Title: Choosing Brands: Fresh Produce versus other Products

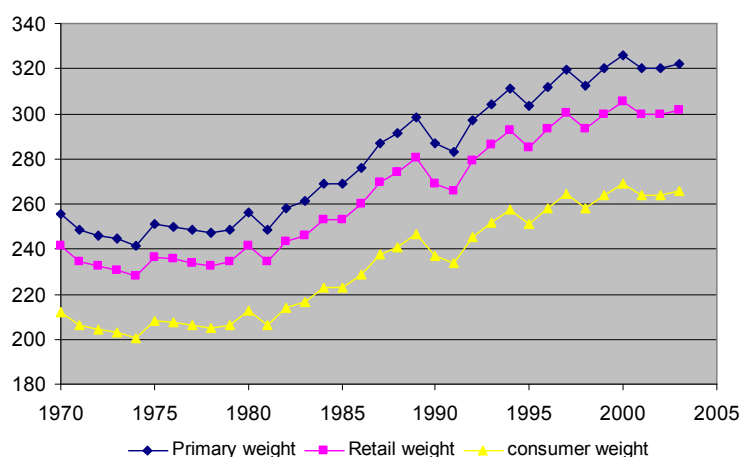**Authors**: Yanhong Jin, David Zilberman and Amir Heiman

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Choosing Brands: Fresh Produce versus Others Products
Yanhong Jin, David Zilberman, and Amir Heiman[1]

1 Introduction

In the last three decades, there has been a dramatic increase in the consumption of fresh vegetables and fruits due to consumers' interest to improve their health and nutritional intake (Dimitri, Tegene, and Kaufman 2003), and the campaign to eat more fruits and vegetables is still on the rise.[2] Figure 1 shows an increasing trend of per capita consumption of fresh fruits and vegetables in the United States between 1970 and 2003. After controlling the losses from the supply chain to the dinner table, the per capita consumption increased 11.40% between 1980 (212.6 pounds) and 1990 (236.9 pounds), and 13.46% between 1990 and 2000 (268.8 pounds).

Figure 1: Per capita consumption of fresh fruits and vegetables in US (1970-2003) [3]
Source: Economics Research Service at USDA

Consumers recognize some brands in fresh produce including Dole, Chiquita, Sunkist, and Del Monte (*Fresh Trend* 2000).[4] However, there are fewer brands of fresh fruits and vegetables

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[2] The National Cancer Institute fueled the "5 A Day for Better Health Program" nationwide. The goal of this program is to recommend seven servings of fruits and vegetables for women and nine for men to promote good health. Details are given at: http://5aday.gov/why/index.html. Last accessed on March 20th, 2005.
[3] Source: Economics Research Service at USDA. The basic consumption estimate is made at a primary distribution level, which is dictated for each commodity by the structure of the marketing system and data availability. There are three measures of per capita consumption, including primary weight, retail weight, and consumer weight after taking the loss into consideration.
[4] The Packer at http://www.thepacker.com/

than of other products (Kaufman et al. 2000; Cook 2001; and Heiman and Goldschmidt 2004). Only 19% of retail fresh produce sales were brand name in 1997 (Kaufman et al. 2000).

To explain the lack of brands of fruits and vegetables, we conducted a survey on consumers' willingness to pay (WTP) for brands of different products. Based on the WTP data, we will investigate the following research questions: (a) Why do consumers prefer brands over generic ones: (b) Do consumers have significantly lower WTP for brands of fresh vegetables and fruits than other product categories controlling relevant socioeconomic variations? (c) To what extent do the optimal premium and corresponding market share of brands of fresh food differ from other products?

Brands are modeled to convey various types of information. They are signals of quality in terms of higher mean and lower variation of product quality. They are superior in terms of design and appearance and convey a prestigious social image. Buying a famous brand reduces uncertainty and reduces the anxiety generated from thoughts that there is a possibility of making a wrong choice. The more famous the brand, the higher it contributes to ego and/or image building and symbolic consumption. Some people may prefer brand name clothing because of better design and prestige, while others prefer to buy brand name shirts because they are concerned that the dye in the fabric may run even if the shirts are carefully sewn. Consumers may be less willing to pay more for brands of fresh fruits and vegetables than other products since they can test the quality and reduce the quality uncertainty by seeing, smelling, touching, and tasting.

The rest of this paper is organized as follows. We present a theoretical model to analyze how the uncertainty about product attributes affect consumers' WTP for brands in the next section. We provide data information in Section 3 and discuss the empirical results in the following section. Section 5 presents simulation results and discusses the optimal price premium and the corresponding market share to brands of different products. Finally, we summarize the concluding remarks in the last section.

2   The Model

When consumers purchase a product, they face a great uncertainty about product performance, sales conditions, and personal fit between the product and their idiosyncratic needs (Roselios 1971; Heiman, McWillams and Zilberman 2001). To reduce the level of uncertainty about product attributes such as quality, design, and appearance, consumers take the following actions: (a) search for more information by reading labels and consumer reports (Teisl, Bockstael

and, Levy 2001 and Kristine 2004); (b) buy a good brand rather than generic products since brand name products generally have better performance (Chu and Chu 1994 and Aaker 1994); (c) conduct test drives and participate in product demonstrations (Smith and Swinyard 1983, Heiman et. al 2001). We mainly focus on the following research question: Does uncertainty about product attributes induce consumers' WTP for brands over generic products and, if so, to what extent? To answer this research question, we present a random utility framework (McFadden 1989; Thompson and Kidwell 1998; Mathios 2000; and Kiesel, Buschena, and Smith 2005) incorporating key elements of product attribute models (Becker 1965, Rosen 1974).

Consumers receive their utility from consuming varieties of products. Let X denote n goods whose price is given by the vector P_X, and Y be the only product with attributes that consumers are uncertain about. Y can be either a brand name ($Y = Y_B$) or generic ($Y = Y_G$) product. We assume that consumers' WTP for a brand name product (W_B) is higher than the generic one (W_G):

$$W_B = W_G(1 + \Delta W),\qquad(1)$$

where $\Delta W > 0$ is an extra percentage that consumers are willing to pay more for brands. The uncertainty about attributes of product Y results in a randomness in consumers' utility. Let λ_Y denote the perceived uncertainty. We assume λ_Y is a random drawn from a distribution with mean μ_Y and variance σ_Y^2 such that the brand name product has a higher mean and a lower variation of a certain attribute than the generic ones:

$$\mu_B = \mu_G + \Delta\mu,\qquad(2\text{-}a)$$

$$\sigma_B^2 = \sigma_G^2 - \Delta\sigma^2.\qquad(2\text{-}b)$$

If λ_Y represents a random component resulting from quality uncertainty, equations (2-a) and (2-b) imply that consumers perceive a higher quality on average from brands and they are less uncertain about quality of brands. We assume that the consumption of the product Y results in one of the utility components, $h(Y, \lambda_Y)$.

Next, we will show how we can derive ΔW in the following steps:

(a) When consumers prefers no brands, they derive utility from consuming X and Y_G, and their constrained expected utility is

$$\max_{X,YG} EU(X, h(Y_G, \lambda_G), I - XP_X - W_G Y_G).\qquad(3)$$

Substituting the optimal solution X^* and Y_G^* into equation (3) yields the maximum utility that consumers could have in this case:

$$V_0(I, \mu_G, \sigma_G^2, W_G) = EU(X^*, h(Y_G^*, \lambda_G), I - X^* P_X - W_G Y_G^*). \tag{4}$$

(b) When consumers are willing to pay for brands, they consume brands, generic ones, or both to maximize their utility. Their constrained utility maximization is

$$\max_{X, YB, YG} EU(X, h(Y_B, \lambda_B), h(Y_G, \lambda_G), I - X P_X - (1 + \Delta W) W_G Y_B - W_G Y_G). \tag{5}$$

Assuming ΔW is unknown, the optimal solution X^*, Y_B^*, and Y_G^* are functions of ΔW. Substituting the optimal solution into equation (5) yields the maximum utility that is a function of ΔW and other parameters:

$$V_1(\Delta W \mid I, \mu_G, \Delta\mu, \sigma_G^2, \Delta\sigma^2, W_G)$$
$$= EU(X^*, h(Y_B^*, \lambda_B), h(Y_G^*, \lambda_G), I - X^* P_X - (1 + \Delta W) W_G Y_B^* - W_G Y_G^*) \tag{6}$$

(c) Equalizing equations (5) and (6) yields the optimal value of ΔW

$$V_1(\Delta W \mid I, \mu_G, \Delta\mu, \sigma_G^2, \Delta\sigma^2, W_G) - V_0(I, \mu_G, \sigma_G^2, W_G) = 0. \tag{7}$$

The optimal value of ΔW, which represents the extra percentage that consumers are willing to pay more for brands over generic products, is a function of all parameters including $I, \mu_G, \Delta\mu, \sigma_G^2, \Delta\sigma^2$, and W_G.

Based on equation (7), we identify the effects of a certain parameter on ΔW below:

$$\frac{d\Delta W}{d\Delta\mu} = E\left(\frac{\partial(V_1 - V_0)}{\partial h} \frac{\partial h}{\Delta\mu}\right) \Big/ E\left(\frac{\partial(V_1 - V_0)}{\partial \Delta W}\right), \tag{8-a}$$

$$\frac{d\Delta W}{d\Delta\sigma^2} = \frac{\partial(V_1 - V_0)}{\partial h} \frac{\partial h}{\partial\Delta\sigma^2} \Big/ E\left(\frac{\partial(V_1 - V_0)}{\partial \Delta W}\right). \tag{8-b}$$

The sign of these two equations depends on the distribution of λ_Y. To gain insights on the effects of uncertainty about product attributes on the WTP for brands, we provide a simply case by making the following assumptions:

(a) Consumers have an additive utility function over consumption of X, Y, and expenditure.

(b) If consumers are willing to buy brands, $B = 1$; otherwise, $G = 1$ if they prefer only generic products. The utility of consuming one unit of product Y has a random component, which can be expressed as a linear function of mean-variance:

$$EU(G, \lambda_B) = \mu_B - r\sigma_B^2, \tag{9-a}$$

$$EU(G, \lambda_G) = \mu_G - r\sigma_G^2, \tag{9-b}$$

where r is a certain risk measure. Under these two assumptions, V_1 and V_0 become

$$V_1 = EU_1 = U(X) + Y_B EU(B, \lambda_B) + I - XP_X - (1 + \Delta W)W_G Y_B, \qquad \text{(10-a)}$$

$$V_0 = EU_0 = U(X) + Y_G EU(G, \lambda_G) + I - XP_X - W_G Y_G. \qquad \text{(10-b)}$$

Equalizing equations (10-a) and (10-b) yields

$$\Delta W = \frac{(\mu_B - \mu_G) - r(\sigma_B^2 - \sigma_G^2)}{W_G} = \frac{\Delta \mu + r\Delta \sigma^2}{W_G}. \qquad \text{(11)}$$

Equation (11) suggests that consumers are willing to pay more for brands if generic ones have a much lower mean quality $\left(\frac{\partial \Delta W}{\partial \Delta \mu} > 0 \right)$ and/or a higher quality variation $\left(\frac{\partial \Delta W}{\partial \Delta \sigma^2} > 0 \right)$ than that of brands. The uncertainty about product attributes does affect consumers' WTP for brands. The question next is as follows: Do consumers care that different attributes have diversified uncertainty sources to different products? Consider the following hypothetical scenario:

(a) Consumers buy either brands or generic ones among four product categories including electronics, clothing, processed food, and fresh vegetables and fruits.

(b) Consumers only care about three product attributes, quality, design or appearance, and fashion and social images. Product design could be an attractive arrangement of fruit salad combining various colors and shapes, or a decent mix of production functions and appearance. Consumers may differentiate themselves from others by consuming certain products since these products could be a symbol of fashion image or social status.

We rank the perceived uncertainty level of electronics, clothing, and processed food in a comparison with that of fresh vegetables and fruits in Table 1.

Table 1: Uncertainty among four different product categories

Product category	Quality	Design/appearance	Fashion
Fresh vegetables and fruits	Base	Base	Base
Processed food	+	+/-	+/-
Clothing	+/-	+	+
Electronics	+	+	+

We expect that consumers are less uncertain about the quality of fresh vegetables and fruits because of the following two reasons: (a) A majority of consumers care about quality but pay little attention to appearance and arrangement of fresh vegetables and fruits. However, other products including electronics and clothing have more diversified uncertainty sources, since consumers pay attention

to attributes other than quality. (b) Consumers can reduce the uncertainty about quality of fresh vegetables and fruits by seeing, touching, smelling, and tasting. Therefore, we formulize the following hypothesis.

Hypothesis: *Consumers are less willing to pay for brands of fresh vegetables and fruits than other products such as electronics, clothing, and processed food.*

3   The Data

A total of 110 in-person surveys were conducted at the supermarket to collect consumers' demographic information and their perception towards to brands. There are four product categories covered in the survey, including electronics, clothing, processed food, and fresh vegetables and fruits. For each product category, each individual in the sample was asked three sets of questions: (a) their brand preference ranking from zero (do not buy brand at all) to 10 (always buy brands); (b) their WTP in terms of an extra percentage to pay for brands other than generic products; and (c) demographic information such as education, gender, household expenditure, and household size. Table 2 provides a summary of brand preference and WTP for each product category. It shows that (a) more people prefer brands of electronics (52.7%) and clothing (28.2%) than brand name fruits and vegetables (10%); (b) more people are willing to pay for brand name electronics (93.6%) and clothing (79.1%) than fruits and vegetables (41.0%); (c) consumers have a higher WTP for brands of electronics and clothing than food; and (d) respondents who prefer brands generally have a high WTP than their counterparts.

Table 2: Summary of brand preference and WTP for brands across product categories

	Electronics	Clothing	Processed food	Fruits and vegetables
Percentage of respondents preferring brands [a]	57.2	28.2	38.2	10.0
Percentage of respondents willing to pay more for brands	93.6	79.1	70.0	41.0
Average WTP among those who are willing to pay more	35.8	34.3	26.2	26.2
Average WTP among those who prefer brands	40.2	41.1	32.6	41.1
Average WTP among those who do not prefer brands	26.0	28.9	32.6	30.1

[a] All respondents rank their brand preference for each product category from zero (do not buy brands at all) to 10 (always buy brands). We assume that respondents prefer brands if their rank is greater than 6.

This survey also provides four alternative reasons why consumers prefer brands in each product category, including quality, appearance and design concerns, and others. Each respondent was asked to weigh these four reasons for each product category. Table 3 suggests the following findings: (a) concern about quality is the main driving force for brand preferences for all products; (b) in comparison with other products, consumers put relatively greater weight on quality advantage than other attributes of brand name fresh fruits and vegetables; and (c) fashion advantage matters more for electronics and clothing. The statistical summary in Table 3 supports our expectations in Table 1.

Table 3: Reasons for brand preference across product categories [b]

	Electronics	Clothing	Processed food	Fruits and vegetables
Quality concerns	67.79%	51.09%	67.77%	73.85%
Appearance/design	16.82%	27.50%	11.22%	8.44%
Fashion	8.84%	10.31%	4.50%	4.09%
Others	6.55%	11.09%	16.50%	13.62%

[b] All respondents were asked to weigh reasons for brand preference including (1) brands convey a fashion imagine, (2) brands have better design or appearance, (3) brands have advantage in quality, and (4) other concerns. The sum of weights across these four reasons is 100%.

4 Econometric Estimation

The dependent variable is WTP measured by an extra percentage that consumers are more willing to pay for brands than generic products specified in equation (7). We also assume that the indirect utility function is linear. Hence, the individual WTP for brands is

$$W_i^* = \beta' Z_i + \varepsilon_i, \qquad (12)$$

where ε is the error term following a normal distribution with a zero mean and variance σ^2, and $Z_i = [z_i^1, z_i^3, \mathsf{L}, z_i^k]'$ consists of all the relevant variables for an individual consumer i. However, the latent WTP is not observable to econometricians. Instead, we only observe a nonnegative value of WTP, which is denoted by W_i for an individual consumer i, such that

$$W_i = \begin{cases} W_i^* & \text{if } W_i^* > 0 \\ 0 & \text{otherwise} \end{cases}. \qquad (13)$$

Following the theoretic discussion in section 2, the vector Z includes product attributes, price difference, and consumers' idiosyncratic characteristics. Particularly, from a managerial and marketing perspective, it is important to identify the following factors:

 (a) ***Product attributes***: People prefer brands for different reasons due to the nature of product attributes. Consumers may prefer brands of durable goods than perishable goods, and they may prefer brands of products that are hard to test before purchase. It is easy for consumers to test the quality of fresh fruits and vegetables by seeing, touching, smelling, and tasting. Therefore, consumers may be less willing to pay for brands of fresh fruits and vegetables than processed food as projected by the hypothesis in section 2. Since the survey did not provide us information about product attributes, we use the product dummies to capture the effects of attribute differences among products.

 (b) ***Brand preferences***: As shown in Table 2, in comparison with their counterparts, brand-preferring consumers are willing to pay approximately 14% more for brand name electronics and clothing, and 9.0% more for brands of fresh fruit and vegetables. Thus, we speculate that consumers who prefer brands tend to have a higher WTP.

 (c) ***Demographic variables***: Retailers and brand managers can assess demographic information in marketing, including market segmentation, retail locations (Ghosh and McLafferty, 1987), and estimation of brand choice (Allenby and Rossi 1991, Chiang 1991, Gupta and Chintagunta 1994, Kalyanam and Putler 1997, Hoch et al. 1995, and Ainslie and Rossi 1998). Therefore, the incorporation of demographic variables in a brand study is conceptually appealing and has numerous managerial benefits. We introduce household income, age, education level, gender, and household size in the model.

Equation (12) shows that coefficients β capture the marginal effect of explanatory variables on the latent WTP rather than the observed WTP. As suggested by McDonald and Mofitt (1980), the marginal effect of Z_i on the observed WTP can be written below:

$$\frac{\partial E(W_i \mid x_i)}{\partial x_i} = \underbrace{E(W_i \mid x_i, W_i > 0)\frac{\partial \operatorname{Prob}(W_i > 0)}{\partial x_i}}_{\text{Marginal effect through the change in probability}} + \underbrace{\operatorname{Prob}(W_i > 0)\frac{\partial E(W_i \mid x_i, W_i > 0)}{\partial x_i}}_{\text{Marginal effect through the change in the conditional mean}} \quad (14)$$

$$= \beta\,\varphi_i\left(\frac{\beta\,x_i}{\sigma} + \frac{\varphi_i}{\phi_i}\right) + \beta\,\phi_i\left(1 - \frac{\varphi_i}{\phi_i}\left(\frac{\beta\,x_i}{\sigma} + \frac{\varphi_i}{\phi_i}\right)\right),$$

where $\varphi_i = \varphi_i\left(\dfrac{\beta x_i}{\sigma}\right)$ and $\phi_i = \phi_i\left(\dfrac{\beta x_i}{\sigma}\right)$ are probability and cumulative probability at $\dfrac{\beta x_i}{\sigma}$.

Equation (14) shows that the marginal effects of explanatory variables on the observed WTP can be decomposed into two elements: (a) *Truncation effect:* the marginal effect on the probability that an observation will fall in the positive part of distribution, which is the first term in equation (14); and (b) *marginal effect on the conditional mean*: the marginal effect on the conditional mean of W_i^* in the positive part of the distribution, which is the second term in equation (14).

4.1 Model Diagnostics

We are aware of the endogeneity problem of brand preference. Unfortunately, we do not have good instruments in the survey data to control endogeneity. Nevertheless, we check the robustness by running regressions with and without the brand preference dummy, and results are robust.

We conducted tests for the Tobit specification using the Heckman two-stage model. We estimate the Heckman model written in equation (13), and assume that W^* is observed if

$$\alpha' Z_i + \eta_i > 0 , \tag{15}$$

where ε_i and μ_i have correlation ρ. Our results show that the χ^2's for the estimation with and without the brand preference are 116.29 and 105.01, respectively. Thus, we reject the null hypothesis of no correlation between two error terms under both cases. The results clearly favor the Tobit specification, and hence we conclude there is a truncation issue.

Several tests for heteroskedasticity are conducted, including the Breusch-Page test and the unrestricted White test. Our results suggest that we reject the null hypothesis of homoskedasticity at the 1% significant level both in the OLS and Tobit regressions. Thus, we report heteroskedasticity-consistent standard errors in both OLS and Tobit regressions.[5]

4.2 Estimation Results

We summarize estimation results in Table 4 and provide the marginal effects of significant variables in Table 5. We found that consumers' WTP, measured by an extra percentage respondents are willing to pay for brands, is significantly sensitive to product categories. After controlling for brand preferences, in comparison with the WTP for brand name clothing relative to the generic ones, consumers are willing to pay 2% more for brands in electronics, 14% less for

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[5] The robust standard errors have different names in the literature, including White standard errors, Eicker-White standard errors, Huber standard errors, robust standard errors, heteroskedasticity-consistent standard errors, and so on. Wooldridge (2002) recommends using the last two names.

national and international strong brands in processed food, and 21% less for fresh fruits and vegetables. If we do not control brand preferences, the differences are 10%, -11%, and -29% for brands of electronics, food, and fresh fruits and vegetables. Therefore, we conclude that consumers' WTP across product categories are in descending order: electronics, clothing, processed food, and fresh fruits and vegetables. The result supports the hypothesis formulized in section 2. That is, consumers are less willing to pay for brands of fresh vegetables and fruits. This result can be mainly explained by two facts: (a) consumers have uncertainty about fewer product attributes, i.e., they care mostly about quality but pay less attention to appearance and social and fashion images; and (b) consumers can reduce uncertainty by testing fresh vegetables and fruits, i.e., they can see, touch, smell and taste before making purchase decisions.

It is of great importance to marketing and managerial practice to identify the quantity the effects of demographic factors. The estimation results show that the following factors have a significant effect on consumers' WTP for brands:

- Individual consumers who finish high school or received s higher education will pay approximately 10% more than those who are less educated.
- Males tend to pay about 4%-10% more for brands than females.
- The intensity of preference for brands affects WTP. Consumers with high preference intensity towards brand name products are willing to pay 17% more for brands than their counterparts.

5   Marketing Implications

The econometric results show that consumers are less willing to pay for brands of fresh vegetables and fruits. The next question is how will differences in WTP for brands across products affect the optimal price premium and the corresponding market share. We assume that consumers are heterogeneous in terms of their WTP an extra percentage for the brand name product Y that is denoted by W_i; W_i ranges from $\underline{W}$ to $\overline{W}$ and has a density distribution $f(W_i)$ such that $\int_{\underline{W}}^{\overline{W}} f(W_i)dW_i = 1$. We also assume a monopoly produces the product Y with an extra marginal cost c and charges an extra percentage p_i for brands in comparison to a generic product, and an individual consumer buys the brand if and only if $p_i \leq W_i$. Hence, the demand of this brand is

$$D_i = \int_{p_i}^{\overline{W}} f(W_i)dW_i . \qquad (16)$$

Hence, the objective function of a profit-maximizing monopoly is

$$\max_{p_i}\left(p_i - c\right)D_i. \tag{17}$$

The optimal premium is achieved when the marginal revenue *MR* equals the marginal cost *c*:

$$MR = p_i - \frac{\int_{p_i}^{\overline{W}} f(W_i)dW_i}{f(p_i)} = c = MC. \tag{18}$$

Equation (18) shows that a one-unit increase in p_i will increase the revenue by p_i but at the

marginal loss $\dfrac{\int_{p_i}^{\overline{W}} f(x_i)dx_i}{f(p_i)}$ resulting from a decrease in the demand. Solving equation (19) yields

the optimal price premium p_i^*. Substituting p_i^* into the demand function in equation (17) yields the

corresponding market share thereafter.

To assess the possible differences of price premiums and market share across product categories, we simulate the market equilibrium by assuming the extra marginal cost required to produce a brand relative to the generic product. Figure 2 provides four empirical demand curves of brands of electronic, clothing, processed food, and fresh fruits and vegetables. The y-axis represents quantity demanded of brands measured by the percentage of respondents who are willing to pay for brands, and the x-axis represents the price premium measured by an extra percentage that respondents are willing to pay for brands.
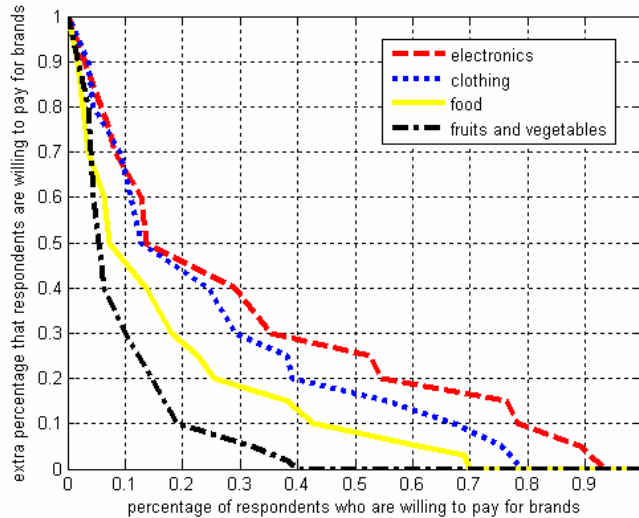
Figure 2: Brand demand of electronics, clothing, food, and fruits and vegetables

The simulation results show that the optimal price premiums for brands in electronics, clothing, processed food, and fruits and vegetables are not significantly different; however, the market shares of brands are. For example, when the extra cost of brands is 10%, the price premium for electronics, clothing, food, and fruits and vegetables are 30%, 28%, 25%, and 30%, respectively; and 40%, 45%, 40%, and 39% when the extra marginal cost is 20%. However, the optimal market shares vary greatly across categories. For example, when the extra marginal cost is 10%, only 10% of the population will buy brands of fruits and vegetables in contrast to 21% in food, 40% in electronics, and 36% in clothing. When the extra cost is 20%, 8% of the population will buy brand name fruits and vegetables, 12% for food, 20% for clothing, and 28% for electronics.

Therefore, the lack of demand can partly explain fewer brands of fresh fruits and vegetables.

Once the optimal price premiums are established, we can identify whether an individual consumer will buy brands of a certain product and assess whether people are consistent with brand preferences across product categories. This assessment will provide insights about store organization and predication of percentage of the population who will shop in each of these stores.

Assuming that the extra marginal cost of brands is 10% relative to the generic one, the optimal price premium is 30% for electronics, 28% for clothing, 25% for processed food, and 25% for fruits and vegetables. Given the optimal pricing, 34.55% of the population will always buy non-brand products and another 9.09% will always buy brand name products. Therefore, at least approximately 43.54% of the population is consistent in terms of their brand preferences for electronics, clothing, processed food, and fruits and vegetables. Therefore, we can identify three types of stores: (1) discount stores that sell nonbrand products targeting 34.55% of the population, (2) elite stores that sell only brand items and attract 9.09% of potential consumers, and (3) supermarkets that sell everything.

6 Conclusions

This study presents a framework to analyze how uncertainty about product attributes affects consumers' WTP for brand name products over generic ones, incorporating key elements of a random utility model and product attribute models. In comparison to electronics, clothing, and processed food, consumers buy brand name vegetables and fruits mainly because of quality uncertainty, and they pay little attention to product appearance and attributes symbolizing social status and fashion images. Consumers can easily reduce uncertainty of product quality of fresh

vegetables and fruits by seeing, touching, smelling, and tasting. Therefore, we expect that consumers are less willing to pay for brands of fresh vegetables and fruits. Our theoretical model presents a way to model the effects of uncertainty on the WTP for brands, and the empirical results confirms this projection. Consumers' WTP for brands, which is measured by an extra percentage of WTP for brands over generic products, is significantly different across product categories. Controlling for everything else including demographic factors, consumers are least willing to pay for brands of fresh vegetables and fruits than that of electronics, clothing, and processed food items. However, simulation results show that brands of fresh fruits and vegetables may have a similar price premium as other products, but they lack the market share. Thus, the main challenge in building brands of fresh produce is to establish a critical mass.

This study also provides the following implications to marketing and managerial practice:

- Consumers have different consistencies in terms of brand purchase. Some people will buy brands of all product categories given the optimal price premium, and they will likely visit a store selling brands of all products, say, elite stores. Nevertheless, some consumers may buy only brands of certain products, and others may prefer no brands. This consistency analysis on brands provides insights on store organization and projection of the market share for stores.

- Demographic information such as education and gender does affect consumers' WTP for brands. Thus, marketing analysis on demographic information is important to project consumers' WTP for brands and, thus, determines the optimal price premium and projects the corresponding market share.

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Table 4: Estimation results of OLS and Tobit regressions

Dependent variable: *WTP*, an extra percentage respondents are willing to pay for brands				
	w/o brand preference		w/ brand preference	
Independent variables:	OLS	Tobit	OLS	Tobit
Intensity of brand preference:				
Ranking=7,8,9,10			0.18***	0.24***
			(0.03)	(0.06)
Product categories (clothing is the base)				
Electronic	0.07**	0.10**	0.01	0.02
	(0.04)	(0.04)	(0.03)	(0.04)
Processed food	-0.09***	-0.11***	-0.11***	-0.14***
	(0.03)	(0.05)	(0.03)	(0.04)
Fruits and vegetables	-0.17***	-0.29***	-0.12***	-0.21***
	(0.03)	(0.05)	(0.03)	(0.05)
Socioeconomic variables				
Household income	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.91)
Education dummies				
Finished high school	-0.06*	-0.11**	-0.06	-0.10**
	(0.04)	(0.06)	(0.04)	(0.05)
College and above	-0.07**	-0.11**	-0.05*	-0.10***
	(0.03)	(0.06)	(0.04)	(0.04)
Gender=male	0.07***	0.09***	0.05**	0.05**
	(0.02)	(0.03)	(0.02)	(0.04)
Household size	0.02	0.02	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.01)
Constant	0.27***	0.29***	0.19***	0.18***
	(0.05)	(0.07)	(0.05)	(0.06)
Number of observations	408	408	408	408
Log-likelihood value		-163.11		-139.02
Pseudo R-square	0.15		0.24	
Adjusted R-square	0.12		0.22	
LR Chi2		84.37		150.28

(a) Standard errors are corrected for heteroskedasticity and reported in parentheses.

(b) ***, **, and * implies that the corresponding variable is statistically significant from zero at the 1%, 5%, and 10% levels.

Table 5: The marginal effects of significant variables

Independent variables	Truncation effect	Marginal effect on *WTP* *	Total effect	Truncation effect	Marginal effect on *WTP* *	Total effect
High brand preference	N.A	N.A	N.A	0.07	0.09	0.16
Electronics	0.03	0.04	0.70	0.00	0.01	0.01
Intl. and national strong food brands	-0.03	-0.04	-0.07	-0.04	-0.06	-0.10
Fresh fruits and vegetables	-0.10	-0.10	-0.20	-0.05	-0.08	-0.13
Finish high school	-0.04	-0.04	-0.08	-0.03	-0.04	-0.07
College and up	-0.04	-0.04	-0.08	-0.03	-0.04	-0.07
Gender	0.03	0.03	0.06	0.02	0.02	0.04