1 clear all           // Clear existing data files
2 macro drop _all    // Drop macros from memory
3 capture log close
4 global filename "NPRSNAP_Ch4TablesFigures-2015-04-29"
5 log using work/${filename}, replace text
6 /*-----*/
7 /* Control Stata                                     */
8 /*-----*/
9 * Generic do file that sets up stata environment
10 version 12.1      // Set Version
11 set more off      // Tell Stata to not pause for --more-- messages
12 set varabbrev off // Turn off variable abbreviations
13 set linesize 80  // Set Line Size - 80 Characters for Readability
14 set matsize 5000 // Set Matrix Size
15
16 /*****/
17 /* Description of Program                               */
18 /*****/
19 // program:      NPRSNAP_Ch4TablesFigures-2015-04-29.do
20 // task:         Create Tables for Dissertation Discussion
21 // project:      Rosenheim 2015 Dissertation
22 // author:       Nathanael Rosenheim \ March 13 2015
23
24 /*****/
25 /* Obtain Data                                         */
26 /*****/
27 use "Work/NPRSNAP_Model1_3_2015-3-13.dta", clear
28 local st = "TX"
29 local state = "Texas"
30 local fyear = "2005"
31 local lyear = "2011"
32 local tyears = 7
33
34 /*-----*/
35 /* Setting panel data                                   */
36 /*-----*/
37 * In this case $countyṽ represents the entities or panels (i)
38 * $yearṽ Represents the time variable (t).
39 * Panel variables need to be real not string
40
41 sort panel year
42
43 xtset panel year
44 * Save first and last year for future programs
45 local yrmin = r(tmin)
46 local yrmax = r(tmax)
47
48 /*-----*/
49 /* Set Provenance                                       */
50 /*-----*/
51
52 global provenance "Provenance: ${filename}.do 'c(filename)' 'c(current_date)'"
```

```

53
54 /*-----*/
55 /* Create Dependent Variable - Within County Redemptions */
56 /*-----*/
57 local dep_var Diff_SNAP_bea
58 /* Demeaned - dependent variable */
59 local dep_var_label: variable label 'dep_var'
60 label variable dm_'dep_var' "Demeaned 'dep_var_label'"
61
62 /*-----*/
63 /* MODEL 1 */
64 /*-----*/
65 local model1_expvars occse01 iccse01 unemployed eall
66
67 /*-----*/
68 /* MODEL 2 */
69 /*-----*/
70 local model2_expvars meanss meansm meansc
71
72 /*-----*/
73 /* MODEL 3 */
74 /*-----*/
75 local model3_expvars lag_meanss lag_meansm lag_meansc
76
77
78 /*-----*/
79 /* Demeaned Variables for MODELS 1-3 */
80 /*-----*/
81
82 * Create Local for model 1 - model 3 demeaned values
83 forvalues i = 1/3 {
84   foreach var of varlist 'model'i'_expvars' {
85     local demeaned_m'i' 'demeaned_m'i'' dm_'var'
86   }
87 }
88
89
90 /*-----*/
91 /* Compare correlation matrix */
92 /*-----*/
93
94 pwcorr 'model1_expvars' 'model2_expvars' 'model3_expvars', listwise sig star(5)
95 pwcorr 'demeaned_m1' 'demeaned_m2' 'demeaned_m3', listwise sig star(5)
96
97 pwcorr 'model1_expvars'
98 pwcorr 'demeaned_m1'
99
100 pwcorr 'model2_expvars'
101 pwcorr 'demeaned_m2'
102
103 pwcorr 'model3_expvars'
104 pwcorr 'demeaned_m3'
105
106 pwcorr 'model1_expvars' 'model2_expvars'

```

```

107 pworth 'demeaned_m1' 'demeaned_m2'
108
109 /*-----*/
110 /* Set Formats for Output Tables and Graphs */
111 /*-----*/
112 * What format would work for the stats?
113 local stat_fmt "%18.0fc"
114 * What format would work for the Model Tables?
115 local coef_fmt "%14.2fc"
116 local se_fmt "%14.2fc"
117
118 * set style for reference categories in output tables
119 local dmrefcat refcat(dm_occse01 "\emph{Mobility}" dm_meanss "\emph{Retail
    Grocery Market}" dm_lag_meanss "\emph{Neighboring Market}",nolabel)
120 * set style for reference categories in output tables
121 local refcat refcat(occse01 "\emph{Mobility}" meanss "\emph{Retail Grocery
    Market}" lag_meanss "\emph{Neighboring Market}",nolabel)
122 /*-----*/
123 /* Clean up variable labels */
124 /*-----*/
125 * Remove Lag of part of label
126 foreach v of varlist 'model3_expvars' {
127     local l'v' : variable label 'v'
128     local temp_label=substr("`l'v'",8,.)
129     label variable 'v' "`temp_label'"
130 }
131
132 * Add an indentation for LaTeX Output
133 foreach v of varlist 'model1_expvars' 'model2_expvars' 'model3_expvars' {
134     label variable 'v' "\hspace{0.1cm} ': variable label 'v'"
135 }
136 * Labels are too long for table
137 * Add an indentation for LaTeX Output
138 * Remove Demeaned part of label
139 foreach v of varlist 'demeaned_m1' 'demeaned_m2' 'demeaned_m3' {
140     local l'v' : variable label 'v'
141     local temp_label=substr("`l'v'",9,.)
142     label variable 'v' "`temp_label'"
143 }
144 * Remove Lag of part of label
145 foreach v of varlist 'demeaned_m3' {
146     local l'v' : variable label 'v'
147     local temp_label=substr("`l'v'",8,.)
148     label variable 'v' "`temp_label'"
149 }
150 label variable dm_Diff_SNAP_bea "Demeaned Diff, (\$)"
151
152 * Add indentation for LaTeX Output
153 foreach v of varlist 'demeaned_m1' 'demeaned_m2' 'demeaned_m3' {
154     label variable 'v' "\hspace{0.1cm} ': variable label 'v'"
155 }
156
157 /*-----*/
158 /* Start LaTeX File */

```

```

159 /*-----*/
160 local depvartitle = "Net SNAP difference"
161 local depvarunits = "in dollars"
162 local RoundDepVar = "NetSNAPDiffm3"
163
164 local dm_depvartitle = "Demeaned 'depvartitle'"
165 local LaTeXFile = "Work/Scratch/${filename}.tex"
166 * Currently I have my project saved in a different place than the latex files
167 local PrjDir = "../..../MyProjects/NPRSNAp/"
168 * Where should STATA save graphic files?
169 * Note * where working directory is set
170 local output_fig = "Work/Scratch/"
171
172 * Create a handle for the file
173 tempname dst
174 * Add comment to Latex file to keep track of model and date that produced table
175 local addcomment1 "% 'prjct' 'time_string'"
176 file open 'dst' using 'LaTeXFile', write replace
177 file write 'dst' "'addcomment1'"_n
178 file close 'dst'
179
180 /*-----*/
181 /* Generate Descriptive Statistics - Net Difference */
182 /*-----*/
183 * Create Descriptive Statistics for dependent variable and demeaned dep var
184 forvalues i = 1/2 {
185   if 'i' == 1 {
186     local demeaned ""
187   }
188   else {
189     local demeaned "dm_"
190   }
191
192 * File name for descriptive statistics output
193 local depvardstatsfile = "Work/Scratch/${filename}_'demeaned'
    Dep_Var_DescriptiveStats.tex"
194 * Caption for Table
195 local depvarcaption = "Summary of "'demeaned'depvartitle' ('depvarunits')."
196 * Table Headings - I am having a real problem getting estout to make
197 * a heading row that I am happy with. Here is the fix... ugly but it works.
198 * Tokenize the heading rows:
199 tokenize Year N Min Max Median Mean SD
200
201 tempname dst2 // Create a handle for the file
202 file open 'dst2' using 'depvardstatsfile', write replace
203 file write 'dst2' "\centering '1' & \multicolumn{1}{c}{'2'} &"
204 file write 'dst2' "\multicolumn{1}{c}{'3'} & \multicolumn{1}{c}{'4'}"
205 file write 'dst2' " & \multicolumn{1}{c}{'5'} & \multicolumn{1}{c}{'6'}"
206 file write 'dst2' "& \multicolumn{1}{c}{'7'}\\"_n
207 file close 'dst2'
208 tokenize // Reset local tokenize macros
209
210 eststo clear
211 estpost tabstat 'demeaned'dep_var', by(year) ///

```

```

212             statistics(min max p50 mean sd count)
213 esttab using 'depvardstatsfile' ///
214             , append fragment ///
215             cells("count(fmt(%16.0fc)) min(fmt('stat_fmt')) max(fmt('stat_fmt')) p50
                (fmt('stat_fmt')) mean(fmt('stat_fmt')) sd(fmt('stat_fmt'))") ///
216             label booktabs nonum gaps noobs collabels(none) nomtitles
217 eststo clear
218
219 file open 'dst' using 'LaTeXFile', write append
220 file write 'dst' "%%%%%%%%%" _n
221 file write 'dst' "\begin{table}[!hbp]" _n
222 file write 'dst' "\centering" _n
223 file write 'dst' "\caption{'depvarcaption'}" _n
224 file write 'dst' "\label{table:Summaryof'demeaned'RoundDepVar'}" _n
225 file write 'dst' "\estauto{'PrjDir' 'depvardstatsfile'}{7}{r}" _n
226 file write 'dst' "\figsource{Author Calculations, USDA, BEA}" _n
227 file write 'dst' "% $provenance" _n
228 file write 'dst' "\end{table}" _n
229 file write 'dst' "%%%%%%%%%" _n
230 file close 'dst'
231 }
232
233 /*-----*/
234 /* Generate Descriptive Statistics - Explanatory Variables */
235 /*-----*/
236 * File name for descriptive statistics output
237 local tablefile = "Work/Scratch/${filename}_Exp_Var_DescriptiveStats.tex"
238 * Caption for Table
239 local depvarcaption = "Basic Descriptive Statistics for SNAP and Mobility
                Related Variables for 'state' Counties 'fyear'-'lyear'"
240 * Table Headings - I am having a real problem getting estout to make
241 * a heading row that I am happy with. Here is the fix... ugly but it works.
242 * Tokenize the heading rows:
243 tokenize Variable N Min Max Median Mean SD
244
245 tempname dst2 // Create a handle for the table file
246 file open 'dst2' using 'tablefile', write replace
247 file write 'dst2' "\centering '1' & \multicolumn{1}{c}{ '2' } &"
248 file write 'dst2' "\multicolumn{1}{c}{ '3' } & \multicolumn{1}{c}{ '4' }"
249 file write 'dst2' " & \multicolumn{1}{c}{ '5' } & \multicolumn{1}{c}{ '6' }"
250 file write 'dst2' "& \multicolumn{1}{c}{ '7' }\\\" _n
251 file close 'dst2'
252 tokenize // Reset local tokenize macros
253
254 eststo clear
255 estpost tabstat 'model1_expvars' 'model2_expvars' 'model3_expvars', ///
256             statistics(min max p50 mean sd count) columns(statistics)
257
258 esttab using 'tablefile' ///
259             , append fragment ///
260             'refcat' ///
261             cells("count(fmt(%16.0fc)) min(fmt(%16.0fc)) max(fmt(%16.0fc)) p50(fmt
                (%16.0fc)) mean(fmt(%16.0fc)) sd(fmt(%16.0fc))") ///
262             label booktabs nonum gaps noobs collabels(none) nomtitles

```

```

263 eststo clear
264
265 file open 'dst' using 'LaTeXFile', write append
266 file write 'dst' "%%%%%%%%%" _n
267 file write 'dst' "\begin{landscape}" _n
268 file write 'dst' "\begin{table}[!hbp]" _n
269 file write 'dst' "\centering" _n
270 file write 'dst' "\caption{depvarcaption}" _n
271 file write 'dst' "\label{table:SummaryofExpVars}" _n
272 file write 'dst' "\estauto{'PrjDir' 'tablefile'}{7}{r}" _n
273 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
7}" _n
274 file write 'dst' "% $provenance" _n
275 file write 'dst' "\end{table}" _n
276 file write 'dst' "\end{landscape}" _n
277 file write 'dst' "%%%%%%%%%" _n
278 file close 'dst'
279
280 /*-----*/
281 /* Generate Descriptive Statistics - Demeaned Explanatory Variables */
282 /*-----*/
283 * File name for descriptive statistics output
284 local tablefile = "Work/Scratch/${filename}_DMExp_Var_DescriptiveStats.tex"
285 * Caption for Table
286 local depvarcaption = "Basic Descriptive Statistics for SNAP and Mobility
Related Demeaned Variables for 'state' Counties 'fyear'-'lyear'"
287 * Table Headings - I am having a real problem getting estout to make
288 * a heading row that I am happy with. Here is the fix... ugly but it works.
289 * Tokenize the heading rows:
290 tokenize Variable N Min Max Median Mean SD Demeaned
291
292 tempname dst2 // Create a handle for the table file
293 file open 'dst2' using 'tablefile', write replace
294 file write 'dst2' "\centering '8' '1' & \multicolumn{1}{c}{ '2' } &"
295 file write 'dst2' "\multicolumn{1}{c}{ '3' } & \multicolumn{1}{c}{ '4' }"
296 file write 'dst2' " & \multicolumn{1}{c}{ '5' } & \multicolumn{1}{c}{ '6' }"
297 file write 'dst2' "& \multicolumn{1}{c}{ '7' } \\" _n
298 file close 'dst2'
299 tokenize // Reset local tokenize macros
300
301 /*-----*/
302 /* Store tabstat estimates */
303 /*-----*/
304 eststo clear
305 estpost tabstat 'demeaned_m1' 'demeaned_m2' 'demeaned_m3', ///
306 statistics(min max p50 mean sd count) columns(statistics)
307
308 esttab using 'tablefile' ///
309 , append fragment ///
310 'dmrefcat' ///
311 cells("count(fmt(%16.0fc)) min(fmt(%16.0fc)) max(fmt(%16.0fc)) p50(fmt
(%16.0fc)) mean(fmt(%16.0fc)) sd(fmt(%16.0fc))") ///
312 label booktabs nonum gaps noobs collabels(none) nomtitles
313 eststo clear

```

```

314
315 file open 'dst' using 'LaTeXFile', write append
316 file write 'dst' "%%%%%%%%%" _n
317 file write 'dst' "\begin{landscape}" _n
318 file write 'dst' "\begin{table}[!hbp]" _n
319 file write 'dst' "\centering" _n
320 file write 'dst' "\caption{'depvarcaption'}" _n
321 file write 'dst' "\label{table:SummaryofDMExpVars}" _n
322 file write 'dst' "\estauto{'PrjDir' 'tablefile'}{7}{r}" _n
323 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
7}" _n
324 file write 'dst' "% $provenance" _n
325 file write 'dst' "\end{table}" _n
326 file write 'dst' "\end{landscape}" _n
327 file write 'dst' "%%%%%%%%%" _n
328 file close 'dst'
329
330
331 /*-----*/
332 /* Summarize Variables by Year */
333 /*-----*/
334 * Tables with all years are too wide, split tables into 2 groups
335 local splityear1 = 2007
336 local splityear2 = 2009
337 * Tokenize will make it possible to call years in different groups
338 tokenize 'yrmin' 'splityear1' 'splityear2' 'yrmax'
339
340 * Two groups
341 forvalues i = 1/3 {
342     local startyr = 'i' // Will call token '1' or '2'
343     local i2 = 'i'+ 1
344     local endyr = 'i2' // Will call token '2' or '3'
345     * File name for descriptive statistics output
346     local tablefile = "Work/Scratch/${filename}_Sum_Var_DescriptiveStats'
startyr'_endyr'.tex"
347     * Caption for Table
348     local depvarcaption = "Sum of SNAP and Mobility Related Variables for '
state' Counties by year."
349
350     eststo clear
351     estpost tabstat t_pop redamt bea_snap 'dep_var' 'modell_expvars' '
model2_expvars' 'model3_expvars' ///
352         if year>='startyr' & year<='endyr', by(year) ///
353         statistics(sum) columns(statistics) listwise nototal
354
355     esttab using 'tablefile' ///
356         , replace fragment ///
357         'refcat' ///
358         label modelwidth(20) main(sum %16.0fc) nostar unstack ///
359         nogaps collabels(none) nomtitle nonumber noobs
360     eststo clear
361
362     file open 'dst' using 'LaTeXFile', write append

```



```

363     file write 'dst'
364         "%%" _n
365 //file write 'dst' "\begin{landscape}" _n
366 file write 'dst' "\begin{table}[!hbp]" _n
367 file write 'dst' "\centering" _n
368 file write 'dst' "\caption{'depvarcaption'}" _n
369 file write 'dst' "\label{table:SummaryofExpvarsbyyear}" _n
370 file write 'dst' "\estauto{'PrjDir' 'tablefile'}{5}{r}" _n
371 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA
372     , LODES 7}" _n
373 file write 'dst' "% $provenance" _n
374 file write 'dst' "\end{table}" _n
375 //file write 'dst' "\end{landscape}" _n
376 file write 'dst'
377     "%%" _n
378 file close 'dst'
379 }
380 /*-----*/
381 /* Generate Descriptive Statistics by Quintile */
382 /*-----*/
383 * File name for descriptive statistics output
384 local tablefile = "Work/Scratch/${filename}_Qunitiles1'dep_var'.tex"
385 * Caption for Table
386 local depvarcaption = "Quintiles of Net Difference: Mean of SNAP and Mobility
387     Related Variables."
388
389 xtile 'dep_var'quint = 'dep_var', nquantiles(5)
390
391 estpost tabstat t_pop redamt bea_snap 'dep_var' 'modell_expvars' ///
392     'model2_expvars', by('dep_var'quint) ///
393     statistics(mean sd) columns(statistics) listwise
394
395 esttab using 'tablefile' ///
396     , replace fragment ///
397     'refcat' ///
398     label modelwidth(20) main(mean %16.0fc) aux(sd %16.0fc) nostar unstack
399     ///
400     nogaps collabels(none) nomtitle nonumber noobs
401
402 eststo clear
403
404 file open 'dst' using 'LaTeXFile', write append
405 file write 'dst' "%%" _n
406 file write 'dst' "\begin{landscape}" _n
407 file write 'dst' "\begin{table}[!hbp]" _n
408 file write 'dst' "\centering" _n
409 file write 'dst' "\caption{'depvarcaption'}" _n
410 file write 'dst' "\label{table:Quintilespl}" _n
411 file write 'dst' "\estauto{'PrjDir' 'tablefile'}{6}{r}" _n
412 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
413     7}" _n
414 file write 'dst' "\fignote{Standard deviation values in parentheses}" _n

```

```

411 file write 'dst' "% $provenance" _n
412 file write 'dst' "\end{table}" _n
413 file write 'dst' "\end{landscape}" _n
414 file write 'dst' "%%%%%%%%%" _n
415 file close 'dst'
416
417 * Part 2
418 * File name for descriptive statistics output
419 local tablefile = "Work/Scratch/${filename}_Qunitiles2'dep_var'.tex"
420 * Caption for Table
421 local depvarcaption = "Quintiles of Net Difference: Mean of Neighboring Market
    Variables."
422
423 estpost tabstat 'model3_expvars' year, by('dep_var'quint) ///
424     statistics(mean sd) columns(statistics) listwise
425
426 esttab using 'tablefile' ///
427     , replace fragment ///
428     'refcat' ///
429     label modelwidth(20) main(mean %16.0fc) aux(sd %16.0fc) nostar unstack
    ///
430     nogaps collabels(none) nomtitle nonumber noobs
431 eststo clear
432
433 file open 'dst' using 'LaTeXFile', write append
434 file write 'dst' "%%%%%%%%%" _n
435 file write 'dst' "\begin{landscape}" _n
436 file write 'dst' "\begin{table}[!hbp]" _n
437 file write 'dst' "\centering" _n
438 file write 'dst' "\caption{'depvarcaption'}" _n
439 file write 'dst' "\label{table:Quintilesp2}" _n
440 file write 'dst' "\estauto{'PrjDir' 'tablefile'}{6}{r}" _n
441 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
    7}" _n
442 file write 'dst' "\fignote{Standard deviation values in parentheses}" _n
443 file write 'dst' "% $provenance" _n
444 file write 'dst' "\end{table}" _n
445 file write 'dst' "\end{landscape}" _n
446 file write 'dst' "%%%%%%%%%" _n
447 file close 'dst'
448
449
450 /*-----*/
451 /* Generate Descriptive Statistics by Quintile - Demeaned Dep Var */
452 /*-----*/
453 * File name for descriptive statistics output
454 local tablefile = "Work/Scratch/${filename}_Qunitiles1dm'dep_var'.tex"
455 * Caption for Table
456 local depvarcaption = "Quintiles of Demeaned Net Difference: Range (Min-Max) of
    SNAP and Mobility Related Variables."
457
458 xtile dm_'dep_var'quint = dm_'dep_var', nquantiles(5)
459
460

```

```

461 estpost tabstat t_pop redamt bea_snap dm_`dep_var' `demeaned_m1' `demeaned_m2'
    ///
462     , by(dm_`dep_var' quint) ///
463     statistics(mean sd) columns(statistics) listwise
464
465 esttab using `tablefile' ///
466     , replace fragment ///
467     `dmrefcat' ///
468     label modelwidth(20) main(mean %16.0fc) aux(sd %16.0fc) nostar unstack
    ///
469     nogaps collabels(none) nomtitle nonumber noobs
470 eststo clear
471
472 file open `dst' using `LaTeXFile', write append
473 file write `dst' "%%%%%%%%%" _n
474 file write `dst' "\begin{landscape}" _n
475 file write `dst' "\begin{table}[!hbp]" _n
476 file write `dst' "\centering" _n
477 file write `dst' "\caption{'depvarcaption'}" _n
478 file write `dst' "\label{table:Quintilespldm}" _n
479 file write `dst' "\estauto{PrjDir`tablefile'}{6}{r}" _n
480 file write `dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODS
    7}" _n
481 file write `dst' "\fignote{Standard deviation values in parentheses}" _n
482 file write `dst' "% $provenance" _n
483 file write `dst' "\end{table}" _n
484 file write `dst' "\end{landscape}" _n
485 file write `dst' "%%%%%%%%%" _n
486 file close `dst'
487
488 * Part 2
489 * File name for descriptive statistics output
490 local tablefile = "Work/Scratch/${filename}_qunitiles2dm_`dep_var'.tex"
491 * Caption for Table
492 local depvarcaption = "Quintiles of Demeaned Net Difference: Range (Min-Max) of
    Neighboring Market Variables."
493
494 estpost tabstat `demeaned_m3' year, by(dm_`dep_var' quint) ///
495     statistics(mean sd) columns(statistics) listwise
496
497 esttab using `tablefile' ///
498     , replace fragment ///
499     `dmrefcat' ///
500     label modelwidth(20) main(mean %16.0fc) aux(sd %16.0fc) nostar unstack
    ///
501     nogaps collabels(none) nomtitle nonumber noobs
502 eststo clear
503
504 file open `dst' using `LaTeXFile', write append
505 file write `dst' "%%%%%%%%%" _n
506 file write `dst' "\begin{landscape}" _n
507 file write `dst' "\begin{table}[!hbp]" _n
508 file write `dst' "\centering" _n
509 file write `dst' "\caption{'depvarcaption'}" _n

```

```

510 file write 'dst' "\\label{table:Quintilesp2dm}" _n
511 file write 'dst' "\\estauto{'PrjDir' 'tablefile'}{6}{r}" _n
512 file write 'dst' "\\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
    7}" _n
513 file write 'dst' "\\fignote{Standard deviation values in parentheses}" _n
514 file write 'dst' "% $provenance" _n
515 file write 'dst' "\\end{table}" _n
516 file write 'dst' "\\end{landscape}" _n
517 file write 'dst' "%%%%%%%%%" _n
518 file close 'dst'
519
520
521 /*-----*/
522 /* Histogram of Dependent Variable */
523 /*-----*/
524
525 * Create histograms for dependent variable and demeaned dep var
526 forvalues i = 1/2 {
527   if 'i' == 1 {
528     local demeaned ""
529   }
530   else {
531     local demeaned "dm_"
532   }
533
534 /*-----*/
535 /* Set Scales Graphs */
536 /*-----*/
537 * Scale for histograms with all observations
538 local y1_scale = 2000
539 local y1_step = 500
540 * Scale for histograms by year
541 local y2_scale = 200
542 local y2_step = 100
543
544 * Summarize to store min and max scalars for all years
545 * This will make all of the graphs on the same scale
546 quietly summarize 'demeaned' 'dep_var'
547 local min = r(min)
548 local min_strng = string('min', " 'stat_fmt' ")
549 local max = r(max)
550 local max_strng = string('max', " 'stat_fmt' ")
551 local mean = r(mean)
552 local mean_strng = string('mean', " 'stat_fmt' ")
553 local sd = r(sd)
554
555 * LaTeX using PDFLatex does not recognize *.eps - *.pdf is the best option
556 local graph_name = "${filename}_hist'demeaned'RoundDepVar"
557 * Caption for Graph
558 local graphcaption = "Histogram of 'demeaned' depvar title ('depvarunits')."
559 histogram 'demeaned' 'dep_var', frequency normal kdensity ///
560     xlabel('min' " 'min_strng' " 'mean' " 'mean_strng' " 'max' " 'max_strng' ")
561     ///
562     xtick('min' ('sd') 'max') ///

```

```

562         xscale(range('min' 'max')) ///
563         ylabel(0('y1_step')'y1_scale') ///
564         scheme(lean2)
565 graph export "'output_fig'graph_name'.pdf"', replace
566
567 file open 'dst' using 'LaTeXFile', write append
568 file write 'dst' "%%%%%%%%%" _n
569 file write 'dst' "\begin{figure}[p]" _n
570 file write 'dst' "\centering" _n
571 file write 'dst' "\caption{'graphcaption'}" _n
572 file write 'dst' "\label{figure:'graph_name'}" _n
573 file write 'dst' "\includegraphics[width=5in]{'PrjDir'output_fig'graph_name'.
    pdf}" _n
574 file write 'dst' "\caption{Author Calculations, USDA, BEA}" _n
575 file write 'dst' "% $provenance" _n
576 file write 'dst' "\end{figure}" _n
577 file write 'dst' "%%%%%%%%%" _n
578 file close 'dst'
579
580 * Normality Test
581 summarize 'demeaned' 'dep_var', detail
582 sktest 'demeaned' 'dep_var'
583
584 /*
585 /*-----*/
586 /* Histogram of Dependent Variable - By Year */
587 /*-----*/
588
589 * LaTeX using PDFLatex does not recognize *.eps - *.pdf is the best option
590 local graph_name = "${filename}_histbyyr'demeaned'RoundDepVar'"
591 * Caption for Graph
592 local graphcaption = "Histogram of "'demeaned'depvar' by Year ('depvarunits
    ')."
593
594 local graphnames ""
595 forvalues yr = 'yrmin'/'yrmax' {
596     quietly summarize dm_'dep_var' if year == 'yr'
597     local min'yr' = r(min)
598     local max'yr' = r(max)
599     local sd'yr' = r(sd)
600     histogram 'demeaned' 'dep_var' if year == 'yr', ///
601         frequency normal kdensity bin(20) ///
602         name(g'yr') nodraw ///
603         subtitle('yr') ///
604         ytitle("") xtitle("") ///
605         xlabel('min'yr' "Min" 'max'yr' "Max") ///
606         xscale(range('min' 'max')) ///
607         xtick('min' ('sd') 'max') ///
608         ylabel(0('y2_step') 'y2_scale') ///
609         yscale(range(0 'y2_step')) ///
610         ytick(0('y2_step') 'y2_scale') ///
611         scheme(lean2)
612     local graphnames 'graphnames' g'yr'
613 }

```

```

614 graph combine 'graphnames', ///  

615         cols(2) xsize(15) ysize(20) scheme(lean2)  

616 graph export "'output_fig'graph_name'.pdf"', replace  

617 graph drop 'graphnames'  

618  

619 file open 'dst' using 'LaTeXFile', write append  

620 file write 'dst' "%%%%%%%%%" _n  

621 file write 'dst' "\begin{figure}[p]" _n  

622 file write 'dst' "\centering" _n  

623 file write 'dst' "\caption{'graphcaption'}" _n  

624 file write 'dst' "\label{figure:'graph_name'}" _n  

625 file write 'dst' "\includegraphics[width=\textwidth]{'PrjDir'output_fig'  

        graph_name'.pdf}" _n  

626 file write 'dst' "\begin{flushleft}" _n  

627 file write 'dst' "\figsource{Author Calculations, USDA, BEA} \par" _n  

628 file write 'dst' "%\fignote{X-axis scale from 'min_strng' to 'max_strng'. \par"  

        _n  

629 file write 'dst' "%Min and Max represent individual years. \par"_n  

630 file write 'dst' "%Y-axis frequency \par}" _n  

631 file write 'dst' "\end{flushleft}" _n  

632 file write 'dst' "% $provenance" _n  

633 file write 'dst' "\end{figure}" _n  

634 file write 'dst' "%%%%%%%%%" _n  

635 file close 'dst'  

636 */  

637 }  

638 /*****/  

639 /* End Log */  

640 /*****/  

641  

642 log close  

643 * Exit Program  

644 exit

```

D.1.3 Tables for Chapter 5

```
1 clear all // Clear existing data files
2 macro drop _all // Drop macros from memory
3 capture log close
4 global filename "NPRSNAP_Ch5TablesFigures-2015-05-14"
5 log using work/${filename}, replace text
6 /*-----*/
7 /* Control Stata */
8 /*-----*/
9 * Generic do file that sets up stata environment
10 version 12.1 // Set Version
11 set more off // Tell Stata to not pause for --more-- messages
12 set varabbrev off // Turn off variable abbreviations
13 set linesize 80 // Set Line Size - 80 Characters for Readability
14 set matsize 5000 // Set Matrix Size
15
16 /*****/
17 /* Description of Program */
18 /*****/
19 // program: NPRSNAP_Ch5TablesFigures-2015-05-14.do
20 // task: Create Tables for Dissertation Discussion
21 // project: Rosenheim 2015 Dissertation
22 // author: Nathanael Rosenheim \ May 14 2015
23
24 /*****/
25 /* Obtain Data */
26 /*****/
27 use "Work/NPRSNAP_Model1_3_2015-3-13.dta", clear
28 local st = "TX"
29 local state = "Texas"
30 local fyear = "2005"
31 local lyear = "2011"
32 local tyears = 7
33
34 /*-----*/
35 /* Set Formats for Output Tables and Graphs */
36 /*-----*/
37 * What format would work for the stats?
38 local stat_fmt "%18.0fc"
39 * What format would work for the Model Tables?
40 local coef_fmt "%14.2fc"
41 local se_fmt "%14.2fc"
42
43 /*-----*/
44 /* Setting panel data */
45 /*-----*/
46 * In this case $county $\bar{i}$  represents the entities or panels (i)
47 * $year $\bar{t}$  Represents the time variable (t).
48 * Panel variables need to be real not string
49
50 sort panel year
51
52 xtset panel year
```

```

53 * Save first and last year for future programs
54 local yrmin = r(tmin)
55 local yrmax = r(tmax)
56
57 /*-----*/
58 /* Set Provenance */
59 /*-----*/
60
61 global provenance "Provenance: ${filename}.do 'c(filename)' 'c(current_date)'"
62
63 /*-----*/
64 /* Create Dependent Variable - Within County Redemptions */
65 /*-----*/
66 local dep_var Diff_SNAP_bea
67 /* Demeaned - dependent variable */
68 local dep_var_label: variable label 'dep_var'
69 label variable dm_'dep_var' "Demeaned 'dep_var_label'"
70
71 /*-----*/
72 /* MODEL 1 */
73 /*-----*/
74 local model1_expvars occse01 iccse01 unemployed eall
75
76 /*-----*/
77 /* MODEL 2 */
78 /*-----*/
79 local model2_expvars meanss meansm meansc
80
81 /*-----*/
82 /* MODEL 3 */
83 /*-----*/
84 local model3_expvars lag_meanss lag_meansm lag_meansc
85
86 order 'dep_var' 'model1_expvars' 'model2_expvars' 'model3_expvars'
87
88 /*-----*/
89 /* Start LaTeX File */
90 /*-----*/
91 local depvartitle = "Net SNAP difference"
92 local depvarunits = "in dollars"
93 local RoundDepVar = "NetSNAPDiffm3"
94
95 local dm_depvartitle = "Demeaned 'depvartitle'"
96 local LaTeXFile = "Work/Scratch/${filename}.tex"
97 * Currently I have my project saved in a different place than the latex files
98 local PrjDir = "../..../MyProjects/NPRSNAP/"
99
100 // Where should STATA save graphic files?
101 * Note * where working directory is set
102 local output_table = "Work/Scratch/"
103 // Where should the table be saved?
104 local LaTeXTable1 = "Work/Scratch/${filename}_REG'RoundDepVar'M1M2.tex"
105 local LaTeXTable2 = "Work/Scratch/${filename}_REG'RoundDepVar'M2M3.tex"
106 local LaTeXTable3 = "Work/Scratch/${filename}_REG'RoundDepVar'M3.tex"

```



```

107
108 * Create a handle for the file
109 tempname dst
110 * Add comment to Latex file to keep track of model and date that produced table
111 local addcomment1 "% ${provenance}"
112 file open 'dst' using 'LaTeXFile', write replace
113 file write 'dst' "'addcomment1'"_n
114 file close 'dst'
115
116
117 /*-----*/
118 /* Clean up variable labels */
119 /*-----*/
120 * Labels are too long for table
121 * Add an indentation for LaTeX Output
122 * Remove Lag of part of label
123 foreach v of varlist 'model3_expvars' {
124     local l'v' : variable label 'v'
125     local temp_table=substr("`l'v'",8,..)
126     label variable 'v' "`temp_table'"
127 }
128 label variable dm_Diff_SNAP_bea "Demeaned Diff, (\\$)"
129
130 * Add indentation for LaTeX Output
131 foreach v of varlist 'modell_expvars' 'model2_expvars' 'model3_expvars' {
132     label variable 'v' "\\hspace{0.1cm} ': variable label 'v'"
133 }
134 /*-----*/
135 /* Store tabstat estimates */
136 /*-----*/
137 /*-----*/
138 /* Set Formats for Output Tables and Graphs */
139 /*-----*/
140 * What format would work for the stats?
141 local stat_fmt "%16.0fc"
142 * What format would work for the Model Tables?
143 local coef_fmt "%14.2fc"
144 local se_fmt "%14.2fc"
145
146 * set style for reference categories in output tables
147 local refcat refcat(occse01 "\\emph{Mobility}" meanss "\\emph{Retail Grocery
    Market, (stores)}" lag_meanss "\\emph{Neighboring Market, (stores)}",nolabel)
148
149 /*-----*/
150 /* Store XTREG Parameters */
151 /*-----*/
152
153 * Table 1 - Comparing Models 1 and 2, with Model 2 variables only
154 * xtreg fixed effects model-
155 eststo: xtreg 'dep_var' 'modell_expvars', fe
156 eststo: xtreg 'dep_var' 'model2_expvars', fe
157 eststo: xtreg 'dep_var' 'modell_expvars' 'model2_expvars', fe
158
159 esttab using ///

```

```

160         'LaTeXTable1' ///
161         , booktabs label replace fragment ///
162         'refcat' ///
163         b('coef_fmt') se('se_fmt') ///
164         mgroups("Model 1" "Model 2v1" "Model 2v2", pattern(1 1 1)
                ///
165         prefix(\multicolumn{@span}{c}{}) suffix({}) ///
166         span erepeat(\cmidrule(lr){@span})) ///
167         alignment(D{.}{.}{-1}) nonumber ar2
168 eststo clear
169
170 * Comparing models 1, 2 and 3
171 eststo: xtreg 'dep_var' 'modell_expvars', fe
172 local modelliccse01 = _b[iccse01]
173 local modelloccse01 = _b[occse01]
174
175 eststo: xtreg 'dep_var' 'modell_expvars' 'model2_expvars', fe
176 local model2meansm = _b[meansm]
177 local model2meanss = _b[meanss]
178
179 test iccse01 = 'modelliccse01'
180 test occse01 = 'modelloccse01'
181
182 eststo: xtreg 'dep_var' 'modell_expvars' 'model2_expvars' lag_meanss, fe
183 * We can test the hypothesis that the coefficient on Inbound Workers in Model 3
184 * is equal to the coefficient on Inbound Workers in Model 1 by typing:
185 test iccse01 = 'modelliccse01'
186 * The F statistic with 1 numerator and 1,234 denominator degrees of freedom is
187     14.04
188 * The significance level of the test is close to 0, so we can strongly reject
189 * the hypothesis that the coefficients on inbound workers in Model 3 is equal to
190     the
191 * coefficient on Inbound Workers in Model 1.
192
193 * We can test the hypothesis that the coefficient on Outbound Workers in Model
194     3
195 * is equal to the coefficient on Outbound Workers in Model 1 by typing:
196 test occse01 = 'modelloccse01'
197 * The F statistic with 1 numerator and 1,234 denominator degrees of freedom is
198     0.0
199 * The significance level of the test is 98.34%--we cannot reject the hypothesis.
200
201 esttab using ///
202         'LaTeXTable2' ///
203         , booktabs label replace fragment ///
204         'refcat' ///
205         b('coef_fmt') se('se_fmt') ///
206         mgroups("Model 1" "Model 2" "Model 3", pattern(1 1 1)
                ///
207         prefix(\multicolumn{@span}{c}{}) suffix({}) ///
208         span erepeat(\cmidrule(lr){@span})) ///
209         alignment(D{.}{.}{-1}) nonumber ar2
210 eststo clear
211

```

```

208 * Comparing Model 3 with all retail lags and only ss and sm
209 * this helps explain why Superstores are important
210
211 eststo: xtreg 'dep_var' 'model1_expvars' 'model2_expvars' 'model3_expvars', fe
212 local model3v1lag_meanss = _b[lag_meanss]
213
214 * We wish to test whether the lag variables, taken as a whole, are significant
215 * by testing whether the coefficients on each are simultaneously zero.
216 * test allows us to specify multiple conditions to be tested, each embedded
    within parentheses:
217 test (lag_meanss=0) (lag_meansm=0) (lag_meansc=0)
218 * test displays the set of conditions and reports an F statistic of 4.96. test
    also reports the degrees
219 * of freedom of the test to be 3, the $dimension of the hypothesis, and the
    residual degrees of freedom,
220 * 1,232. The significance level of the test is close to 0, so we can strongly
    reject the hypothesis of no
221 * difference between the neighboring county retail grocery market.
222 test lag_meanss = 0
223 test lag_meansm = 0
224 test lag_meansc = 0
225
226 test meansm = 'model2meansm'
227 test meanss = 'model2meanss'
228
229
230 eststo: xtreg 'dep_var' 'model1_expvars' 'model2_expvars' lag_meanss lag_meansm,
    fe
231 test lag_meanss = 'model3v1lag_meanss'
232 exit
233
234 test lag_meanss lag_meansm
235 test lag_meansm = 0
236
237 esttab using ///
238     'LaTeXTable3' ///
239     , booktabs label replace fragment ///
240     'refcat' ///
241     b('coef_fmt') se('se_fmt') ///
242     mgroups("Model 3 v1" "Model 3 v2", pattern(1 1)           ///
243     prefix(\multicolumn{@span}{c}{}) suffix()) ///
244     span erepeat(\cmidrule(lr){@span}) ///
245     alignment(D{.}{.}{-1}) nonumber ar2
246 eststo clear
247
248 xtreg 'dep_var' 'model1_expvars' 'model2_expvars' lag_meansm, fe
249 xtreg 'dep_var' 'model1_expvars' 'model2_expvars' lag_meansc, fe
250
251 exit
252
253 /*-----*/
254 /* Create LaTeXFile With Table */
255 /*-----*/
256 * Caption for Table

```

```

257 local depvarcaption = "Parameter Estimates from Models of 'depvartitle'."
258
259 file open 'dst' using 'LaTeXFile', write append
260 file write 'dst' "%%%%%%%%%" _n
261 file write 'dst' "\begin{landscape}" _n
262 file write 'dst' "\begin{table}[!hbp]" _n
263 file write 'dst' "\centering" _n
264 file write 'dst' "\caption{'depvarcaption'}" _n
265 file write 'dst' "\label{table:Xtregof'RoundDepVar'm1m2}" _n
266 file write 'dst' "\estautop{'PrjDir' 'LaTeXTable1'}{3}{.}" _n
267 file write 'dst' "\sestats" _n
268 file write 'dst' "\starnote" _n
269 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
    7}" _n
270 file write 'dst' "% $provenance" _n
271 file write 'dst' "\end{table}" _n
272 file write 'dst' "\end{landscape}" _n
273 file write 'dst' "%%%%%%%%%" _n
274
275 file write 'dst' "%%%%%%%%%" _n
276 file write 'dst' "\begin{landscape}" _n
277 file write 'dst' "\begin{table}[!hbp]" _n
278 file write 'dst' "\centering" _n
279 file write 'dst' "\caption{'depvarcaption'}" _n
280 file write 'dst' "\label{table:Xtregof'RoundDepVar'm1m3}" _n
281 file write 'dst' "\estautop{'PrjDir' 'LaTeXTable2'}{3}{.}" _n
282 file write 'dst' "\sestats" _n
283 file write 'dst' "\starnote" _n
284 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
    7}" _n
285 file write 'dst' "% $provenance" _n
286 file write 'dst' "\end{table}" _n
287 file write 'dst' "\end{landscape}" _n
288 file write 'dst' "%%%%%%%%%" _n
289
290 file write 'dst' "%%%%%%%%%" _n
291 file write 'dst' "\begin{table}[!hbp]" _n
292 file write 'dst' "\centering" _n
293 file write 'dst' "\caption{'depvarcaption'}" _n
294 file write 'dst' "\label{table:Xtregof'RoundDepVar'm3}" _n
295 file write 'dst' "\estautop{'PrjDir' 'LaTeXTable3'}{2}{.}" _n
296 file write 'dst' "\sestats" _n
297 file write 'dst' "\starnote" _n
298 file write 'dst' "\figsource{Author Calculations, USDA, SAIPES, BLS, BEA, LODES
    7}" _n
299 file write 'dst' "% $provenance" _n
300 file write 'dst' "\end{table}" _n
301 file write 'dst' "%%%%%%%%%" _n
302
303 file close 'dst'
304
305
306 /*****
307 /* End Log */

```

```
308 /*****  
309  
310 log close  
311 * Exit Program  
312 exit
```