Agribusiness
An International Journal

Product Differentiation by Package Size

Sanatan Shreay
Gilead Sciences, Foster City, California. E-mail: sshreay@gmail.com

Hayley H. Chouinard
School of Economic Sciences Washington State University, Pullman, Washington. E-mail: chouinard@wsu.edu

Jill J. McCluskey
School of Economic Sciences, Washington State University, Pullman, Washington. E-mail: mccluskey@wsu.edu

ABSTRACT

Quantity surcharges exist when a larger-sized package has a higher per-unit price than its smaller-sized counterpart. This article argues that quantity surcharges can be explained by the fact that different sizes of the same product are imperfect substitutes and thus are differentiated products. To test this hypothesis, we utilize grocery store scanner data to estimate a demand system and the associated cross-price elasticities. We focus our empirical investigation on canned tuna, which often exhibits quantity surcharges. A random coefficients logit demand approach is used to calculate elasticities. There is evidence to support the hypothesis that quantity surcharges in canned tuna are driven by firms catering to heterogeneous consumer preferences. [EconLit citations: L25; L66]. © 2015 Wiley Periodicals, Inc.

1. INTRODUCTION

Consumers often have strong expectations about the relative prices of products found in different sized packages. Quantity discounts occur when the price per unit of a brand's larger-sized package is less than the price per unit of the same brand's smaller-sized package. In contrast, quantity surcharges exist when a larger-sized package of a product has a higher per unit price then its otherwise equivalent smaller-sized counterpart. Most studies find evidence of quantity surcharges, with the size of the surcharges ranging from 7% to 34% (Abdulai, Kuhlgatz, & Schmitz, 2009). Many researchers compare per-unit prices of products to examine nonlinear pricing, specifically looking for quantity surcharges (Granger and Billson, 1972; Nason & Della Bitta, 1983; Manning, Sprott, & Miyazaki, 2003; Abdulai et al., 2009).

Consumers often react negatively to quantity surcharges. Previous research finds that when consumers discover quantity surcharges, they often feel that the retailer has engaged in deceptive pricing practices or has eliminated a preferred course of action (e.g., purchasing the larger package) for the consumer and this may decrease the likelihood of purchasing the surcharged brand or shopping in that retail outlet (Manning, Sprott, & Miyazaki, 2003). Consumers may feel exploited as they begin to associate a brand or store with quantity surcharges (Widrick, 1979).

Cost differentials have been offered as justification for differences in per-unit prices across homogeneous products. Examining quantity for paper towels, Cohen (2008) estimates a structural model of consumer behavior and firm conduct to decompose the extent to which quantity discounts are consistent with second-degree price discrimination as opposed to cost differences across package sizes. A cost-based argument is harder to make for the case of quantity surcharges. For some perishable food products, it may be more expensive to refrigerate larger packages of some goods, which can drive cost-based quantity surcharges.

In the marketing literature, some suggest that retailers may be exploiting consumers who do not notice quantity surcharges (Agrawal, Grimm, & Srinivasan, 1993; Gupta & Rominger, 1996). Alternatively, retailers may not intentionally set prices that result in quantity surcharges. These retailers may actively compete with other retailers on specific sizes of fast-moving items

Agribusiness, Vol. 32 (1) 3–15 (2016)
Published online in Wiley Online Library (wileyonlinelibrary.com/journal/agr).

DOI: 10.1002/agr.21425

and drive the price of that package size down, which can result in a quantity surcharge for the larger-sized product (Sprott, Manning, & Miyazaki, 2003).

In contrast, Gerstner and Hess (1987) consider a model fully informed consumers who are heterogeneous in terms of their consumption needs, storage costs, and transaction costs of going to the store. They find these differences across consumers can result in demand-driven variations across package sizes with unit prices that may reflect quantity surcharges or discounts. We offer an explanation for the existence of quantity surcharges that goes one step further by arguing that some goods sold in different package sizes can represent differentiated products to consumers.There may be quality and/or convenience factors associated with size, so that one larger unit is not equivalent to two smaller units.If this is the case, then consumers should not expect an additive price relationship between these products. We focus our empirical investigation on canned tuna, which often exhibits quantity surcharges (Agrawal et al., 1993; Manning, Sprott, & Miyazaki, 2003). In a complementary theoretical paper, Joseph,Subramaniam and Patil(2013) introduce "consumption hassle" to show that some consumers are willing to pay more per unit for a larger package to mitigate this cost.

Product attributes differentiate many products, including canned tuna, which is differentiated with respect to meat type and canning medium. We hypothesize that package size also differentiates many products. Two 6-ounce cans of tuna may not be viewed as equivalent to a single 12-ounce can. In other words, from the consumer perspective, they are imperfect substitutes. Motivations for product differentiation based on package size include that different-sized packages may require different usage and storage options, both before and after the package is opened, or the use of the product may differ for a given size. Another possible explanation comes from the convenience of opening and using a larger package. Under these scenarios, it is realistic to assume that product size may form a basis to differentiate canned tuna products in addition to other product characteristics.

Given product differentiation based on size, consumers should not expect the price per unit of various sizes to be the same or less for larger packages in the same way as they do not expect the per-unit price of "albacore" tuna and "chunk light" tuna to be the same. Different sizes of the same products may have different demand curves, and firms should make their pricing decisions based on these different demand elasticities.This can result in different sized packages of the same product with unequal unit prices. Our hypothesis is that different sizes of canned tuna are imperfect substitutes, which can result in quantity surcharges.

The degree of product differentiation of all products in a market can be assessed by examining cross price elasticities (Bresnahan, 1981; Berry, 1994; Feenstra & Levinsohn, 1995). Our objective is then to estimate demand elasticities for differentiated products using market scanner data. Discrete choice models are often used to provide estimates of elasticities in differentiated products. Conditional logit models (McFadden, 1973) have been applied to several of these problems (Shaked & Sutton, 1982; Perloff & Salop, 1985; Anderson, Depalma, & Thisse, 1988). Recent research on random coefficient (RC) models has focused on how to account for endogeneity while investigating market power, innovation, and product differentiation. Berry (1994) examines discrete choice model of product differentiation with instrumental variables to account for the endogeneity of prices. Berry, Levinsohn, and Pakes (1995, hereinafter BLP) apply this technique to the automobile industry.

BLP's approach has also been applied at the city level and the national levels to food products, including breakfast cereals (Nevo, 2000, 2001; Chidmi & Lopez, 2007), yogurts (Villas-Boas, 2007), frozen foods (Mojduszka, Caswell, & Harris, 2001), and margarine (Kim, 2008). Nevo (2001) uses a RCs logit model to estimate the price-cost margins for ready-to eat cereal. He estimates a brand-level demand system to obtain demand elasticities and then uses these to identify market power from product differentiation, multiproduct pricing, and price collusion. Villas-Boas (2007) uses BLP's approach to calculate elasticities for yogurts at three individual grocery stores to explore alternative vertical relationships between retailers and manufacturers. Chidmi and Lopez (2007) use elasticities calculated using BLP's approach in their study of ready-to-eat breakfast cereals and find that retail markups increase and marginal costs decrease as grocery market shares increase, attesting to oligopoly power with efficiencies.

The remainder of this articleis organized as follows. In Section 2, we present a model of product differentiation based on product size using product characteristic space and explain how we measure product differentiation empirically. In Section 3, we describe the retail-level scanner data that is used in this analysis. In Section 4, we discuss the estimation procedures. In Section 5, we present the empirical results. We conclude in Section 6.

2. MODEL

In this section, we consider package size to be a product attribute, and this provides an alternative justification for the existence of quantity surcharges. Consumer preferences are defined over the characteristics space, rather than the products themselves and thus, consumers are willing to pay more for variants that are better suited to their own tastes. If different sized products are used by consumers differently, then they may have different demand curves with different elasticities.

When choosing a product, the consumer maximizes utility driven by the brand characteristics, including product size, as well as his/her own characteristics. Here, we incorporate size as one of the product characteristics. The indirect utility of consumer *i*from buying the product *j* in market *m*is given by

$$U_{ijm} = \beta_i X_{jm} + \alpha_i p_{jm} + \xi_{jm} + \varepsilon_{ijm}, \text{ for } i = 1, \ldots n; \; j = 1, \ldots, J; \; m = 1, \ldots\ldots M, \tag{1}$$

where X_{jm} is a vector of the *observed* characteristics of brand *j* (excluding price) in market *m*, p_{jm} is the price of the product *j* in market *m*, ξ_{jm} denotes the *unobserved* (to the researcher) product characteristics, α_i and β_i are parameters that depend on individual *i*'s tastes, and ε_{ijm} represents the distribution of consumer preferences around the unobserved product characteristics with a probability density function $f(\varepsilon)$. Following BLP, let

$$\alpha_i = \alpha + \lambda D_i + \gamma V_i, \tag{2}$$

$$\beta_i = \beta + \phi D_i + \rho V_i, \tag{3}$$

where D_i denotes observed consumer characteristics with probability density function $h(D)$, v_i denotes the unobserved consumer characteristics with probability density function $g(v)$. Substituting (2) and (3) into (1) yields:

$$Uijm = \beta Xjm + \alpha pjm + \zeta jm + \phi DiXjm + \rho ViXjm + \lambda Dipjm + \gamma ViPjm. \tag{4}$$

The indirect utility given in Equation (4) can be decomposed into two parts:

$$\delta_{jm} = \beta X_{jm} + \alpha p_{jm}, \tag{5}$$

$$\mu_{ijm} = \zeta_{jm} + \phi D_i X_{jm} + \rho V_i X_{jm} + \lambda D_i p_{jm} + \gamma V_i P_{jm}. \tag{6}$$

Using (5) and (6), we can write (4) as following:

$$U_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm}. \tag{7}$$

The first term δ_{jm} represents the mean utility level of product *j* in market *m*. It is a product-specific term common to all consumers. The other terms $\mu_{ijm} + \varepsilon_{ijm}$ represent the deviation from the meanlevel utility, which captures the effects of the RCs. If we assume that μ_{ijm} in (7) is zero, then we will have traditional logit model. In the logit model, consumers' tastes enter only

TABLE 1. Description and Summary Statistics of Variables

Variable	Description	Mean	Standard Deviation	Min	Max
Market share	Observed market share of canned tuna	0.083	0.166	0.001	0.847
Oil	1 if packed in oil; 0 otherwise	0.333	0.471	0.000	1.000
Albacore	1 if solid white tuna; 0 otherwise	0.333	0.471	0.000	1.000
Price	$ per ounce	0.187	0.088	0.000	0.310
Std. Dev. of income	Log of standard deviation of income	10.083	0.101	9.920	10.25
Single household	Share that are single household	0.289	0.076	0.220	0.550
No car	Share with no car	0.146	0.174	0.020	0.550

through the additive error term ε_{ijm}, and the product characteristics and price parameters are the same for all consumers. The problem with the own- and cross-price elasticities implied by the logit model has been well documented (McFadden, 1981; BLP).

To complete the model and to define the market (and, hence, market shares), an outside good is included to complete the specification of demand system. Consumers may decide not to purchase any of the products. The indirect utility of the outside good is normalized to $U_{i0m} = \varepsilon_{i0m}$. This means that the parameters of the outside good indirect utility are normalized to zero. The share of the outside good is defined as the total size of the market less the shares of the market goods (Nevo, 2001).

Let $k = 0$ denote an outside good if the consumer decides not to buy any of the J products in the set of products ($j = 1, \ldots, J$). As each consumer purchases a unit of the product that yields the highest utility or the outside good, aggregating over consumers, the market share of the $j$thbrand corresponds to the probability the $j$thbrand is chosen. That is,

$$S_j(\delta, x, p, \theta) = \int I\{D_i, v_i, \varepsilon_{ij} : U_{ij} \geq U_{ik} \forall k = 0, \ldots.j\} dH(D)dG(v)dF(\varepsilon), \tag{8}$$

where θ determines the impact of preferences on utility, and $H(D)$, $G(v)$, and $F(\varepsilon)$ are cumulative density functions for the indicated variables and are assumed to be independent. The price elasticities of the market shares for individual products are:

$$\eta_{jkm} = \frac{\partial s_{jm} p_{km}}{\partial p_{km} s_{jm}} = \begin{cases} -\dfrac{p_{jm}}{s_{jm}} \displaystyle\int \alpha_i s_{ijm}(1 - s_{ijm}) d\hat{p}^*_D(D) dP^*_v(v) & \text{if } j = k, \\ \dfrac{p_{jm}}{s_{jm}} \displaystyle\int \alpha_i s_{ijm} s_{ijm} d\hat{p}^*_D(D) dP^*_v(v) & otherwise, \end{cases} \tag{9}$$

where $s_{ijt} = \frac{\exp(\delta_{jt}+\mu_{ijt})}{1+\sum_{k=1}^{k}\exp(\delta_{kt}+\mu_{jkt})}$ is the probability of individual i purchasing product j. These patterns of substitution depend on price sensitivity, not functional form, and substitution between brands will depend on product characteristics, not market shares. The flexibility of this model provides accurate measures of the cross-elasticity between products. However, this model does not have an analytic closed form solution. In the full RCs model, the demand system is solved numerically.

3. DATA

We utilize data from Dominick's Finer Food grocery store chain located in the Chicago area. The data were collected in cooperation between Dominick's and the Kilts Center for Marketing in the Graduate School of Business at the University of Chicago. The descriptive statistics for our data are presented in Table 1. For this analysis, a market is defined as activity in a specific store in a specific week. We examine 10 stores over 4 weeks, and thus we consider 40 markets. The 10 stores are located in various neighborhoods across Chicago. The 4 weeks cover the period of May 31, 1990 through June 27, 1990. The products examined included canned tuna from three brands: Chicken of the Sea (COS), Star-Kist (SK), and Bumble Bee (BB). They offer canned tuna in various sizes and various types of packing characteristics. Eleven products are utilized in this analysis. We created a 12th product as an outside good if the purchase was not made from 11 products selected. Approximately 18% of the products exhibit quantity surcharges in our data.

We include three product attributes that can be observed by consumers. The first attribute is canning medium (oil or water). Oil is observed for 3 out of 11 products in the data. The second observable attribute is meat type (albacore or chuck light). Albacore is observed in three products. The third attribute is "size." All products came in two sizes of either 12.5 ounces or 6.12 ounces.

The dependent variable in the estimation is the market share of the product. To determine the market share, we consider that in 1990 the U.S. per-capita consumption of canned tuna was 3.7 pounds. This equates to 1.14 ounces of canned tuna consumption per person, per week. The total available market for canned tuna in each store in each week is the number of customers in the store each week multiplied by 1.14. The market share for each product equals the total ounces of the product sold divided by the total available market. The price of the products is recorded for each store per week and is measured per ounce. Although each market consists of the same grocery chain, there is considerable variation of prices by market across stores and across weeks.

The demographics are based on the store-specific information. The data comes from the U.S. Government 1990 census for the Chicago metropolitan area. The firm Market Metrics processed the data to generate demographic profiles for each store. The demographic variables include: single household (share of demographics that are single household), no car (share of demographics with no car), and logarithm of standard deviation of income. We select the proportion of single households to examine whether being single affects the purchasing decisions for canned tuna. Most single people are expected to purchase small canned tuna. Similarly, people with no car are restricted in their mobility which may impact their ability to search for their desired products. To obtain consistent estimates, instrumental variables must be used to account for the endogeneity of prices. We use prices of the products at other Dominick stores in the Chicago area during different weeks. These prices are correlated with the original prices but will not include the unobserved characteristics that lead to the endogeneity.

4. EMPIRICAL SPECIFICATION

The characterization of the demand system and the choice of estimation techniques are especially important as more restrictive logit models impose structure on the cross-price elasticities. The restrictive models include the assumption that substitution between brands occurs in proportion to market shares, regardless of brand characteristics. For example, if six ounce cans of COS chunk light tuna packed in water and six ounce cans of SK tuna packed in oil have similar market shares, then substitution from six ounce cans of BB chunk light tuna packed in water will be the same for the COS and SK tuna.

The RC logit model does not force substitution patterns to be functions of market share by allowing prices to be correlated with the econometric term. In this model, products are defined by a set of characteristics that influence demand. Producers and consumers observe all the product characteristics. However, the econometrician only observes some of the characteristics. From this point of view, the econometric error term captures the unobserved characteristics. The unobserved characteristics influence the price of the product, and prices are endogenous. Therefore, it is desirable to model a system in which choices are correlated. Ideally, this correlation should be a function of product and consumer characteristics. Substitution patterns between products will then be similar for similar products, and consumers with similar demographics

TABLE 2. Demand Parameter Estimates

Variables	RC Estimate	RC Std. Error	MNL Estimate	MNL Std. Error
Mean Utility				
Price (F)	−1.707	0.081**	−7.313	1.795**
Oil (U)	−0.031	0.008**	−1.529	0.531**
Albacore (U)	0.184	0.014**	−1.169	0.678**
Deviation from the Mean Utility				
Oil	1.997	9.582		
Albacore	0.571	5.329		
Interaction with Demographics				
Oil X Standard deviation of income	−3.631	15.662		
Oil X Proportion of single household	−8.075	45.385		
Oil X People with no car	4.029	16.193		
Albacore X Standard deviation of Income	1.458	12.595		
Albacore X Proportion of single household	−13.242	46.423		
Albacore X People with no car	5.702	16.509		
Constant (from GMM)	0.290	0.010**		
Log likelihood value	−99.340		−74.410	

Notes. Price (F) is fixed parameter. Oil (U) and Albacore (U) are random parameters with Uniform distribution.
The Constant term is obtained from GMM minimization procedure.
**indicates statistically significant.

will exhibit similar choice behavior. Such a system more accurately describes selection behavior and generates better estimates of cross-price elasticities. The estimation strategy employed in the present study is a straightforward application of BLP's estimation technique.

The first step involves the estimation of predicted market shares using Equation (8). Since the integral in Equation (8) does not have a closed-form solution, it must be solved numerically. Once we have obtained the predicted and original market shares, then the criterion is to minimize the distance between them. The estimation objective is the following

$$\underset{\theta}{\text{Min}} \left\| S(p,x,\theta) - s \right\|, \tag{10}$$

Where $S(.)$ denotes predicted market shares (from Equation (8)) and S denotes observed market shares. However, this approach requires a nonlinear minimization procedure that is difficult to perform, as most parameters enter (8) in nonlinear manner. Berry (1994) suggests inverting the market share function, which yields the mean utility valuation δ (from Equation (5)) that equates the predicted market shares with observed market shares. We use a standard logit model to obtain mean utility value δ. The next step is to define the error term as the deviation from that mean. That is,

$$\omega_j = \delta_j(S_j; \theta) - (\beta X_{jm} + \alpha p_{jm}). \tag{11}$$

The error obtained in (11) is then interacted with instrument Z (prices of the products at other stores and during different weeks) to form the Generalized Methods of Moments objective function:

$$f = \omega(\theta)' Z A^{-1} Z' \omega(\theta), \tag{12}$$

where A is a consistent estimate of $E[Z'\omega\omega' Z]$. Minimization of (12) provides the solution, which yields the demand parameters.

TABLE 3. Estimates of Own-Price and Cross-Price Elasticities*

		12.5 oz			6.12 oz							
Products**		(CLO)	(CLW)	(CLW)	(SWW)	(CLW)	(CLO)	(SWW)	(SWO)	(CLW)	(CLO)	(CLW)
	COS (CLO)	−**0.678 (0.058)**	0.006 (0.000)	0.005 (0.000)	0.001 (0.000)	0.004 (0.001)	0.312 (0.027)	0.001 (0.000)	0.052 (0.008)	0.001 (0.000)	0.309 (0.027)	0.005 (0.001)
12.5 oz	COS (CLW)	0.001 (0.000)	−**0.818 (0.075)**	0.173 (0.010)	0.026 (0.007)	0.117 (0.004)	0.001 (0.000)	0.026 (0.007)	0.000 (0.000)	0.019 (0.005)	0.001 (0.000)	0.142 (0.001)
	STK (CLW)	0.001 (0.000)	0.174 (0.011)	−**0.877 (0.053)**	0.026 (0.007)	0.117 (0.004)	0.001 (0.000)	0.026 (0.007)	0. 000 (0.000)	0.019 (0.005)	0.001 (0.000)	0.142 (0.001)
	STK (SWW)	0.001 (0.000)	0.095 (0.021)	0.094 (0.021)	−**1.042 (0.065)**	0.065 (0.018)	0.001 (0.000)	0.254 (0.085)	0.002 (0.001)	0.233 (0.075)	0.000 (0.000)	0.078 (0.020)
	STK (CLW)	0.001 (0.000)	0.174 (0.011)	0.173 (0.010)	0.026 (0.007)	−**2.065 (0.187)**	0.001 (0.000)	0.026 (0.007)	0.000 (0.000)	0.019 (0.005)	0.001 (0.000)	0.141 (0.001)
	STK (CLO)	0.314 (0.029)	0.005 (0.000)	0.006 (0.001)	0.001 (0.000)	0.004 (0.001)	−**0.737 (0.035)**	0.001 (0.000)	0.052 (0.008)	0.001 (0.000)	0.309 (0.027)	0.005 (0.001)
6.12 oz	BB (SWW)	0.000 (0.000)	0.095 (0.021)	0.094 (0.021)	0.334 (0.125)	0.065 (0.018)	0.000 (0.000)	−**1.769 (0.115)**	0.002 (0.001)	0.233 (0.075)	0.000 (0.000)	0.078 (0.020)
	BB (SWO)	0.220 (0.033)	0.004 (0.001)	0.003 (0.001)	0.011 (0.003)	0.002 (0.000)	0.220 (0.034)	0.009 (0.002)	−**1.521 (0.217)**	0.008 (0.002)	0.219 (0.034)	0.003 (0.001)
	BB (CLW)	0.000 (0.000)	0.096 (0.21)	0.094 (0.021)	0.334 (0.125)	0.065 (0.018)	0.000 (0.000)	0.254 (0.085)	0.002 (0.001)	−**1.95 (0.131)**	0.000 (0.000)	0.078 (0.020)
	BB (CLO)	0.313 (0.029)	0.006 (0.001)	0.006 (0.001)	0.001 (0.000)	0.004 (0.001)	0.312 (0.027)	0.001 (0.000)	0.052 (0.008)	0.001 (0.000)	−**0.675 (0.061)**	0.005 (0.001)
	COS (CLW)	0.001 (0.000)	0.174 (0.110)	0.173 (0.010)	0.026 (0.007)	0.117 (0.004)	0.001 (0.000)	0.026 (0.007)	0.000 (0.000)	0.019 (0.005)	0.001 (0.000)	−**1.641 (0.142)**

*() Values in parenthesis are standard deviations.

**CLO-Chunk Light Oil, CLW-Chunk Light Water, SWW-Solid White Water, SWO-Solid White Oil.

TABLE 4. Cross-Price Elasticities between Tuna and Outside Good

Product Type	RC	MNL
COS (12.5 oz chunk light oil)	0.001	0.032
COS (12.5 oz chunk light water)	0.177	0.150
STK (12.5 oz chunk light water)	0.176	0.149
STK (6.12 oz solid white water)	0.015	0.044
STK (6.12 oz chunk light water)	0.120	0.103
STK (6.12 oz chunk light oil)	0.001	0.032
BB (6.12 oz solid white water)	0.012	0.035
BB (6.12 oz solid white oil)	0.000	0.007
BB (6.12 oz chunk light water)	0.011	0.032
BB (6.12 oz chunk light oil)	0.001	0.032
COS(6.12 oz chunk light water)	0.146	0.125

5. EMPIRICAL RESULTS

The demand parameter estimates are presented in Table 2. For comparison purposes, we present the results of both the RC model and the multinomial logit (MNL) model. The MNL model has a closed-form solution but does not allow for free substitution across the products. The parameter estimates of the mean utility are all statistically significant for both the RC model and the MNL model. As expected, price has a negative coefficient in both the models. When we compare the mean utility estimates of the RC procedure and the MNL, we find that all coefficients have similar signs with the exception of albacore. In the RC model, the albacore coefficient indicates that solid albacore tuna is a positive attribute for canned tuna. The oil coefficient is negative, indicating that it is a negative attribute for canned tuna. While albacore is considered to be a premium attribute, it is in short supply. On the other hand, oil is perceived as unhealthy. Thus consumers' tastes for canned tuna depend on the balance between brand, meat type (albacore preferred to chunk light), and canning medium type (packed in water is preferred to packed in oil). Taking into account consumer heterogeneity, taste parameter for oil as a canning medium is not preferred by consumers who reside in single households, and oil is preferred by consumers who do not have a car. The taste parameter for albacore is less preferable for consumers who reside in single households but preferable for consumers who do not have a car.

The estimated elasticities are presented in Table 3. The diagonal elements in the table represent own-price elasticities and off-diagonal elements represent cross-price elasticities of products. The standard deviations were estimated with a bootstrapping approach. The means of all the own-price and the cross-price elasticities are significantly different from zero. As expected, all the own-price elasticities are negative, and all cross-price elasticities are positive and finite. The own-price elasticities range from –0.678 to –2.057, and the cross-price elasticities range from 0.000 to 0.334.

If the cross-price elasticities between larger-sized cans (12.5 ounces) and smaller-sized cans (6.12 ounces) are close to zero, then the results provide empirical support for our hypothesis. The results (see Table 3) indicate that there is evidence of product differentiation across different sized packages. For example, SK (6.12 ounces, solid albacore, packed in water) has low cross-price elasticities with all three 12.5-ounce products with values 0.001, 0.026, and 0.026, respectively, indicating almost no substitution. On the other hand, there are higher cross-price elasticities between similar sized products, such as BB (6.12 ounces, solid albacore, packed in water) and BB (6.12 ounces, chunk light, packed in water) with values 0.334 for both, indicating higher substitution. A similar observation can be made with respect to product BB (6.12 ounces, solid albacore, packed in water). It has higher cross-price elasticities with similar sized products, such as SK (6.12 ounces, solid albacore, packed in water) and BB (6.12 ounces, chunk light, packed in water), and lower cross-price elasticities with all three similar products that are the

TABLE 5. Examples of Market Shares Under Four Different Scenarios of Changes in Price and Attributes

5(a) Scenario where price per unit of BB (6.12 oz solid albacore water) is increased by 50 cents				5(b) Scenario where prices per unit of COS (12.5 oz chunk light water) and STK(12.5 oz chunk light water) were increased by 75 cents			
Choice	Base % Share	Scenario % Share	Scenario - Base % Change Share	Choice	Base % Share	Scenario % Share	Scenario - Base % Change Share
COS (12.5 oz chunk light oil)	0.000	0.000	0.000	COS (12.5 oz chunk light oil)	0.000	20.651	20.651
COS (12.5 oz chunk light water)	17.134	17.334	0.200	COS (12.5 oz chunk light water)	17.134	0.082	−17.052
STK (12.5 oz chunk light water)	16.506	16.699	0.193	STK (12.5 oz chunk light water)	16.506	0.079	−16.427
STK (6.12 oz solid white water)	3.600	4.133	0.534	STK (6.12 oz solid white water)	3.600	3.975	0.375
STK (6.12 oz chunk light water)	5.344	5.407	0.063	STK (6.12 oz chunk light water)	5.344	6.438	1.094
STK (6.12 oz chunk light oil)	0.000	0.000	0.000	STK (6.12 oz chunk light oil)	0.000	0.000	0.000
BB (6.12 oz solid white water)	1.924	0.055	−1.869	BB (6.12 oz solid white water)	1.924	2.124	0.200
BB (6.12 oz solid white oil)	0.000	0.000	0.000	BB (6.12 oz solid white oil)	0.000	0.000	0.000
BB (6.12 oz chunk light water)	1.634	1.877	0.243	BB (6.12 oz chunk light water)	1.634	1.804	0.170
BB (6.12 oz chunk light oil)	0.000	0.000	0.000	BB (6.12 oz chunk light oil)	0.000	0.000	0.000
COS (6.12 oz chunk light water)	7.911	8.004	0.093	COS (6.12 oz chunk light water)	7.911	9.527	1.616
Outside	45.948	46.491	0.543	Outside	45.948	55.321	9.373
Total	100.000	100.000	0.000	**Total**	100.000	100.000	0.000

(*Continued*)

TABLE 5. Continued

5(c) Scenario where prices per unit of COS (12.5 oz chunk light water) is increased by 25 cents and all the products were made chunk light				5(d) Scenario where prices per unit of STK(6.12 oz chunk light water) and COS (6.12 oz chunk light water) were increased by 50 cents and all the products were made chunk light			
Choice	Base % Share	Scenario % Share	Scenario - Base % Change Share	Choice	Base % Share	Scenario % Share	Scenario - Base % Change Share
COS (12.5 oz chunk light oil)	0.000	0.000	0.000	COS (12.5 oz chunk light oil)	0.000	0.000	0.000
COS (12.5 oz chunk light water)	17.134	8.405	−8.729	COS (12.5 oz chunk light water)	17.134	16.583	−0.551
STK (12.5 oz chunk light water)	16.506	51.008	34.502	STK (12.5 oz chunk light water)	16.506	15.982	−0.524
STK (6.12 oz solid white water)	3.600	5.769	2.169	STK (6.12 oz solid white water)	3.600	11.376	7.777
STK (6.12 oz chunk light water)	5.344	2.624	−2.719	STK (6.12 oz chunk light water)	5.344	0.129	−5.215
STK (6.12 oz chunk light oil)	0.000	0.000	0.000	STK (6.12 oz chunk light oil)	0.000	0.000	0.000
BB (6.12 oz solid white water)	1.924	3.075	1.151	BB (6.12 oz solid white water)	1.924	6.057	4.133
BB (6.12 oz solid white oil)	0.000	0.000	0.000	BB (6.12 oz solid white oil)	0.000	0.000	0.000
BB (6.12 oz chunk light water)	1.634	2.611	0.977	BB (6.12 oz chunk light water)	1.634	5.146	3.512
BB (6.12 oz chunk light oil)	0.000	0.000	0.000	BB (6.12 oz chunk light oil)	0.000	0.000	0.000
COS (6.12 oz chunk light water)	7.911	3.890	−4.021	COS (6.12 oz chunk light water)	7.911	0.192	−7.719
Outside	45.948	22.618	−23.330	Outside	45.948	44.536	−1.412
Total	100.000	100.000	0.000	**Total**	100.000	100.000	0.000

12.5 ounces size. These results provide evidence of little-to-no substitution between 6.12 ounce cans and 12.5 ounce cans in tuna.

The evidence for our hypothesis is further strengthened if we take into account substitution with the outside good. Table 4 presents cross-price elasticities of all products with the outside good for both the MNL and the RC estimation. From Table 4, BB (6.12 ounces, solid albacore, packed in oil) shows no substitution with the outside good (indicating that all substitution is going within the selected products). The cross-price elasticities are close to zero with all the three 12.5-ounce cans of tuna. This provides further empirical support for the hypothesis that different sizes of canned tuna are imperfect substitutes and differentiated products.

We also find evidence of substitution among canned tuna products based on characteristics other than size. For example, COS (12.5 ounces, chunk light, packed in oil) has low cross-price elasticities with the other two 12.5-ounce cans of tuna. However, it has higher cross-price elasticities (0.314) with SK (6.12 ounces, chunk light, packed in oil) and BB (6.12 ounces, chunk light, packed in oil). In this case, the oil characteristic appears to be the dominant characteristic in substitution.

We also offer examples using the RC model to test how changes in attributes and price impact the choice probabilities for each of alternatives, which are presented in Table 5. The base share provides the original market shares of each products predicted by the model. The scenario share demonstrates how the changes specified by hypothetical scenarios impact the base choice market shares. We test how the increase in the per-unit price of a small-sized canned tuna affects market shares of other small-sized canned tuna and large-sized canned tuna. Finally, we use the difference of the scenario share and the base share to calculate the change in the choice shares. Table 5(a) demonstrates the scenario in which the per-unit price of BB (6.12 ounces, solid albacore, packed in water) is increased by 50 cents. As expected, the market share for this product went down by –1.87%. On the other hand, the market share for SK (6.12 ounces, solid albacore, packed in water) went up by 0.53%. Similarly, when prices per unit of COS (12.5 ounces, chunk light, packed in water) and SK (12.5 ounces, chunk light, packed in water) were increased by 75 cents, both these products experienced losses in market shares of 17.05% and 16.43%, respectively (see Table 5b). Under same scenario, the market shares for COS (12.5 ounces, chunk light, packed in oil) went up by 20.65%. Results from Tables 5(a) and 5(b) indicate that increases in price for either small- or large-sized cans of tuna lead to decreases in the market share of the product in question and an increase in the market shares of products that are of similar sized.

Similar results are obtained when we increase the per-unit prices of COS (12.5 ounces, chunk light, packed in water) and SK (6.12 ounces, chunk light, packed in water) by 25 cents and 50 cents, respectively (Tables 5c and d). Under both scenarios, the market share of similar sized products increases. The four examples indicate substitution amongst the same-sized cans of tuna and smaller-to-no substitution between different-sized cans of tuna, indicating size-based product differentiation in canned tuna.

6. CONCLUSIONS

This article offers empirical support for the hypothesis that quantity surcharges may be based on *package size* as a product characteristic. Goods sold in different package sizes may represent differentiated products to consumers, and consumers should not expect an additive price relationship between these products. This work demonstrates that a large can of tuna should not be considered equivalent to two small cans of tuna, in the same way as albacore tuna is differentiated from chuck light tuna. Quantity surcharges in canned tuna then can be viewed as stemming from product differentiation.

From the firm's standpoint, product differentiation is profit maximizing and can result in divergence from marginal-cost pricing. Hence, product differentiation can be useful from both consumer utility and firm's profit point of view. From this point of view, retailers are not engaging in "tricky" pricing techniques. Rather, they are choosing package sizes and prices to maximize profits. Therefore, consumers should not expect to find a consistent decline in per-unit prices when package size increases. Of course, we qualify our results as they may not apply to all incidences of quantity surcharges. There are some products for which package size does not affect convenience or quality, and thus, multiple smaller units are equivalent to a larger unit. Also, there are consumers for whom package size is not a significant product characteristic.

An interesting issue for future research is the relative impacts that specific characteristics have on differentiation. Although we find evidence in support of similar size substitution, we also find evidence of substitution across different sizes along the same characteristics. It would be interesting to test for product differentiation by size in other more homogeneous products that exhibit quantity surcharges, such as ketchup and cooking oil. In other future research, we would like to obtain individual-level data and assign a random parameter to the price variable.

ACKNOWLEDGMENT

The authors wish to thank Ron Mittelhammer, Kyle Stiegert, and David Sprott for helpful discussion and comments. The authors gratefully acknowledge funding from the Food System Research Group at the University of Wisconsin and the Agricultural Research Center at Washington State University.

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Sanatan Shreay *is associate director at Gilead Sciences. He earned his PhD in 2009 from Washington State University. His research interests lie generally in health economics and applied econometrics*

Hayley Chouinard *is associate professor atSchool of Economic Sciences, Washington State University. She received her PhD in 2002 from UC Berkeley. Her research interests include consumer demand for food products, natural resource allocation and policy, and auction and lottery allocation theory*

Jill McCluskey *is a professor atSchool of Economic Sciences, Washington State University. She received her PhD in 1998 from UC Berkeley. Her research interests include industrial organization, consumer preferences for food, technology, and information, and the economics of reputation.*