Choosing Brands: Fresh Produce versus Other Products

Yanhong H. Jin, David Zilberman, and Amir Heiman

Assuming that brands contribute to quality risk reduction, prestige, and design, we derive and test hypothesis on the willingness to pay (WTP) for brands across different product categories (electronics, clothing, packaged food, and fresh produce). Using the random effect tobit model on the stated point value of WTP and the ordered probit model on the stated range of WTP, we find that WTP for brands of fresh produce is least among the four product categories controlling for relevant demographic variations. Simulations show that fresh produce has a higher optimal price premium for brands but with a much smaller market share.

Key words: brands, fresh produce, hedonic pricing, maximum entropy, ordered probit, tobit, willingness to pay.

Brands tend to generate significant premiums, and thus their uses have been considered in enhancing the value added of farming (Hayes and Lence 2002). Yet, brands are less commonly used in fresh agricultural produce than other products (Kaufman et al. 2000). With the greater emphasis on product differentiation, research on agricultural marketing strategies requires understanding the reasons for the relative paltry use of brands in the farm sector. In addition, it is important to assess the relative gains from introducing brands of fresh agricultural products and to identify features of their likely buyers. This article develops a methodological and empirical strategy to answer these questions and applies it to data collected in College Station and Bryan, Texas, in fall 2006.

We will investigate the following questions to explain the lack of brands of fresh produce: (a) Do the same causes of preferring brands over generics apply to fresh produce? (b) Do consumers have significantly lower willingness to pay (WTP) for brands of fresh produce than other product categories? (c) To what extent are brands' premiums and market shares of produce different from other products? (d) To what extent are consumers consistent in their brand preference across product categories?

The rest of this article is organized as follows. We present a simple framework to explain different components that contribute to the brand premium. We then provide data information and discuss the empirical results. Our estimation results show that (a) consumers have a lower WTP for brands of fresh produce than in other categories including electronics, clothing, and packaged food; and (b) certain sociodemographic factors play an important role in WTP for brands, including income, education, age, race, gender, and household size. The simulation results suggest that brands of fresh produce have a higher optimal price premium but a much smaller market share than those of other products. The simulation results also show that individuals are consistent in their WTP for brands across product categories, and thus there is a potential gain from selling brands of fresh fruits and vegetables in outlets selling brands of other products.

The Simple Brand Value Equation and the Basic Hypothesis

Adopting Rosen's hedonic pricing methodology (Rosen 1974), we introduce a simple formulation to compare the relative gain of brand products over generic across different product categories. The term, "the value of the product to a consumer," is used here to denote the consumer's WTP for the product, i.e., the price that will make the consumer indifferent

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to purchasing or not purchasing the product. The value of the product to a consumer is a function of the features of the product and the characteristics of the buyer. The literature suggests that branded products are more valuable because consumers associate them with better performance in three key areas:

- *Quality/reliability*. Erdem, Zhao, and Valenzuela (2004) find that both the perceived average and variability levels of quality explain the premium received by national brands over store brands for different products across countries.
- *Design*. Brands may have more attractive appearance and better performance related to design than generic products. Vranešević and Stančec (2003) suggest that appearance is viewed as a distinct characteristic of a food brand.
- *Prestige*. Aaker and Joachimsthaler (2002) find that brands provide "self-expressive benefits," as the association with brands contributes to the buyer's self-image.

Let ΔV be the value difference to consumers between a brand product and a generic product, i.e., the perceived extra value of the brand product relative to the generic product's original value, V. We assume that this difference can be simply decomposed into three hedonic components relating to quality/reliability, design, and prestige:

$$\Delta V = \Delta D + \Delta P + \Delta Q. \tag{1}$$

ΔD is the extra value attributed to improved design of the brand product, i.e., a better design contributes to more attractive appearance and/or better functionality of the product. ΔP is the added value reflecting the prestige added by a brand. The value of the extra quality added by the product is denoted by ΔQ. We narrowly interpret quality to mean improved reliability, reflecting risk reduction due to a lower probability of product failure and a lower loss in case of failure. The quality gain can be further decomposed to

$$\Delta Q = q_G L_G - q_B L_B = \Delta q L_B + \Delta L q_G \tag{2}$$

where q_G and q_B are the product failure probabilities, and L_G and L_B are the losses *after* product failure for the generic and the brand varieties, respectively. It is plausible to assume that brands reduce the probability of loss, and this reduction is $\Delta q = q_G - q_B > 0$. Brands are likely to cause less loss in case of product failure since they tend to have a better product support, for example, better warranties or money-back guarantee programs, thus we assume $\Delta L = L_G - L_B > 0$. Therefore, brands provide better quality in the sense of a reliable product, so $\Delta Q > 0$. Similarly, we assume brands provide extra value in terms of prestige and design. However, the relative gains from brands vary across product categories. We rely on prior studies to hypothesize on the relative value gains from brands for the four product categories we consider, in terms of value in quality, design, and prestige effects.

The relative contributions of the brand's quality effect. Two factors determine the quality gain from buying brands of products, *ex ante* consumer *learning* and *durability*. *Ex ante* consumer learning, where consumers use demonstrations and in-store tests to reduce product quality uncertainty, is a partial substitute to brands in providing information about product quality. Brands have significant value in providing information about quality of experience goods when *ex ante* learning is limited, as is the case with electronics and packaged foods, in contrast to fresh produce and clothing. The second factor is durability. Caves and Greene (1996) state that the value of brands as a quality signal is larger for durables because buyers cannot frequently adjust purchasing behavior. Electronics and clothing are durable experience products, while food products are frequently purchased items; hence, the brand effect for electronics and clothing is greater than for food. Therefore, brands provide extra value as quality signals for electronics both because they are durable goods and because of limited *ex ante* consumer learning. For clothing, brands convey quality information mostly because of durability, but provide limited *ex ante* consumer learning because clothing is tried on pre-purchase. In the case of packaged food products, the quality value of brands stems from the lack of effective *ex ante* means to assess quality, but is limited by the nondurable nature of the product. Both lack of durability and high availability of *ex ante* learning reduce the value of brands in fresh produce. Based on this analysis, we conjecture

$$\left(\frac{\Delta Q}{V}\right)_{\text{electronics}} > \left(\frac{\Delta Q}{V}\right)_{\text{clothing}} > \left(\frac{\Delta Q}{V}\right)_{\text{packaged food}} > \left(\frac{\Delta Q}{V}\right)_{\text{fresh produce}}. \tag{3}$$

The relative contributions of the brand's design effect. Design and appearance are major attributes of brand fashion products (Moore, Fernie, and Burt 2000). The additional value gain in brand electronics is stronger when products are differentiated in their external design (Holbrook 1992). Fresh fruits and vegetables can be "designed" by plant breeding and cultural practices, and design features like size and color strongly affect produce prices (Parker and Zilberman 1993), but we could not find evidence that consumers associate better design with produce brands. The above suggests

$$(4)\quad \left(\frac{\Delta D}{V}\right)_{\text{clothing}} > \left(\frac{\Delta D}{V}\right)_{\text{electronics}} > \left\{\left(\frac{\Delta D}{V}\right)_{\text{packaged food}}, \left(\frac{\Delta D}{V}\right)_{\text{fresh produce}}\right\}.$$

The relative contributions of the brand's prestige effect. Auty and Elliott (1999) find that brand fashion products affect the self-image of buyers, and Holbrook (1992) argues that image effects contribute to the value of brands in electronics to the extent that consumption is seen by others. Thus, clothing will likely provide the most prestige, as it has the most exposure to other people, followed by electronic gadgets. Brand products of food items are the least valuable source of prestige. We are aware that consumers may convey certain images by buying organic food, fair-trade food, etc., but the prestige impact is certainly much lower than for clothing or electronics. This discussion suggests an inequality similar to equation (4), namely,

$$(5)\quad \left(\frac{\Delta P}{V}\right)_{\text{clothing}} > \left(\frac{\Delta P}{V}\right)_{\text{electronics}} > \left\{\left(\frac{\Delta P}{V}\right)_{\text{packaged food}}, \left(\frac{\Delta P}{V}\right)_{\text{fresh produce}}\right\}.$$

The results of inequalities relating to three dimensions of brand value to consumers allow some comparison of the relative contributions of brands to the product values. They suggest that brands make relatively the least contribution for fresh produce, and for packaged foods the contribution of brands to value is likely to be smaller than in electronics and clothing, i.e.,

$$(6)\quad \left\{\left(\frac{\Delta V}{V}\right)_{\text{electronics}}, \left(\frac{\Delta V}{V}\right)_{\text{clothing}}\right\} > \left(\frac{\Delta V}{V}\right)_{\text{packaged food}} > \left(\frac{\Delta V}{V}\right)_{\text{fresh produce}}.$$

The inequalities in (6) provide basic hypotheses for our empirical analysis, but these hypotheses are not complete. If the quality effects dominate the prestige and design effects for all product categories, then the extra value of brands in electronics is the highest, and vice versa. However, the shares of the effects of these three dimensions in the overall brand values may significantly vary among the four product categories, which limits our ability to have complete hypotheses about the ranking of the perceived brand value among the products. Furthermore, fresh produce faces a greater uncertainty in the production process that makes it harder to maintain a standard of quality and design. A possible inconsistent quality of a brand will reduce the likelihood of repeated purchases, generate adverse images (word of mouth), and undermine the investment in brands (Heiman and Goldschmidt 2004). This process uncertainty will unavoidably challenge brands of fresh produce. Nevertheless, our analysis suggests that, relative to the base generic value, consumers have the lowest WTP for brands of fresh produce, followed by brands of packaged foods, and they have the highest WTP for brands of clothing and electronics.

Our analysis compares the WTP for brands across broad product categories, but each of these categories includes different products, and there is variation in WTP within a category. For example, refrigerators and toaster ovens are both electronics, but it is likely that brand premiums for refrigerators are higher because they generally last longer and represent a larger investment. Similarly, there are likely to be different brand premiums for different types of food products and different food categories (organic versus nonorganic). Because organic foods are credence goods, where quality depends on unobserved farmer behavior, and hence greater uncertainty, having brands may be more valuable. Some value of brands may be reduced with the introduction of organic certification programs, but in this case, the brand of the certifying agency acts as a brand in and of itself. Another issue for food items is geographic identification. In many cases, products differ by regions, and as a result there is growing usage of regional designated products (Champagne, Burgundy, and Napa Valley wines; Washington apples; etc.). However, within each region, there may still exist WTP for a brand (Sunkist versus a more generic Florida orange brand). In some cases, regional indicators may substitute for a brand. In our analysis, we elicit only consumer responses for brands in packaged food and fresh produce as broad food categories along with clothing and electronics. Future research should investigate WTP for brands within subcategories such as organics and the extent to which regional identification substitutes for brands.

Individuals with different socioeconomic backgrounds may have different attitudes toward brands. Retailers and brand managers may utilize sociodemographic information to create market segmentation (Gupta and Chintagunta 1994), choose retail locations (Ghosh and McLafferty 1987), forecast brand choices (Allenby and Rossi 1991; Chiang 1991; Kalyanam and Putler 1997; and Ainslie and Rossi 1998), etc.

Individuals' WTP for brands is likely to be related to informational gain that brands provide. As a source of information, brands will be substitutes to time and skills in the product quality assessment. They will provide extra informational value to (a) those lacking education, skills, experience, or product knowledge to detect quality and (b) those whose time is constrained or too valuable to intensively engage in pre-purchase product quality assessments. Zeithaml (1988) shows that women whose time constraint is more binding relied on brands when purchasing orange juice. Individuals with higher income have higher opportunity cost of search time, which leads them to have higher WTP for brands. Individuals who have sufficient status may not gain as much prestige from a brand as individuals without that status. Brands may be more valuable as status symbols to less educated individuals, as Fussell (1983) suggests for clothing.

Data

We conducted a survey on consumers' perception toward brands at one HEB store, two Albertson stores, one Wal-Mart Supercenter, and one local grocery store in College Station and Bryan, Texas, in fall 2006. We did not have permission to conduct a survey in other stores, including one Albertson store, three Kroger stores, and one HEB store in the study area. A total of 302 usable observations were collected among 305 in-person surveys conducted. As shown in table 1, the usable sample well represents the population of the study area based on the demographic information, including gender, age, race, household size, education, and income. Of the usable sample, 55% are females compared with 48% of the population in College Station and 53% in Bryan. The average household size in the usable sample is 2.43 versus 2.25 for College Station and 2.49 for Bryan. The race distribution of the usable sample is similar to the population. Obviously, the sample is affected by who collected the data and where the collection was done. Because the data were collected by a Chinese-Canadian student in a college town, the percentage of Asian respondents is higher than otherwise. Similarly, the percentage with college education is higher than the U.S. Census Bureau data for the overall population because the Census Bureau does not account for students.

Respondents were asked to report their brand preference of four products (electronics, clothing, packaged food, and fresh fruits and vegetables), including the brand preference ranking from zero (do not buy brands at all) to 10 (always buy brands), and the choice of the WTP range as well as the best point estimate of WTP.

Individuals with a brand preference ranking of 8, 9, or 10 are considered to have a strong brand preference, and a WTP greater than zero is called positive WTP. Table 2 shows that (a) more than half exhibit strong brand preference for electronics but much fewer for food (less than 30%); (b) almost all respondents are willing to pay more for brands in the electronics product category (97%) but fewer for fresh produce (78%); (c) among people with strong brand preference in the associated product category, the average WTP of fresh produce and clothing is higher than that for electronics and packaged food; and (d) among people who are willing to pay more for brands, the average additional WTP for durable goods (electronics

Table 1. Sample Representativeness

Demographic Variables	Census Data: College Station	Census Data: Bryan	Survey Data
Gender: Female (%)	47.80	53.00	55.30
Age distribution			
18 years and over (%)	82.00	72.40	92.05
65 years and over (%)	4.60	7.20	6.62
Race			
White (%)	71.50	53.94	64.24
Black or African American (%)	7.41	12.62	5.63
Asian (%)	7.59	2.08	22.85
Hispanic (%)	11.27	24.59	5.30
Others (%)	2.23	6.77	1.99
Household size	2.25	2.49	2.43
Education among population 25 years and over			
High school graduate or higher (%)	93.70	72.50	100.00
Bachelor's degree or higher (%)	57.70	32.20	85.38
Income			
Median household income ($)	24,218	30,012	53,344
Income per capita ($)	18,770	16,567	21,978

Note: Census data are from the 2005 American Community Survey Data of the U.S. Census Bureau.

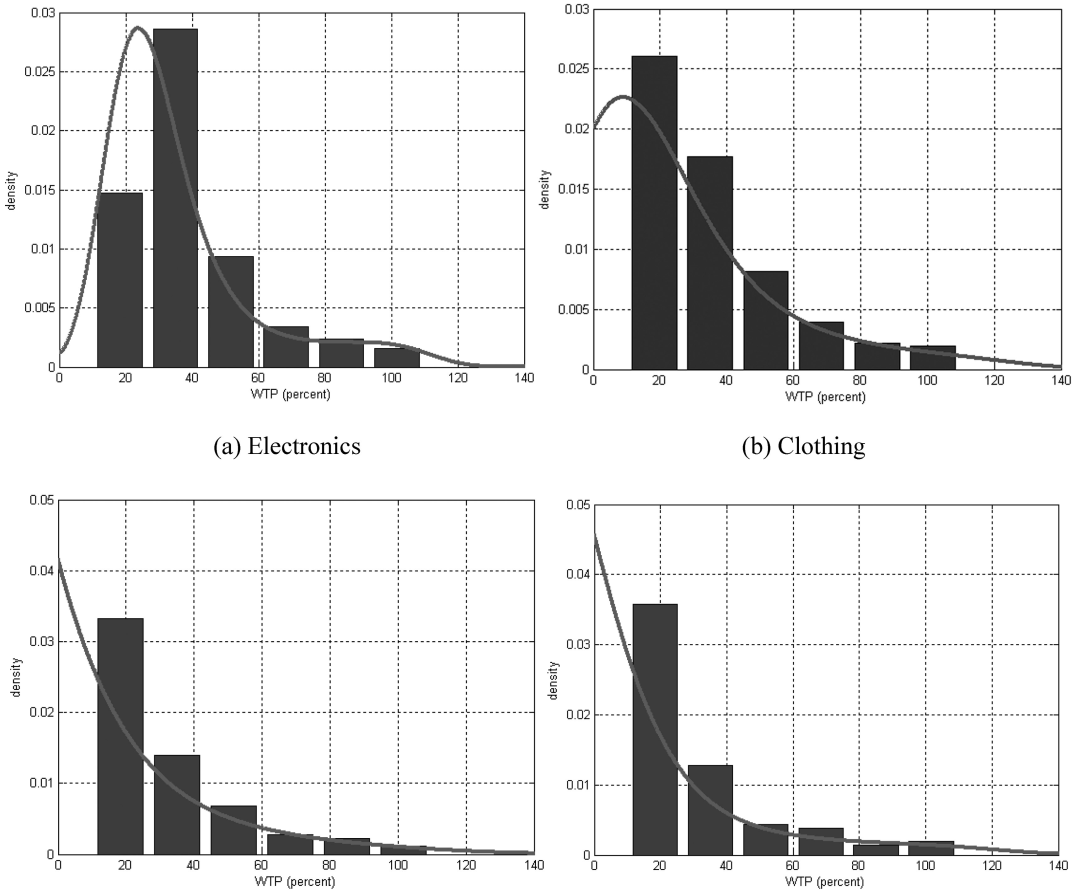
Table 2. Summary Statistics of Brand Preference and WTP for Brands

	Electronics	Clothing	Packaged Food	Fresh Produce
Attitude toward the brand of the particular product				
% of respondents with strong brand preference	65.12	30.46	22.85	27.81
% of respondents with positive WTP	96.69	85.10	87.09	78.48
Average WTP among all respondents	31.34	28.49	22.63	21.64
Average WTP among those with strong brand preference	34.51	45.58	30.79	41.44
Average WTP among those with positive WTP	32.41	33.48	25.98	27.57
Attitude toward brand of all the four products				
% of respondents with strong brand preference toward all the products	6.95			
% of respondents with positive WTP to brands of all the products	69.87			
Average WTP among those with strong brand preference to all the products	36.09	53.57	21.72	22.89
Average WTP among those with positive WTP toward brands of all the products	33.94	32.26	27.90	28.24

and clothing) is about 32%, while the average for food products is 26%. Furthermore, table 2 also shows some patterns of brand preference and WTP for brands in four product categories. For example, about 70% of respondents have a positive WTP for brand products and 7% of respondents state a strong brand preference toward all of the four categories. The WTP for brands of fresh produce is almost as high as in electronics and clothing among those who have a positive WTP for brands in all four of these product categories.

We asked respondents to choose the closest range of WTP for brands among six intervals (0–20%, 20–40%, 40–60%, 60–80%, 80–100%, and at least 100%). Based on their choices of WTP ranges, we estimate the empirical probability density function of the underlying WTP for brand products relative to generic ones using the maximum entropy density method. Adopting the methodology of Wu and Perloff (2007), we use a flexible functional form that nests many commonly used distributions,

$$f\left(W_{ik}^{*}\right) = \exp\left(-\sum_{m=0}^{M} \lambda_m \left(W_{ik}^{*}\right)^m\right) \tag{7}$$



(a) Electronics (b) Clothing

(c) Packaged food (d) Fresh vegetables and fruits

Figure 1. Estimated density and histogram based on the stated WTP ranges for brand products of each product category

where W^*_{ik} is the underlying WTP of consumer i for brands of product category k that is unobservable to researchers, λ_m's are parameters to be estimated, and $m = 0, 1, \ldots, M$ are polynomial orders. As figure 1 shows, the estimated density function based on the interval frequencies matches well with the histogram based on the perceived WTP ranges for each product category. Furthermore, the Pearson's χ^2 test for each product category also suggests a good fit. Based on the estimated density of WTP, we are able to conduct statistical tests on the mean difference of WTP between products (see table 3). The results indicate the highest WTP for brands of electronics, a substantial WTP for brands of clothing, followed by packaged food, and the lowest in fresh produce. However, the mean difference of WTP for food brands is not statistically significant.

We have not found empirical evidence of WTP for brands in the literature. To assess our results, we compare prices at one of the stores we surveyed, a Wal-Mart Supercenter, in Bryan, Texas. A typical example for electronics is the digital camera where the price of a Cannon Powershot with 6MP is over 50% more than similar products of other brands. We picked jeans as a typical case for clothing—the price of men's Levi-Strauss signature regular-fit is about 30% more than other brands. Regarding food items, Del Monte's fruit cans are 10% more than Dole's and 25% more than Great Value's, Wal-Mart's private label. Minute Maid's 1-gallon orange juice (pulp free) is 25% more than Tropicana's and 42% more than Great Value's. These antecedent evidences suggest that the stated WTP in the survey are comparable with actual brand premiums.

Of course, there are some confounding factors including demographic characteristics attributed to the differences of WTP for

Table 3. WTP for Brand Products Based on the Stated Point WTP or the Estimated WTP Based on the Stated WTP Ranges

	Electronics	Clothing	Packaged Food	Fresh Produce
Mean of the stated point WTP	31.34	28.49	22.62	21.64
	[24.27]	[38.29]	[23.77]	[25.76]
Mean of the estimated WTP	34.97	31.09	25.53	24.78
	[22.55]	[27.03]	[25.49]	[27.08]

Test for the difference of the average WTP between two product categories

	On the stated point WTP	On the estimated WTP
$\text{mean}(\text{WTP}_e) > \text{mean}(\text{WTP}_c)$	2.85*	3.87**
	(1.35)	(1.91)
$\text{mean}(\text{WTP}_e) > \text{mean}(\text{WTP}_p)$	8.71***	9.43***
	(6.39)	(4.82)
$\text{mean}(\text{WTP}_e) > \text{mean}(\text{WTP}_f)$	9.70***	10.19***
	(6.17)	(5.02)
$\text{mean}(\text{WTP}_c) > \text{mean}(\text{WTP}_p)$	5.86***	5.56***
	(2.70)	(2.60)
$\text{mean}(\text{WTP}_c) > \text{mean}(\text{WTP}_f)$	6.85***	6.31***
	(3.15)	(2.87)
$\text{mean}(\text{WTP}_p) > \text{mean}(\text{WTP}_f)$	0.98	0.75
	(0.91)	(0.35)

Note: Figures in brackets are standard deviations of the average WTP for brands, and figures in parentheses are *t*-statistics of the test for the difference of the average WTP for brands between two product categories. The single, double, and triple asterisks (*,**,***) represent 1%, 5%, and 10% significance levels, respectively.

brands across product categories. To investigate whether the WTP for brands is still sensitive to product categories, we conduct econometric estimation to control for the relevant sociodemographic variations.

Econometric Estimation and Discussion

The underlying WTP for brands of product category k that is denoted by W^*_{ik} for consumer i is not completely observable to researchers. Instead, we conduct survey and collect the perceived nonnegative value and the range of WTP for brands of each product category. Let IW_{ik} and W_{ik} denote the perceived range of WTP and the perceived point WTP for brands of product category k for consumer i. To fully utilize the survey data, we investigate both IW_{ik} and W_{ik}..

Furthermore, we assume that the latent WTP is linear for all relevant explanatory variables,

$$W^*_{ik} = \beta' X + \mu_i + \varepsilon_{ik} \tag{8}$$

where $X = [IP_k, Z_i, IPREF_k]$ is a covariate matrix, B's are associated coefficients, and μ_i and ε_{ik} are components of error terms. IP_k for $k = 1, 2, 3, 4$ are the product category dummies that capture the effects of product attributes. People prefer brands for different reasons due to the nature of product attributes and consumers' idiosyncratic characteristics. The product category dummies will allow for testing and quantifying the results of inequality (6), in particular, to quantify how much lower the WTP is for fresh produce than other products. Z_i consists of the relevant socio-demographic characteristics of an individual consumer i. We introduce household income per member in thousand dollars (*inc*) and its quadratic term (*inc*^{2}), age (*age*) and its quadratic term (*age*^{2}), education indicators (*edu*1 and *edu*2), where *edu*1 equals one for respondents with bachelor's degree or higher and zero otherwise and *edu*2 reflects whether a respondent is currently enrolled in college, gender dummy (*gender*), race dummies, and household size (*hsize*). $IPREF_{ik} = 1$ indicates that consumer i has a strong brand preference for product k, and zero otherwise. Table 2 shows that brand-preferring respondents are willing to pay more than their counterparts for brands of any product category. Hence, we expect a positive sign of $IPREF_{ik}$. μ_i and ε_{ik} depict individual heterogeneity among consumers and idiosyncratic disturbances, respectively.

Econometric Estimation Based on W_{ik}

Suppose researchers observe a nonnegative value of the perceived WTP,

$$W_{ik} = \begin{cases} W_{ik}^* & \text{if } W_{ik}^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where W_{ik}^* is given in equation (8). We conduct six estimation analyses on W_{ik}, including OLS, tobit, and random-effect tobit (RE-Tobit) models with and without brand preference. The estimation results are reported in table 4. Before we move on to the detailed discussion of estimation results, we report some test results on model specifications.

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

Table 4. Estimation Results of Six Models on the Stated Point WTP for Brand Products (W_{ik}^*)

	Estimated Coefficients						
	OLS	Tobit	RE-Tobit	OLS	Tobit	RE-Tobit	Marginal Effects
IPREF: Strong brand preference = 8, 9, 10	/	/	/	0.17***	0.20***	0.19***	0.16
				(0.02)	(0.02)	(0.02)	[0.01]
IP = E: Electronic	0.10***	0.13***	0.13***	0.03*	0.06***	0.06***	0.05
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	[0.01]
IP = C: Clothing	0.07***	0.08***	0.08***	0.06***	0.08***	0.08***	0.06
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	[0.01]
IP = P: Packaged food	0.01	0.03	0.03	0.02	0.04*	0.04**	0.05
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	[0.01]
INC: Income per capita	0.002*	0.002*	0.002	0.002*	0.002*	0.002	
	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	0.001
INC^2: Income square	−0.00**	−0.00	−0.00	−0.00**	−0.00	−0.00	[0.00]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
age: Age	−0.01**	−0.01**	−0.01	−0.01***	−0.01***	−0.01*	
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	−0.002
age^2: Age square	0.00**	0.00**	0.00	0.00***	0.00**	0.00*	[0.00]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
edu1: College and above	−0.10***	−0.12***	−0.11***	−0.07***	−0.09***	−0.09**	−0.07
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	[0.01]
edu2: Current college student	0.03***	0.04	0.03	0.03*	0.04	0.03	0.03
	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.04)	[0.00]
IG: Gender = female	0.06***	0.06***	0.06**	0.06***	0.06***	0.06**	0.05
	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	[0.01]
Black and African American	0.20***	0.24***	0.24***	0.20***	0.22***	0.22***	0.19
	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)	(0.06)	[0.02]
Asian	0.04**	0.05**	0.05*	0.03	0.04*	0.04	0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	[0.00]
Hispanics	0.07**	0.09**	0.09*	0.06*	0.08**	0.08	0.06
	(0.03)	(0.04)	(0.06)	(0.03)	(0.04)	(0.06)	[0.01]
Other races	−0.03	−0.08	−0.09	−0.02	−0.06	−0.07	
	(0.06)	(0.07)	(0.10)	(0.06)	(0.07)	(0.10)	
hsize: Household size	−0.02***	−0.02***	−0.02**	−0.02***	−0.02***	−0.02***	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	[0.00]
Constant	0.38***	0.37***	0.38***	0.35***	0.33***	0.34***	
	(0.06)	(0.07)	(0.10)	(0.06)	(0.07)	(0.10)	
Log likelihood	−163	−396	−304	−117	−346	−250	
Pseudo R-square	0.08	0.13		0.15	0.24		

Note: Figures in parentheses are White heteroskedastic consistent standard errors and figures in brackets are standard errors of the estimated marginal effects. Single, double, or triple asterisks (*,**,***) represent significance at the 1%, 5%, and 10% levels, respectively.

- *Testing for heteroskedasticity, including the Breusch-Page test and the unrestricted White test in the OLS regressions*: Our results reject the null hypothesis of homoskedasticity at the 1% significance level for the OLS models with or without brand preference. Hence, we report heteroskedasticity-consistent standard errors for the OLS models.
- *Testing for the presence of individual heterogeneity*: If the model does not actually contain the individual heterogeneity, the panel estimator is not significantly different from the pooled estimator. The absence of an individual heterogeneity effect is statistically equivalent to $H_0 : \sigma_\mu^2 = 0$ (Wooldridge 2002, p. 264). A likelihood ratio test for $H_0 : \sigma_\mu^2 = 0$ rejects the null hypotheses at the 1% significance level ($\chi^2(1) = 192$ and $\chi^2(1) = 185$ with or without brand preference, both having a zero p-value). Hence, the RE-Tobit estimation is more appropriate than the tobit estimation on the pooled data.

Table 4 shows that the results of the six models on W_{ik} are qualitatively similar and robust. Based on the tests discussed above, we report the marginal effects and discuss the estimation results based on the RE-Tobit model with brand preference.

We found that consumers are willing to pay 5–6% more for brands of electronics, clothing, and packaged food than in fresh produce after controlling for brand preferences, and 9–10% without controlling for brand preference. The results confirm that consumers are willing to pay substantially less for brands in fresh produce than other product categories after controlling for sociodemographic variations. The empirical results also support our expectations regarding the impacts of sociodemographic factors on WTP for brands. In particular:

- The income per household member increases the WTP for brand products, while the marginal increase declines as income goes up in the OLS estimations. However, the marginal effect of income is minimal.
- An increase in age decreases the WTP for brands while the marginal effect of age increases as age goes up. The results suggest that both younger and elder respondents are more likely willing to pay for brands than the rest of the population.
- Females are willing to pay approximately 5% more for brand products than males.
- Less educated people have a 7% higher stated WTP for brands than more educated individuals.
- White respondents have significantly smaller WTP for brands compared with other ethnic groups. Among all ethnic groups, African Americans have the highest stated WTP for brands—19% more than white respondents.
- The intensity of preference for brand products affects the level of WTP. Consumers with stronger brand preference are willing to pay approximately 16% more for brand products than their counterparts.

Econometric Estimation Based on IW_{ik}

Rather than using the double-bounded contingent valuation method approach (Hanemann, Loomis, and Kanninen 1991) to directly estimate WTP, we use the ordered probit (OPROBIT) model to investigate the impacts of product category and demographic variations on the WTP for brands. The OPROBIT model is built around a latent regression as in the tobit model except the OPROBIT has an ordered categorical dependent variable. The OPROBIT model assumes that the underlying WTP denoted by W_{ik}^* in equation (8) is unobservable, and respondents' choices of the WTP ranges denoted by IW_{ik} are observable to researchers. In this case, the ordered categorical choice of the WTP ranges between six intervals, 0–20%, 20–40%, 40–60%, 60–80%, 80–100%, and at least 100%,

(10)

$$IW_{ik} = \begin{cases} 1 & \text{if } 0 \leq W_{ik}^* < C_1, \\ j & \text{if } C_{j-1} \leq W_{ik}^* < C_j \\ & \qquad \text{for } j = 2, 3, 4, 5, \\ 6 & \text{if } C_5 \leq W_{ik}^*, \end{cases}$$

where the C's are unknown parameters to be estimated together with β's in equation (8). The probability of having $IW_{ik} = j$ is the probability that W_{ik}^* lies between a pair of cut points, C_{j-1} and C_j. Let $\Phi(\cdot)$ denote the standard normal cumulative distribution function. We have the following probabilities,

(11)

$$P(IW_{ik} = j) = \begin{cases} P\left(0 \le W_{ik}^* < C_1\right) \\ \quad = \Phi(C_1 - \beta' X) \\ \quad -\Phi(-\beta' X) & \text{for } j = 1, \\ P\left(C_{j-1} \le W_{ik}^* < C_j\right) \\ \quad = \Phi\left(C_j - \beta' X\right) \\ \quad -\Phi\left(C_{j-1} - \beta' X\right) & \text{for } j = 2, 3, 4, 5, \\ P\left(C_6 \le W_{ik}^*\right) \\ \quad = 1 - \Phi\left(C_5 - \beta' X\right) & \text{for } j = 6. \end{cases}$$

The results presented in table 5 suggest that results are robust with or without incorporating brand preference. Hence, we only report the marginal effects and discuss the results based on the OPROBIT model with brand preference. The comparison of the observed and predicted frequencies for each WTP range in the bottom part of table 5 suggests that overall the OPROBIT models fit data well. For example, 45.70% of respondents indicate that their WTP is less than 20%, and the OPROBIT model predicts 45.01% of such respondents. Similar to the tobit panel estimation on the perceived WTP, the OPROBIT model suggests the following results: (a) respondents' WTP for brands in fresh produce is significantly less than in electronics, clothing, and packaged food; (b) age has a negative effect at an increasing rate on the WTP range; (c) more educated consumers have a lower WTP range than less educated; (d) female respondents likely have a higher WTP level than males; and (e) white respondents are likely less willing to pay more for brands than other ethnic groups including African-American, Asian, and Hispanic respondents.

Marketing Implications with Simulated Brand Premiums

Our results so far show that consumers have a lower WTP for brands of fresh produce compared with electronics, clothing, and packaged food regardless of whether the sociodemographic variations are controlled for. The lower WTP for brands of fresh produce can be a driver for either a low brand price premium or a small market share, or both. In order to identify the likely consequence, we simulate the price premium and the corresponding market share in this section.

We assume consumers are heterogeneous by their WTP for brands. As we discussed in the data section, we estimate the empirical density function of the underlying WTP based on the perceived WTP ranges using the maximum entropy method. Assuming that the estimated density function of WTP for brands of product category k is $\hat{f}(W_{ik}^*)$, $\int_{\underline{W}_k}^{\bar{W}_k} \hat{f}(s)\,ds = 1$, where $\bar{W}_k$ and $\underline{W}_k$ are the upper and lower bound of W_{ik}^*. We assume a monopolistic competitive market in a sense that brands are substitutes for generic products to some extent. A firm produces a brand product with an extra marginal cost c and charges an extra percentage p_k relative to the generic product. An individual consumer will buy the brand if and only if $p_k \le W_{ik}^*$. Hence, the market share of this brand is

$$(12) \quad D_k = \int_{p_k}^{\bar{W}_k} \hat{f}(s)\,ds.$$

This monopolistic firm will choose the optimal premium to maximize profits,

$$(13) \quad \max_{p_k} (p_k - c) N D_k$$

where N is the total number of consumers. The optimal premium is achieved when the marginal revenue equals the marginal cost c:

$$(14) \quad p_k - \frac{\int_{p_k}^{\bar{W}_k} \hat{f}(s)\,ds}{\hat{f}(p_k)} = c.$$

Equation (14) shows that a one-unit increase in p_k will increase the revenue by p_k, but at the marginal loss, $\frac{\int_{p_k}^{\bar{W}_k} \hat{f}(s)\,ds}{\hat{f}(p_k)}$, resulting from a decrease in the demand. Solving equation (14) yields the optimal price premium p_k^*. Substituting p_k^* into equation (12) yields the corresponding market share thereafter.

The simulation results show that the optimal price premiums for brands in fresh produce actually are higher than brands of electronics, clothing, and packaged food; however, the market shares of fresh produce brands are much smaller. For example, when the extra cost of brand products is 10%, the price premium for electronics, clothing, processed food, and fresh fruits and vegetables are 29%, 37%, 39%, and 44%, respectively; and 39%, 48%, 49%, and 59% when the extra marginal cost is 20%. However, the optimal market shares for brands of fresh produce are much smaller

Table 5. Estimation Results and Marginal Effects of the Ordered Probit Models on the Stated WTP Ranges (IW_{ik})

Independent Variables:	Estimated Coefficients: OPROBIT	Estimated Coefficients: OPROBIT	Marginal Effects On The OPROBIT Model with Brand Preference: P ($IW = 1$)	P ($IW = 2$)	P ($IW = 3$)	P ($IW = 4$)	P ($IW = 5$)	P ($IW = 6$)
IPREF: Brand		0.70***	−0.27	0.05	0.08	0.06	0.04	0.04
preference > 7	/	(0.08)	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
IP=E: Electronic	0.58***	0.34***	−0.14	0.03	0.04	0.03	0.02	0.02
	(0.07)	(0.08)	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
IP=C: Clothing	0.33***	0.33***	−0.14	0.03	0.04	0.03	0.02	0.02
	(0.08)	(0.08)	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
IP=P: Packaged	0.07*	0.13**	−0.05	0.01	0.01	0.01	0.01	0.01
food	(0.06)	(0.06)	[0.03]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]
INC: Income per	0.01	0.01	−0.0016	0.0004	0.0004	0.0003	0.0002	0.0003
capita	(0.01)	(0.01)						
INC^2: Income	−0.00	−0.00	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
square	(0.00)	(0.00)						
age: Age	−0.04*	−0.04**	0.0036	0.0007	−0.0010	−0.0007	−0.0005	−0.007
	(0.04)	(0.02)						
age^2: Age square	0.00*	0.00*	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	(0.00)	(0.00)						
*edu*1*:* College and above	−0.38**	−0.30*	0.12	−0.02	−0.04	−0.02	−0.02	−0.02
	(0.17)	(0.17)	[0.06]	[0.01]	[0.02]	[0.02]	[0.01	[0.01]
*edu*2: Current	0.13	0.14	−0.06	0.01	0.02	0.01	0.01	0.01
college student	(0.14)	(0.14)	[0.05]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
IG:Gender=	0.25**	0.26**	−0.10	0.03	0.03	0.02	0.01	0.01
female	(0.11)	(0.11)	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]
Black & African American	0.96***	0.93***	−0.31	−0.02	0.09	0.08	0.07	0.09
	(0.21)	(0.22)	[0.06]	[0.03]	[0.02]	[0.02]	[0.02]	[0.04]
Asian	0.19*	0.15	−0.06	0.01	0.02	0.01	0.01	0.01
	(0.13)	(0.13)	[0.05]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
Hispanics	0.47**	0.44**	−0.17	0.02	0.05	0.04	0.03	0.03
	(0.20)	(0.22)	[0.08]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
Other races	−0.29	−0.24	0.10	−0.03	−0.03	−0.02	−0.01	−0.01
	(0.61)	(0.40)	[0.16]	[0.06]	[0.05]	[0.02]	[0.01]	[0.01]
Hsize: Household	−0.10	−0.06	0.02	−0.01	−0.01	−0.00	−0.00	−0.00
size	(0.40)	(0.04)	[0.02]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Cut Points	Estimated Cut Points		Probability	Observed	Predicted
C_1	−0.65	−0.52	$prob(IW_{ik} = 1) = prob(0 \leq W^*_{ik} < C_1)$	45.70%	45.01%
	(0.43)	(0.44)			
C_2	0.24	0.41	$prob(IW_{ik} = 2) = prob(C_1 \leq W^*_{ik} < C_2)$	30.38%	33.95%
	(0.42)	(0.44)			
C_3	0.74	0.93	$prob(IW_{ik} = 3) = prob(C_2 \leq W^*_{ik} < C_3)$	11.92%	11.80%
	(0.42)	(0.43)			
C_4	1.11	1.32	$prob(IW_{ik} = 4) = prob(C_3 \leq W^*_{ik} < C_4)$	5.79%	5.02%
	(0.42)	(0.43)			
C_5	1.50	1.74	$prob(IW_{ik} = 5) = prob(C_4 \leq W^*_{ik} < C_5)$	3.39%	2.62%
	(0.41)	(0.42)			
			$prob(IW_{ik} = 6) = prob(C_5 \leq W^*_{ik})$	2.81%	1.60%
No. of OBS	1208	1207			
Pseudo R^2	0.05	0.07			

Note: Figures in parentheses are standard errors of the estimated coefficients adjusted for 302 clusters (there are 302 respondents in total). Single, double, or triple asterisks (*,**,***) represent significance at the 1%, 5%, and 10% levels, respectively. Figures in brackets are standard errors of the estimated marginal effects.

than in other product categories. For example, when the extra marginal cost is 10%, only 18% of the population will buy brand products of fresh produce in contrast to 23% for packaged food, 30% for clothing, and 50% for electronics. When the extra cost is 20%, 12% of the population will buy brand products of fresh produce, 16% for packaged food, 20% for clothing, and 30% for electronics. The small market share 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 insight to store organization and prediction 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, almost half of the respondents will always buy generic products and another 9.27% will only buy brand products. In total, at least 58.94% of the potential consumers are consistent in terms of their brand preferences for electronics, clothing, packaged food, and fresh produce. We can at least identify three types of stores: (a) discount stores that sell generic products targeting half of the potential consumers, (b) elite stores that sell only brand items and attract 9.27% of the potential consumers, and (c) supermarkets that sell everything. Our analysis suggests that elite stores with brand products are attractive to the consumer segment sharing consistent high brand preferences as well as WTP across product categories. Harry and David is one example of a company that takes advantage of the upper end of the distribution (http://www.harryanddavid.com/).

Overall, the simulation results suggest two things: (a) if we market brands of fruits and vegetables, we have to target a small market segment and charge a high price; and (b) since we find that people who are willing to pay for brands of fruits and vegetables are also willing to pay for brands in other categories, our results suggest targeting outlets that focus on brands of products in all categories, for example, high-end malls, like sky malls, or brand-focused retailers, like Macy's, Nordstrom, or Neiman Marcus.

Conclusions

The basic premise of this article is that brand value comes from its contribution to reduction in quality risk, the prestige it confers, and from superior design. The features for brand products are likely to vary in value among products and be appreciated differently by individuals with different sociodemographic characteristics. Based on this premise, we hypothesize that the relative value of brands in fresh produce is much smaller than in electronics, clothing, and packaged food. We also investigate the roles of sociodemographic factors on the WTP for brands.

Empirical results based on the data from College Station and Bryan, Texas, on WTP for brands of four product categories support our hypotheses. Tests on the mean difference of WTP across product categories based on the stated WTP or the estimated WTP distribution using the maximum entropy method suggest that WTP for brands in fresh produce is much smaller than in electronics, clothing, and packaged food. Using the random effect tobit model on the stated point WTP and the ordered probit model on stated range of WTP, we also find similar results that WTP for brands of fresh produce is least among four product categories controlling for relevant demographic variations. The empirical study also shows (a) the nonlinear effects of income and age (income increases WTP at a diminishing rate and age decreases WTP at an increasing rate); (b) females, less educated people, or smaller households are willing to pay more for brands; and (c) white respondents are less willing to pay for brands than other ethnic groups including African Americans, Asians, and Hispanics.

Based on the distribution of WTP for each product, we determined the optimal brand premium and the corresponding market share. The simulations suggest a potential for a small market of brands of fresh produce with a high margin relative to the generic products. Since consumers with strong brand preferences in other product categories tend to have a higher WTP for brands of produce, one strategy is to introduce brands in outlets that emphasize brands across the board. Another is to target market segments with consumers who are more likely to buy brands regardless of product categories, like high-income individuals, young people, and female shoppers.

The empirical results of this article are based on the stated preferences and not actual behavior. In spite of the obvious limitation of the data, it allowed us to compare preferences to brands in several product categories and relate WTP with sociodemographic variables.

However, further empirical work with actual purchasing behavior is needed to further study the role and potential of brands of fresh produce.

Second, while we found WTP for brands of food products in general, it is useful to assess WTP for subgroups (e.g., organic versus nonorganic products), as well as different types of foods (vegetables versus fruits). Further research should assess the value of brands of organic food as well as the role of geographic indictor labeling as substitutes and/or complements to brands.

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References

Aaker, D., and E. Joachimsthaler. 2002. *Brand Leadership: The Next Level of the Brand Revolution*. London, U.K.: Simon and Shuster.

Ainslie, A., and P.E. Rossi. 1998. "Similarities in Choice Behavior across Product Categories." *Marketing Science* 17(2):91–106.

Allenby, G.M., and P.E. Rossi. 1991. "Quality Perceptions and Asymmetric Switching Between Brands." *Marketing Science* 10(3):185–204.

Auty, S., and R. Elliott. 1999. "Fashion Involvement, Self-Monitoring and the Meaning of Brands." *Journal of Product and Brand Management* 7(2):109–123.

Caves, R. E., and D. P. Greene. 1996. "Brands' Quality Levels, Prices, and Advertising Outlays: Empirical Evidence on Signals and Information Costs." *International Journal of Industrial Organization* 14(1):29–52.

Chiang, J. 1991. "A Simultaneous Approach to the Whether, What and How Much to Buy Questions." *Marketing Science* 10(4):297–315.

Erdem, T., Y. Zhao, and A. Valenzuela. 2004. "Performance of Store Brands: A Cross-Country Analysis of Consumer Store-Brand Preferences, Perceptions, and Risk." *Journal of Marketing Research* 41(1):86–100.

Fussell, P. 1983. *Class: A Guide through the American Status System*. New York: Touchstone.

Ghosh, A., and S.L. McLafferty. 1987. *Location Strategies for Retail and Service Firms*. Lexington, KY: D. C. Heath.

Gupta, S., and P.K. Chintagunta. 1994. "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models." *Journal of Marketing Research* 31(1):128–136.

Hanemann, W.M., J. Loomis, and B. Kanninen. 1991. "Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation." *American Journal of Agricultural Economics* 73(4):1255–1263.

Hayes, D., and S.H. Lence. 2002. "A New Brand of Agriculture? Farmer-Owned Brands Reward Innovation." AgDM newsletter article. Available at http://www.extension.iastate.edu/agdm/articles/hayes/HayDec02.htm (Last accessed in July 2007).

Heiman, A., and E. Goldschmidt. 2004. "Testing the Potential Benefits of Brands in Horticultural Products: The Case of Oranges." *HorTechnology* 14(1):28–32.

Holbrook, B.M. 1992. "Product Quality, Attributes, and Brand Name as Determinants of Price: The Case of Consumer Electronics." *Marketing Letters* 3(1):71–83.

Kalyanam, K., and D.S. Putler. 1997. "Incorporating Demographic Variables in Brand Choice Models: An Indivisible Alternative Framework." *Marketing Science* 16(2):166–181.

Kaufman, P., C.R. Handy, E.W. McLaughlin, K. Park, and G.M. Green. 2000. "Understanding the Dynamics of Produce Markets: Consumption and Consolidation Grow." USDA/ERS AIB-758.

Moore, C.M., J. Fernie, and S. Burt. 2000. "Brand without Boundaries—The Internationalization of the Designer Retailer's Brand." *European Journal of Marketing* 34(8):919–937.

Parker, D.D., and D. Zilberman. 1993. "Hedonic Estimation of Quality Factors Affecting the Farm-Retail Margin." *American Journal of Agricultural Economics* 75(2):458–466.

Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *The Journal of Political Economy* 82(1):34–55.

Vranešević, T., and R. Stančec. 2003. "The Effect of the Brand on Perceived Quality of Food Products." *British Food Journal* 105(11):811–825.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press.

Wu, X.M., and J. Perloff. 2007. "GMM Estimation of Maximum Entropy Density with Interval Data." *Journal of Econometrics* 138(2): 532–546.

Zeithaml, A.V. 1988. "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence." *Journal of Marketing* 52(3):2–22.