QUALITY DIFFERENTIATION AND HETEROGENEOUS CONSUMER PREFERENCES

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GO COUGS!!
QUALITY DIFFERENTIATION AND HETEROGENEOUS CONSUMER PREFERENCES

Abstract

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This dissertation consists of three independent but related papers. All of them are devoted to estimate demand functions in presence of unobservable product attributes, such as quality, using different identification strategies. The first two exercises are based on a discrete choice model using the product-market approach developed by Berry (1994) with aggregate data information for gum and beer consumption. The third paper uses a control function approach as an identification strategy in order to estimate the choice model using disaggregated (micro level) data on household choices. These exercises reveal the importance of controlling for price endogeneity due to the existence of unobservable product attributes incorporating substantial bias in the coefficients when ignored.
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CHAPTER ONE

INTRODUCTION
I. Introduction

The estimation of the parameters that govern the behavior of consumers and producers is at the core of the economics discipline. After the foundational work of Adam Smith at the end of the eighteenth century in the context of the Enlightenment also known as the “Age of Reason,” the efforts to summarize peoples’ behavior have evolved from simplified versions of reality to sophisticated and comprehensive models whose application is possible because of the recent developments in computational capacity. This increased computational power has allowed not only to create and maintain new data sets, but also to analyze them accordingly. The existence of this analytical capacity has fueled important developments in econometric modeling and empirical applications. It has also enhanced the power of economic policy by replacing the representative agent paradigm and accounting for agents’ heterogeneity; this is the difference between consumers or firms. In this framework, an important opportunity exists to use this new knowledge in modeling to evaluate its performance in empirical research and in terms of the policy recommendations that can be derived from them.

In the context of this dissertation, I will take advantage of the knowledge accumulation in discrete-choice theory and methods, pioneered by Daniel McFadden in the 1970’s, and especially, of the relatively recent developments in the field of oligopolistic pricing firms models with heterogeneous products and consumers.

This dissertation presents three different applications. In the first paper, I use a discrete-choice model with oligopolistic pricing firms for estimating the demand parameters in the gum market in presence of unobserved product attributes, such as quality in flavoring ingredients. State level market information is used to analyze the consumers’ choices based on gum flavor,
especially mint flavored gum, which is the most important flavor in the U.S. market.

The second paper presents a similar discrete-choice model with oligopolistic pricing firms for estimating a differentiated product demand model for beer in the presence of unobserved product characteristics. As in the first case, this model uses aggregate data information, but now I employ an aggregate dataset at the store level of beer sales in Chicago to analyze the preferences of the consumers with respect to the type of beer they consume. Beer is classified as one out of three categories: mass-produced, imported, and craft beers.

The first two papers demonstrate the advantages of using aggregate market information in Nested Logit (NL) demand models where unobservable product characteristics are important (Berry, 1994). I compare the estimation results with other models: Multinomial Logit (MNL) model and a base case in which the existence of endogeneity of prices is ignored. The results confirm that the coefficients are closer to theory than when the unobservable product characteristics are omitted from the model. In these two cases, the NL model is preferred over the more computationally demanding random coefficients model, such as the Berry, Levinsohn and Pakes (1995) model, because I endeavor to model substitution effects that depend only on predetermined classes of products, as in this case the different types of gum and beer.

Finally, in the third paper we revisit the estimation of the demand for mint-flavored gum products, now using disaggregated household level data and accounting for consumers’ valuation of quality. As in the first document, we consider the existence of unobserved product attributes, such as flavor quality. However, in this case we use a control function approach in the context of a conditional logit (CL) choice model using disaggregated data on household choices.
CHAPTER TWO
QUALITY DIFFERENTIATION WITH FLAVORS: DEMAND ESTIMATION OF UNOBSERVED ATTRIBUTES
II. Quality Differentiation with Flavors: Demand Estimation of Unobserved Attributes

Abstract

This article estimates the demand for mint-flavored gum products using grocery store sales data and accounting for consumers’ valuation of quality. Unobserved product attributes, such as flavor quality, are important elements to consider when estimating the demand for gum. The estimation results suggest that gum is an inelastic product. A positive relationship between willingness to pay and unobserved quality was identified, implying that gum industry should be able to command a premium for higher quality mint flavored products.

Key Words: Quality differentiation, unobserved product attributes, demand estimation, gum.

1. **Introduction**

Chewing gum is one of the best performing segments within the confectionery market, and the global market for gum is forecast to reach US$20.7 billion by the year 2015 (GIA, 2011). The industry is characterized by its product innovation, focused on novel and unique flavors, new ingredients, different product shapes, varied colors, and distinctive packaging techniques (GIA, 2011). The production of gum requires ingredients such as a gum base, sweeteners and a variety of flavors. The gum base is usually a standard mix of synthetic latex and natural rubber extracted from the Sapodilla trees. This ingredient is not a source of product differentiation since only two different gum textures are commercialized, chewing and bubble gum, with 83% and 17% of the market share, respectively. The case of sweeteners is similar, just two categories can be identified, sugar and sugar-free gum, with a share of 42% and 58% respectively. Flavor is the major source of product differentiation. This is reflected in the high number of products available in the market with differentiated flavors.

Mint is the flavor that displays the largest market share, accounting for approximately 50%, followed by fruit flavored gum with 19% (Nielsen, 2005), of total market share. Mint oil is an important product to the Pacific Northwest (Washington, Oregon, and Idaho), which is responsible for 83% of the United States spearmint production and 50% worldwide. However,

the share of mint oil supplied by U.S. producers has been falling in recent years. Mint oil imports now account for approximately 25% of this market. Dealers buy cheaper and lower quality oil from China and India and then blend these oils with the more expensive high quality U.S. oil to accommodate each gum manufacturer standard. From 1993 to 2010, the number of acres harvested dropped 37% and the price per pound dropped 23%.

The supply chain of mint oil involves three parties: (1) the mint oil producers who sell mint oil to the dealers, (2) the dealers who mix different mint oils to generate the final flavoring oil mixtures, and (3) gum manufacturers who buy the oil mixtures from dealers to produce gum. For each flavor of mint gum (e.g. “doublemint,” mint splash, or cool mint), the gum manufacturer demands a specific mixture of mint oils from the dealer. This specific mint oil mixture is the result of blending mint oils from different qualities, which are measured in terms of the presence of oil components such as limonene, menthone, purene, esthers, among others. The less mixture of oils from different growing regions used in the final product leads to the higher flavor quality which is measured in terms of strength and duration.

An investigation of the elasticity of substitution between high quality domestically

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2 Based on personal communications with Rod Christensen, President of Far West Spearmint Oil Administrative Committee, August 8, 2010.


4 Typically, mint oil contains menthofuran. This substance reduces palatability. Oils that contain high levels of menthofuran are considered lower quality, whereas oils with lower level of this substance are considered high quality. Personal communication with mint dealer company representative, August 8 2010.
produced oil and low quality imported oil is important to the U.S. mint oil industry, as their market share has been decreasing with the increase of imports and they have been losing negotiating power with gum manufacturers. However, it is not possible for the researcher to observe or measure differences in the quality of the mint oil mixed to produce each gum flavor, simply because each gum recipe is private information for the manufacturing firms. One alternative is to analyze the consumers’ price elasticity for mint gum accounting for product heterogeneity and unobservable (to the econometrician) product characteristics such as flavor quality.

We assume that consumers have a predetermined ranking of mint flavors based on their previous consumption and their own preferences. Based on the differences in flavor profiles across products, consumers know which flavor delivers the highest utility in consumption. It is necessary to highlight that although the differentiation is purely subjective, the differences in flavor profiles for each gum product are real rather than merely perceived by the consumers. For a discussion of price competition in a setting when product differentiation is purely subjective, see Tremblay and Polasky (2002). From the literature on product differentiated oligopolistic models, we know that unobservable product attributes generate endogeneity of prices, leading to biased estimators. The present study considers the unobserved attributes surrounding flavor quality and compares the results using different estimation strategies.

Only a few studies have been conducted on brand choice and products using mint oil as flavoring ingredient, such as in gum and other mint flavored products. For toothpaste, previous studies include Kaya et al. (2010), Gutierrez (2005), Yang et al. (2005) and Shin (2008), and for
chewing gum Chung and Szymanski (1997). All of these studies examine factors that affect brand selection. However, no study has analyzed mint flavored product choice in the presence of unobservable product quality.

The aim of this study is to estimate the demand for mint-flavored gum accounting for the existence of unobservable flavor quality attributes. We postulate that demand for gum can be depicted by a discrete-choice model in an oligopoly context in which prices are endogenously determined by price-setting firms. We also consider the existence of product characteristics unobservable (to the econometrician), but fully considered by gum manufacturers when setting prices and by consumers when purchasing the products. We use 2005 quarterly aggregated gum retail sales data, arranged in a three-dimensional panel of quantities and prices for 49 contiguous states (Nielsen, 2005).

The article is organized the following way. In the next section, the data is described. Following that, we present two different modeling strategies: the multinomial logit (MNL) and the nested logit (NL) model. In the subsequent section, we introduce the estimation results and comparisons across the different modeling strategies. Next, counterfactual scenarios are simulated to estimate the changes in market shares derived from changes in the consumer’s valuations of the unobservable attributes of the products. Finally, implications are discussed and conclusions are drawn.
2. Data

The database consists on bubble and chewing gum household purchases obtained from the AC Nielsen Homescan survey aggregated by brand for each state. Summary statistics for our data set are presented in Table 1. We define each state as an independent market with information for 2005 four quarters (each quarter is composed of 3 months). The definition of the level of aggregation that constitutes a market was made based on the information availability for each brand within the geographical aggregation. Although information for the state and county levels are both available, in most of the cases, there are not enough individuals to statistically represent each county. On the other hand, for each state, there is sufficient individual-level information.

The chewing gum industry is highly concentrated with three firms (Wrigley, Cadbury, and Amurol) dominating the market (see Table 2). The three-firm concentration ratio (CR3) is almost 90%. The Herfindahl-Hirschman Index (HHI), calculated with considering “other producers” as not having a significant share, is 4364. According to the Federal Trade Commission (FTC), an HHI above 2500 indicates high concentration. We do not have information about most of the small producers, but we know that all of the “other firms” have

\[ \text{HHI} = \sum_{i=1}^{n} x_i^2 \]

\[ \text{CR3} = \frac{\sum_{i=1}^{3} x_i}{\sum_{i=1}^{n} x_i} \]

\[ \text{HHI} = 100 \times \frac{\sum_{i=1}^{n} x_i^2}{\left(\sum_{i=1}^{n} x_i\right)^2} \]

\[ \text{CR3} = \frac{\text{Market Share of Top 3}}{\sum_{i=4}^{n} \text{Market Share of Other Firms}} \]

5 We choose the year 2005 because it contains more information about product attributes and consumers characteristics than any other year available in the survey.

6 Cadbury is a subsidiary of Hershey.
less than one percent of the market and do not to affect the HHI substantially.\textsuperscript{7}

In this case, in spite of the existence of many gum varieties and brands (67 in the dataset), most of them are produced by a few number of firms. Ninety seven percent of gum sales were grouped in 66 different brands, the remaining 3\% of the sales observations were gum products sold by brands with a frequency of less than 100 observations and they were aggregated into one label as “other brands.” Thus, the total of number of brands in the sample is 67.

Table 3 presents a description of the gum sales data by flavor. The average price (in dollars per unit) paid is 82 cents with a standard deviation of 34 cents. Mint flavored gum accounts for 51\% of the total sales share. The highest average price is paid for sour flavored gums, $1.20, followed by variety\textsuperscript{8} flavor. The prices for mint, fruit, and spice are substantially lower than variety, sour, and other flavors in Table 3\textsuperscript{9}. In terms of the form or shape of the product, 94\% of the gum is sold as pieces or sticks, the average price paid for the consumers is 87 cents for gum in pieces form and 75 cents for gum in stick form.

The mint flavor category (51\% of the sample) is divided into three sub categories, peppermint (19.6\%), spearmint (13.8\%) and other, not recognizable or artificial types of mint

\begin{itemize}
\item \textsuperscript{7} In fact, the calculated HHI considering “other producers” as just one firm with 11\% of the market share is 4481.
\item \textsuperscript{8} Variety stands for packages of assorted flavors.
\item \textsuperscript{9} The category “other” corresponds to those products with no available information about their flavor and for which was not possible to assign one by product name, such as: Gourmet, Holiday Stripe, Island Squeeze, Mystery Magic, and Radical Red.
\end{itemize}
According to the U.S Department of Agriculture (Economic Research Service, 1995), “In the United States, the taste of peppermint is preferred to spearmint. As a result, peppermint has more end uses than does spearmint. Peppermint is the number-one mint used in chewing gum, which is the most important use of mint,” (page 11). Peppermint gum has a higher average price per unit than spearmint, 84 cents versus 78 cents (see Table 4). Classifying by texture, the data consists of 83% chewing gum and 17% bubble gum. With respect to the sugar content, almost 60% of the purchases registered in the sample are sugar free.

Based on the product diversity in our data, consumers’ preferences are varied with respect to observable characteristics, such as flavor and form. Unfortunately, we as econometricians cannot observe all flavor quality attributes especially those in terms of strength and duration. Consequently, in order to model the consumers’ behavior, we rely on the subset of observable attributes in addition to our knowledge of the existence of other unobserved attributes. The AC Nielsen survey data allow us to observe socioeconomic characteristics, including household size, age, income level, presence of children in the household, and marital status. These socioeconomic characteristics are used as covariates in the estimations.

10 This category includes types of mint agglomerate products flavors, such as “Arctic Chill” and “Cool Frost” in which it was not possible to determine clearly which type of mint was used.
3. **Empirical Framework**

For purposes of estimation, we define the combination of brand and flavor as a product. This definition allows us to divide the set of differentiated products into subsets of homogeneous products. Examples of brands with their flavors are: peppermint, used in brands such as Wrigley's Doublemint, Wrigley's Extra, and Wrigley's Freedent. Spearmint is used in brands such as Wrigley's spearmint or Care-Free Koolerz. Fruit flavors are used in brands such as Wrigley's Juicy Fruit, Adams Bubblicious, or Adams Dentyne Tango. Spicy flavors are used in brands as Wrigley's Big Red or Adams Dentyne Fire. Also, we control for other elements such as the form of the gum and size of the package.

The use of a discrete choice model for estimation is advantageous for several reasons. First, it allows us to utilize aggregate-level information. Specifically, in the context of the demand estimation in presence of unobserved product attributes, considering that unobserved product attributes are correlated with prices, endogeneity of prices can be addressed in an aggregate discrete choice model. However, our main purpose is to examine whether and how the observed price variation can be attributed to unobserved product attributes rather than to understand consumers’ preference heterogeneity. In this sense, the present study does not account for any individual consumer preferences. Second, using a discrete choice model allows us to solve the dimensionality problem by projecting the products onto characteristics space. Third, it provides a tractable link between consumer theory and econometrics, allowing one to
study markets with differentiated products in a structural model framework. Finally, since the estimation must account for non observable product-specific characteristics or demand factors, the model allows for the possibility of prices being correlated with unobserved demand factors.

We start by assuming the indirect utility of consumer $i$, for product $j$ depends on the characteristics of the product and the consumer, $U(x_j, \xi_j, p_j, \nu_i; \theta_d)$, where $x_j$ and $\xi_j$ are the observed and unobserved product characteristics, respectively. The price of each product is represented by $p_j$. Consumer-specific terms affecting utility are $\nu_i$ and $\theta_d$. The vector $x_j$ represents the observable characteristics including flavor, if the product is sugar free, the form of the product, texture, and size. Vector $\xi_j$ represents the unobserved product characteristics or the product attributes that the econometrician cannot measure or observe, but producers consider when setting their prices, and the consumers take into the account to make their choices, e.g. the average quality of each product derived from the individual consumer’s valuation.

Consider a specification for the log indirect utility function where the unobserved consumer specific taste parameters are captured by the error terms:

$$u_{ij} = x_j \beta - \alpha p_j + \xi_j + \epsilon_{ij}$$  \hspace{1cm} (1)

The random term $\xi_j$ can be interpreted as the mean of consumers’ valuations of all the unobserved product characteristics, and the error term ($\epsilon$) represents the distribution of consumer preferences around $\xi_j$. However, we must consider that gum manufacturers know their own product characteristics, including those that are unobserved to the econometrician. Factors, such
as higher quality ingredients, are considered to estimate their production costs, and they likely use this information to set the prices of their products. In this way, product prices ($p_j$) are likely to be correlated with those unobservable product attributes ($\xi_j$).

Another source of market price variation is the competition among products. Greater variety of products in a specific market implies intense price competition, affecting the prices of the products negatively. Recent literature has incorporated the product assortment as an endogenous variable to the model (see Draganska, et al. 2008, Draganska, et al., 2009, Mazzeo 2002, Seim 2006, and Allender, et al. 2010). Taking advantage of the modeling strategy developed by this literature, we assume product assortment is exogenous and it affects the price.

Other strategies that affect product pricing may include, for example, the introduction of “private labels” which are brands developed by individual retailers as a strategic tool to compete with national brands. This strategy seems to increase retailers’ profits and national brand prices (Bontemps, et al., 2008, and Cotterill, et al., 2000). However, there is no record of private labels in the case of gum products.

3a. Multinomial and Nested Logit Models Setup

Assuming that the error term is independently and identically distributed (i.i.d.) across products and consumers as an “extreme value” distribution, we can represent the traditional market shares multinomial logit (MNL) model in the usual way:
The functional form characterized in Equation 2 is the closed-form of the MNL model, representing the probability of choosing good \( j \) among all other goods, including an outside good. Where \( \delta_j = x_j\beta - \alpha p_j + \xi_j \) stands for the mean utility for product \( j \), and \( k = 0 \) is the outside good that represents the consumer’s expenditure in any other goods but gum. In this case, we use the state population as reference for potential market for the product to define the outside good.

Following Berry (1994), demand can be estimated by “inverting” the market-share equation to find the implied mean levels of utility for each good. A feature of the method is that allows for estimation by traditional instrumental variables (IV) techniques. By normalizing the mean utility of the outside good to zero and assuming the relation between observed and predicted market shares is invertible, we can represent this relation in a linear form as:

\[
\ln(s_j) - \ln(s_0) = \delta_j = x_j\beta - \alpha p_j + \xi_j \tag{3}
\]

On the left hand side of the equation is the observed market share of each product \( j \) relative to the outside good, and on the right hand side is the mean utility for product \( j \).

As we pointed out previously, gum manufacturers know their own product
characteristics, including those unobserved for the econometrician, and they use this information to set the prices of their products. In this way, product prices ($p_j$) are likely to be correlated with those unobservable product characteristics ($\xi_j$), so the explanatory “observable” variables are not completely exogenous to the model, specifically the price, generating an identification problem due to endogeneity.

An additional potential problem with the MNL approach is that assumes that the probability of each alternative is related equally with the probability of other alternatives, this is the independence of irrelevant alternatives (IIA) assumption does not hold. An approach to this problem is allowing consumer tastes to be correlated across products $j$ in a restricted fashion by using the nested logit (NL) modeling approach.

Preserving the assumption that tastes are distributed via extreme value, but allowing consumer tastes to be correlated across products $j$ in a restricted way, we also setup a nested logit (NL) model. We can then group gum products into exhaustive and mutually exclusive sets according to their flavor $g = 0, 1, ..., 6$, where the outside good $g = 0$, is assumed to be the only member of group 0\(^1\). If we denote the set of products in group $g$ as $\mathcal{g}_g$, for product $j \in \mathcal{g}_g$, the indirect utility of consumer $i$ can be represented by:

$$u_{ij} = \delta_j + \zeta_{ig} + (1 - \sigma_g)\epsilon_{ij}, \quad (4a)$$

\(^1\)The rest of the categories were assigned as: fruit ($g=1$), mint ($g=2$), other ($g=3$), sour ($g=4$), spice ($g=5$) and variety ($g=6$).
Where $\delta_j = x_j \beta - \alpha p_j + \xi_j$ and $\epsilon_{ij}$ is i.i.d. extreme value. For consumer $i$, the variable $\zeta$ is common to all products in group $g$ and has a distribution function that depends on $\sigma_g$, with $0 \leq \sigma_g < 1$. Parameter $\sigma_g$ measures similarity of products within each group. As the parameter $\sigma_g$ approaches one, the within-group correlation of utility levels goes to one, and as $\sigma_g$ approaches to zero, the within group correlation goes to zero.

We can interpret Equation 4a as a model involving random coefficients $\zeta_{ig}$ only on group-specific dummy variables. That is, if $d_{ig}$ is a dummy variable equal to one if $j \in g_g$ and equal to zero otherwise, we can rewrite Equation 4a as:

$$u_{ij} = \delta_j + \sum_g d_{ig} \zeta_{ig} + (1 - \sigma_g) \epsilon_{ij}$$

(4b)

Thus, we can derive an analytic expression for mean utility levels similar to the MNL model represented by Equation 3 with just one additional term for each group as$^{12}$:

$$\ln(s_j) - \ln(s_0) = \delta_j \equiv x_j \beta - \alpha p_j + \sum_{g=0}^6 \sigma_g \ln (\tilde{s}_{j/g}) + \tilde{\xi}_j$$

(5)

The new element compared with Equation 3 is the natural log of the within-group market

$^{12}$ For details refer to Berry (1994).
share \( (\bar{s}_{j/g}) \). Using the NL model represented by Equation 5, the estimates of \( \beta \), \( \alpha \), and \( \sigma_g \) can be obtained from a linear instrumental variables (IV) regression of differences in log market shares on product characteristics, prices, and the log of the within-group share.

However, as in the case of prices in MNL model specification, since the within-group share is also related with the unobserved characteristics via consumer preferences, \( \bar{s}_{j/g} \) is endogenous, suggesting the need for additional exogenous variables that are correlated with the within group share but not with the unobserved product valuation. In both specifications, the MNL given by Equation 3 and the NL given by Equation 5, the error term \( (\xi_j) \) is a structural component of the model and represents the average consumer valuation of the unobserved product attributes such as quality.

Summarizing, the differences between models is that the NL model relaxes the assumptions of the MNL model. The basic idea of the NL model is to extend the MNL model in order to allow groups of alternatives to be similar to each other in an unobserved way; that is, to have correlated error terms (Heiss, 2002). In addition, as highlighted by Berry (1994), the NL model may be preferred when the researcher wants to model substitution effects depending only on predetermined classes of products, as it is the case in this project.

Basically, both the two models describe how market shares are generated from modelers’ mind. Evaluated at the “true” value of parameters, the difference between the predicted (from the models) and observed market share depends only on the unobserved product attributes. These models can then be identified if we have a set of instruments, conditional on which the mean of the unobserved product attributes is zero. The relevance of the two models is that in both cases
MNL and NL, Equations 3 and 5, the specification is linear in parameters, allowing the use of traditional instrumental variables (IV) to eliminate endogeneity.

3b. **Instruments**

Recall that the endogeneity originates in the relation between prices and the product specific characteristics. We use a set of instrumental variables (IV) that are related with the prices but not with the unobserved characteristics captured by the error term (\( \xi_j \)). As instruments, we use two groups of variables: the prices of the same products in other markets (Hausman, 1996) and the distance from the production plants to account for the geographical location of each market. In this sense, prices of brand \( j \) in different markets will be correlated due to the common marginal costs, but they will be uncorrelated with the market-specific valuations of the product\(^{13}\). The distances from the production plants as IV for prices are proxy variables for the transportation costs, which are determinant of the supply function, so it is related with the prices but not with the unobservable market-specific valuation of the product\(^{14}\).

Assuming the use of the correct instrumental variables the conditional mean of the error term equals zero given the repressors, so we can interpret the coefficients as the structural parameters

\[^{13}\text{We try different sets of instruments like: market structure (number of firms), rival products characteristics and wages.}\]

\[^{14}\text{We estimate a first stage regression using other prices and distances as determinants of prices for each product. In both cases the coefficients were statistically significant and an R2 of 67\%.}\]
of the model, see Cameron, et al. (2005). In the case of the NL model, where the within-group share is also endogenous, we use the within number of products as a variable of the market structure or the degree of competition. The market structure is correlated within each group, but not with the unobservable attributes\(^\text{15}\).

By construction, the number of products is inversely correlated with the within market shares, but uncorrelated with the market-specific valuation of the product. From economic theory, we can support the use of number of products within the market as instruments by framing the situation as a sequential-decision game. The decision made by each firm on the number of products is made before the realization of consumer preferences. At this stage, firms do not know consumers’ preferences. Hence, the number of products is not related with the consumers’ valuations of the unobservable product attributes. Even though this approach allows consumer tastes to be correlated across products, giving more reasonable substitution patterns compared to the MNL model, the grouping of products or the choice of sets is made a priori without any basis in theory or empirical support, but instead is justified by the market segments we are interested in analyze, according to flavor. Given the set of instruments in both models, we have more moment conditions than parameters to be estimated, so it is a case of over-identified parameters that we estimate using the two stages least squares (2SLS) estimator.

\(^{15}\) Other instruments evaluated were rival product characteristics, some demographics, and advertisement expenditure. Even though the results were not very different from what we present, the tests show that these other instruments where weaker than those we use.
4. Estimation Results

In this section, we present the results of the estimations of the MNL and NL models. The results for the initial benchmark estimation are presented in column 1 in Table 5, these coefficients correspond to an estimation ignoring the non-orthogonal relation between covariates and error term, specifically the relation between prices and unobservable product attributes. The coefficient for price is not statistically different from zero, which suggests that the demand for gum is completely inelastic to prices, which is inconsistent with economic theory. This anomaly is likely caused by an endogeneity problem, and could be explained if unobserved product quality is considered. As in Trajtenberg (1989), prices appear to have a positive, or in this case nil, effect on consumers.

From the estimation results, it is also possible to see the positive marginal utilities generated by some of the product characteristics such as flavor, sugar and texture. In the case of the size, the marginal utility is negative, suggesting that consumers prefer to carry smaller packages of gum. The second column in Table 5 presents the coefficients for the MNL model represented by Equation 3, now controlling for the presence of endogenous variables by using the prices of other products and the distances from the production plants as IVs, specifically to address the endogeneity of prices (column 2). In this estimation, the results are more compatible with economic theory. The coefficient for price is negative, as expected, and statistically significant.
Column 3 presents the estimation results for the NL model represented by Equation 5. As in the previous case, we use prices of other products and the distances from the production plants as IVs to address the endogeneity of prices, but we also use the within-market number of products as instrument for the within-market shares to allow for product heterogeneity. In this case, the coefficient on price increases in absolute value when the model incorporates the IVs. An interpretation of this finding is that products with higher unmeasured quality characteristics sell at higher prices. These results suggest that ignoring the correlation between price and the demand error can lead to findings of upward sloping demand curves and other anomalies. In this case, we notice that the coefficient for price in the first estimation is not statistically different from zero. In contrast, when endogeneity is accounted for with the use of IVs, the coefficients are negative and statistically significant, which is consistent with economic theory.

In terms of the coefficients of the observable product characteristics, when we account for endogeneity, the form of the product, the size, and the flavor are statistically significant in explaining the market shares. If the gum is in the form of a stick, the market share decreases with respect to the other forms of products. If the size of the product decreases, the market share of the product increases. If the product is mint flavored, the probability of a higher market share also increases. In terms of consumers’ socioeconomic characteristics, the income level and the age both decrease the probability of purchasing the good (see Table 5). The decrease in gum consumption with the income level might be related to substitution effects with respect to other type of non-gum breath freshener products, such as Althoids or Mentos, which are not included in the sample.
One can also understand the importance of unobservable characteristics by examining the fit of the logit demand estimation. The explanatory power of the model increases after product heterogeneity is allowed by the nesting strategy. In the case of the MNL-IV model, the $R^2$ statistic is 30%. For the NL-IV, the $R^2$ statistic increases to 52%, reducing significantly the percentage of the variance in mean utility levels associated with the unobserved product characteristics (see Table 5).

In Table 6, we present results indicated similarities of products within each group. Recall that the parameter $0 < \sigma_g < 1$ measures this similarity. When the parameter is closer to one, the products within the group are more similar. When it is closer to zero, the products within each group are more heterogeneous. The empirical results support the theory, and all the coefficients are within the unit interval. Additionally, products with fruit, mint, or even spice flavor, are closer to each other within their group than the products classified as sour, variety, and other. This group of categories is expected to be the most heterogeneous because in each of the products in this category different flavor profiles are present. For example, sour gums can have fruit, mint or even spice flavor. In the case of the variety, or assorted packages, the parameter value is half way between the two extremes. We calculate the elasticities for different flavor profiles. We find that mint-flavored gum is slightly more inelastic (-0.1003) than non mint (-0.1203), but the difference in the coefficients is not statistically significant.

With respect to income elasticities, the parameters are small for all flavor categories, but statistically different from zero, on the order of 0.00023 and 0.0004 for mint and non mint flavor categories, respectively. The small, almost nil income elasticity, supports the fact that in the case
of gum products, the budget constraint is not binding. We used household income for the estimation, which is high compared with the price of gum products.

After controlling for unobservable product characteristics, just in the case of mint flavored products, we observe some correlation between product prices and the product unobserved quality in the case of mint, 21%. This is the consumers’ willingness to pay increase with the quality of mint flavor (see Figure 1). The study of gum demand using this approach, contrast with the larger computational burden of the Berry, Levinsohn, and Pakes (BLP) model (Berry, et al., 1995). The NL model may be preferred when the researcher wants to model substitution effects depending only on predetermined classes of products (Berry, 1994), such as flavors, in this case.

4a. Counterfactual Exercises

In this section, using the estimation results, we answer hypothetical questions about the market. Counterfactual scenarios can help us to understand the role of the unobservable product attributes such as quality on the market shares. We partition the sample according to the consumer’s quality valuation in two sub groups: high-quality goods (HQ) and lower-quality goods (LQ), according to the distribution around the mean of the consumers’ valuations of the unobserved product characteristics. We find that the actual (and predicted) market shares for the first group in average is 3.5%, meanwhile for the second group is 1.2%. In terms of the predicted market shares, considering changes in the factors that affect the consumer’s quality
valuation, e.g. The quality of the inputs used in the production process, we note the following: If the products are the same, the consumer’s quality valuation is the average for all products, then the market shares of the industry are more homogeneous, around 1.8% for each product.

Consider a case not as extremely homogeneous as the previous one. If the perceived differentiation by the consumers for HQ products reduces by half, and at the same time the perceived differentiation by the consumers for LQ products doubles, the market shares of the industry are more homogeneous, 2.3% for HQ and 1.3 for LQ.

5. Conclusions

In this study, we estimate demand for mint-flavored gum products with retail sales data while accounting for consumers’ valuation of unobserved quality and other product attributes. We find that the unobserved product attributes are important to consider when estimating the demand for heterogeneous products. With a nested logit model, almost 47% of the variance in mean utility levels is associated with the unobserved product characteristics such as flavor quality. In terms of the parameter estimates, we find that the presentation of the product in terms of its form is important to consumers. Smaller packaged products have an advantage in terms of their market shares, and socio-economic characteristics such as income level and age, both decrease the probability of purchasing the good.

Our estimation results suggest that mint-flavored gum is more inelastic to changes in
price than other flavors, and there exists an important variability in the valuation for quality among gum products. Given that mint-flavored gum is more inelastic to changes in prices than other flavors and the positive relationship identified between willingness to pay and unobserved quality, mint gum industry should be able to command a premium for higher quality product. The finding that U.S. consumers are willing to pay a premium for higher quality products is useful information for the U.S. mint oil industry, as they compete with cheaper foreign imports and lose negotiating power with gum manufacturers. Even though the tradeoff between lower costs and higher quality is not going to disappear, consumer preferences for high quality products seems to guarantee the existence of a significant market share for high quality mint oils in the U.S. gum market.
6. Chapter References


<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Type</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
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<tr>
<td>Price</td>
<td>Numerical</td>
<td>Per unit</td>
<td>0.8249</td>
<td>0.3473</td>
<td>0.005</td>
<td>2.89</td>
</tr>
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<td>Units</td>
<td>Numerical</td>
<td>Number of units of the item purchased.</td>
<td>1.5275</td>
<td>1.2119</td>
<td>1</td>
<td>29</td>
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<td><strong>Product Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Form</td>
<td>Categorical</td>
<td>Pieces, sticks or other.</td>
<td>1.5870</td>
<td>0.6039</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Flavor</td>
<td>Categorical</td>
<td>Mint, fruit, spice, variety, sour, other flavors.</td>
<td>2.2300</td>
<td>1.7019</td>
<td>1</td>
<td>6</td>
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<tr>
<td>Mint Flavor</td>
<td>Categorical</td>
<td>Peppermint, spearmint, and other</td>
<td>1.0499</td>
<td>1.1737</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Texture</td>
<td>Categorical</td>
<td>1 if chewing gum and 0 if bubble gum</td>
<td>0.8288</td>
<td>0.3767</td>
<td>0</td>
<td>1</td>
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<td>Brand</td>
<td>Categorical</td>
<td>Brand code</td>
<td>106535.4</td>
<td>65655.44</td>
<td>4817</td>
<td>196550</td>
</tr>
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<td>Categorical</td>
<td>Name of the producer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume</td>
<td>Categorical</td>
<td>Size of the package in ounces.</td>
<td>17.15</td>
<td>17.68</td>
<td>1</td>
<td>380</td>
</tr>
<tr>
<td>Sugar Content</td>
<td>Dummy</td>
<td>1 if Sugar-Free</td>
<td>0.5854</td>
<td>0.4926</td>
<td>0</td>
<td>1</td>
</tr>
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<td>Coupon</td>
<td>Dummy</td>
<td>1 if Coupon</td>
<td>0.1004</td>
<td>0.3006</td>
<td>0</td>
<td>1</td>
</tr>
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<td><strong>Household Characteristics</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household Size</td>
<td>Numerical</td>
<td>Number of individuals in the household.</td>
<td>2.8672</td>
<td>1.4476</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Income Level</td>
<td>Categorical</td>
<td>Income intervals begin with annual incomes under $5,000 and the highest interval is $100,000 and over.</td>
<td>19.41</td>
<td>5.6428</td>
<td>3</td>
<td>27</td>
</tr>
<tr>
<td>Children</td>
<td>Dummy</td>
<td>1 If children under 18 in the household</td>
<td>0.4008</td>
<td>0.4900</td>
<td>0</td>
<td>1</td>
</tr>
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<td>Marital Status</td>
<td>Dummy</td>
<td>1 If married</td>
<td>0.6783</td>
<td>0.4671</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age</td>
<td>Categorical</td>
<td>Ages interval starting at 25, top is 65+</td>
<td>6.4799</td>
<td>1.8355</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td><strong>Other Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Projection61k</td>
<td>Numerical</td>
<td>Expansion factor.</td>
<td>3184.6</td>
<td>3427.41</td>
<td>139</td>
<td>31230</td>
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<tr>
<td>Producers</td>
<td>Categorical</td>
<td>Code for each producer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Categorical</td>
<td>East, west, south, central.</td>
<td>2.7458</td>
<td>0.9158</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>State</td>
<td>Categorical</td>
<td>49 contiguous states.</td>
<td>27.870</td>
<td>16.3244</td>
<td>1</td>
<td>56</td>
</tr>
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</table>

Source: AC Nielsen Homescan survey
Table 2. Gum Producers Market Shares by Quarter (2005)

<table>
<thead>
<tr>
<th>Producer</th>
<th>Quarter</th>
<th></th>
<th></th>
<th></th>
<th>Average</th>
</tr>
</thead>
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<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>WRIGLEY'S</td>
<td>60.0</td>
<td>60.0</td>
<td>58.0</td>
<td>55.0</td>
<td>58.3</td>
</tr>
<tr>
<td>HERSEY</td>
<td>25.0</td>
<td>28.0</td>
<td>29.0</td>
<td>29.0</td>
<td>27.8</td>
</tr>
<tr>
<td>AMUROL</td>
<td>1.8</td>
<td>1.5</td>
<td>1.8</td>
<td>2.5</td>
<td>1.9</td>
</tr>
<tr>
<td>OTHER PROD</td>
<td>14.0</td>
<td>11.0</td>
<td>12.0</td>
<td>14.0</td>
<td>12.8</td>
</tr>
<tr>
<td>CR3</td>
<td>86.8</td>
<td>89.5</td>
<td>88.8</td>
<td>86.5</td>
<td>87.9</td>
</tr>
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</table>

Source: AC Nielsen Homescan dataset expanded by population projection.
Table 3. Price Distribution of Gum by Flavor

<table>
<thead>
<tr>
<th>Flavor</th>
<th>Freq.</th>
<th>Price</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mint</td>
<td>51%</td>
<td>0.79</td>
<td>0.28</td>
</tr>
<tr>
<td>Fruit</td>
<td>19%</td>
<td>0.75</td>
<td>0.30</td>
</tr>
<tr>
<td>Spice</td>
<td>12%</td>
<td>0.78</td>
<td>0.35</td>
</tr>
<tr>
<td>Variety</td>
<td>4%</td>
<td>1.1</td>
<td>0.57</td>
</tr>
<tr>
<td>Sour</td>
<td>2%</td>
<td>1.2</td>
<td>0.42</td>
</tr>
<tr>
<td>Other</td>
<td>13%</td>
<td>1.0</td>
<td>0.42</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>0.82</td>
<td>0.34</td>
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</table>

Source: AC Nielsen Data, calculations by the authors.
Table 4. Mint Flavors Market Shares and Prices

<table>
<thead>
<tr>
<th>Mint Types</th>
<th>Share</th>
<th>Avg. Unit. Price</th>
<th>S.D. Unit Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peppermint</td>
<td>19.54</td>
<td>0.84</td>
<td>0.31</td>
</tr>
<tr>
<td>Spearmint</td>
<td>13.85</td>
<td>0.78</td>
<td>0.27</td>
</tr>
<tr>
<td>Other Mint</td>
<td>17.92</td>
<td>0.74</td>
<td>0.26</td>
</tr>
<tr>
<td>No Mint</td>
<td>48.58</td>
<td>0.86</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Source: AC Nielsen Data, calculations by the authors.
Table 5. Gum Demand Estimation Results

<table>
<thead>
<tr>
<th>Covariates</th>
<th>(1) BASE</th>
<th>(2) MNL-IV</th>
<th>(3) NL-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>-0.030</td>
<td>-0.266 ***</td>
<td>-0.130 *</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.079)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Form (Piece)</td>
<td>0.008</td>
<td>0.269 ***</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.067)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Form (Stick)</td>
<td>0.011</td>
<td>-0.163 **</td>
<td>-0.112 *</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.074)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.029 ***</td>
<td>-0.120 ***</td>
<td>-0.088 ***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.026)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Sugar-Free</td>
<td>0.161 ***</td>
<td>0.001</td>
<td>-0.024</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.050)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Texture</td>
<td>0.184 ***</td>
<td>0.444 ***</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.058)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Mint</td>
<td>0.316 ***</td>
<td>0.752 ***</td>
<td>0.723 ***</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.053)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Incomes</td>
<td>-0.007</td>
<td>-0.093 ***</td>
<td>-0.072 ***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.022)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Household Size</td>
<td>0.016</td>
<td>0.022</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.030)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Children</td>
<td>-0.008</td>
<td>-0.032</td>
<td>-0.034</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.032)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.036 ***</td>
<td>-0.076 ***</td>
<td>-0.053 ***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.024)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Observations</td>
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<td>4403</td>
<td>4403</td>
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<tr>
<td>$R^2$</td>
<td>0.118</td>
<td>0.305</td>
<td>0.529</td>
</tr>
</tbody>
</table>

Legend: * $p<.1$; ** $p<.05$; *** $p<.01$, controlling for number of firms, producers, time period, and region. Standard Errors in parenthesis. Calculations by the authors.
### Table 6. Coefficients of Product Similarity within Groups

<table>
<thead>
<tr>
<th>Parameters</th>
<th>NL-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>σ(g=Fruit)</td>
<td>0.148*</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
</tr>
<tr>
<td>σ(g=Mint)</td>
<td>0.156**</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
</tr>
<tr>
<td>σ(g=Other)</td>
<td>0.290***</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
</tr>
<tr>
<td>σ(g=Sour)</td>
<td>0.303***</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
</tr>
<tr>
<td>σ(g=Spice)</td>
<td>0.152*</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
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<tr>
<td>σ(g=Variety)</td>
<td>0.268***</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
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</tbody>
</table>

**Legend:** * p<.1; ** p<.05; *** p<.01, controlling for producers, time period, and region. Standard Errors in parenthesis. Calculations by the authors.
Figure 1. Mint Flavor Products: Prices and Estimated Quality

Source: AC Nielsen Data, calculations by the authors.
CHAPTER THREE

SUBSTITUTION BETWEEN MICRO AND MACRO BREWS
Abstract

Although mass producers’ market share still represents the vast majority of beer sales, the trend of consumers switching from mass to craft beer seems irreversible. The aim of this study is to estimate price, income, and substitution elasticity of craft beers with respect to mass produced beers. We verify the hypothesis of that beer is a normal good with inelastic demand. We also find that the elasticity of substitution between categories of beer is almost zero, which suggests there is very little substitution between categories of beer.

Key Words: Beer, craft, demand estimation, elasticity.

1. Introduction

In 1974, there were 421 traditional breweries in operation in the United States. Currently, competition and economies of scale has led a beer industry with only twenty macro brewing firms offering a relatively homogeneous product, American lager beer. The opposite trend has occurred with microbrew or specialty breweries. There were just two specialty breweries in 1978. However, in 2011, there were 1,740 microbreweries offering a wide variety of differentiated products (Brewers’ Association Magazine, 2012). The increase in the number of specialty breweries is prodigious, especially after 1991, when their tax advantage was enlarged. The Federal excise tax rate for brewers increased from $9 to $18 per barrel, but brewers with annual sales of less than 2 million barrels continued to pay $7 per barrel on their first 60,000 barrels sold annually (see Tremblay and Tremblay, 2005).

Although macro brewers still account for the vast majority of sales, the growth of the craft beers seems irreversible. According to Tremblay, et al. (2005), “homogenization of the beer produced by macro brewers, changes in local demand conditions, and a more favorable regulatory environment created profitable niches in many local markets for micro brewery beer, and entry into this sector occurred at a phenomenal rate from 1977 to 1998.” However, they argue, “The microbrewery boom appears to be over, but firm turnover and market competition will remain high in the specialty sector given low entry barriers, foreign competition, and consumer demand for variety”, see Tremblay et al., (2005), p. 322. (See Figure 1)
Although many studies have estimated the demand elasticity of beer (Hogarty et al., 1972; Tegene, 1990; Lee et al., 1992; Nelson, 1999; and Freeman, 2001), and some authors have estimated brand-level elasticities, (Hausman et al., 1994; Rojas et al., 2008; and Bray et al., 2009), to our knowledge, no one has estimated it for any particular style or category of beer. The aim of this article is to identify the price, income and substitution elasticity between craft, imported, and mass produced beers. We use scanner data from Dominick's supermarkets in Chicago. This database contains approximately nine years of store-level data for more than 700 beer products distributed in 100-store chain. This dataset includes information about product and consumer characteristics.

For the purposes of this study, we define mass produced beers as those with similar characteristics of lightness, fermentation methods (bottom fermenting yeast), and the use of adjuncts such as corn or rice. Imported beers are those produced abroad, and finally, the rest of the beers are classified as “craft” beers. It is important to highlight that some beers produced by traditional breweries are considered part of the craft segment because of the differences in taste and the use ingredients. For example, Blue Moon Belgian White, Henry Weinhard's Private Reserve, and Leinenkugel's Sunset Wheat are produced by Miller-Coors Brewing Co., but in our database they are classified as craft beers.

The objective of the present study is to estimate own- and cross-price elasticities of demand between types of beer, accounting for consumer valuation for product specific

16 Data set contains weekly information of beer sales starting on 06/06/91 up to 05/07/97.
unobserved (by the econometrician) quality and other attributes such as freshness, bitterness, sweetness, among others. The theoretical framework follows Berry (1994) in estimating an aggregate demand functions. Section two discusses the related literature on consumers’ preferences for alcoholic beverages. Section three presents descriptive statistics for the sample; section four develops the empirical framework. The fifth section is devoted the estimation results, and finally the conclusions are presented in section six.

2. Alcoholic Beverages in the Literature

2.a. Consumer Preferences

Several approaches have been used to study the consumption of alcoholic beverages. In this section, we summarize some of the main characteristics and findings of these models. The Almost Ideal Demand System (AIDS) model (Deaton, et al., 1980) has been applied frequently to estimate demand for alcoholic beverages, including beer (Clements et al., 1983; Heien et al., 1989; and Blake et al., 1997). Clements et al. (1983) show that when the consumer’s utility function is appropriately separable in alcoholic beverages and all other goods, it is possible to confine the attention to the three main categories of alcoholic beverages (wine, beer and spirits) and ignore all other goods. Heien et al. (1989) estimate a demand system treating all beverages simultaneously in presence of demographic effects. Finally, Blake, et al., (1997) use an AIDS model to estimate beer demand in the United Kingdom.

Other empirical approaches for the estimation of the demand parameters rely on
empirical estimations evaluating different factors. Colen et al. (2011) study beer consumption across countries over the time. They examine the factors that affect beer consumption across time and nations, such as income level, openness to trade, globalization, climatic conditions, religion, and relative prices. Other modeling strategies have been used with different purposes. Heufer (2010) analyzes social alcohol consumption with a game theory approach to model the strategic improvement of the informational content of a noisy exogenous signal. Other researchers have focused on the dynamics of the demand for alcoholic beverages. Levy et al. (1985) analyze the period between 1940 and 1980. They utilize a Cobb-Douglass consumption function in which per capita consumption of alcoholic beverages depends on real per capita disposable personal income and the relative price of alcoholic beverages to personal income. They find that total demand for alcoholic beverages is inelastic and weak evidence of higher propensity to consume alcoholic beverages by those under 21. Fenn et al. (2001) build on Becker et al’s (1988) theory of rational addiction to analyze an inter-temporal utility maximization problem. This leads to a demand equation where the consumption depends on prices and past and future consumption linearly.

In the current study we use a product-market identification strategy, following Berry (1994), Berry et al (1995), Nevo (2000, 2001) and Rasmusen (2007), we assume the preferences of the consumers are described by an indirect utility function that is a linear function of observed and unobserved (by the researcher) product and individual characteristics.
3. Data

We use a limited, but convenient, data set to study preferences. It is limited because provides scanner data information from a major grocery chain from one metropolitan area (Chicago) during the 1990’s. The Dominick's dataset is available from the Kilts Center for Marketing at the University of Chicago, Booth School of Business. The data base is composed of approximately 1.4 million sales observations. It contains information weekly sales information on 484 Universal Product Codes (UPCs) for 343 different brands of beer sold in 60 stores over seven years (from 1991 to 1997). The data set contains product information as well as information about the distribution of the socio-demographic variables for the areas where each store is located. We define each store-year as an independent market \( (m) \) where each consumer \( (i) \) finds different brands of beer \( (j) \), each brand can be categorized as one of three types: mass, craft or import beer. The variables available associated with the product are the type of beer, whether it is mass produced (American lager), import, or craft. The total quantities sold of each item in each store, as well as the price of the item, size, color, and alcohol content. Other product characteristics were constructed using information from ratebeer.com and beeradvocate.com.

The vast majority of sales correspond to mass produced beer with 86% of the market share. Approximately 8% of sales are for imported beer, and the remaining 5% is the share for craft beers (see Table 1). Prices are also different for each segment or type of beer, the cheapest
beer is the mass produced, 54 cents per unit, which may be somewhat explained by the economies of scale generated in their mass production and distribution and the use of lower-cost grains such as corn and rice. In contrast, craft beers, on average, command a price premium of 26 cents per unit over the price of mass produced beers. In the case of imported beers, the price premium is, on average, 41 cents. Additional cost factors that may be incorporated into the price of imported beers include transportation costs and import taxes.

In order to consider similar products, we include in our analysis only the most common unit of production, 12-ounce units (either can or bottle), bundled in different numbers, from four units bundle up to 30 units. By far, the most popular choice of package is a six-unit bundle or “six-pack” with 54% of the market share. Mass produced beer can also be differentiated from the high-end beers with respect to its packaging strategy. While most of the craft and import segments are sold in six-packs, 93% and 86% respectively, more than half of the total mass produced beer (57%) is sold in bundles with more than 12 units. Thus, American lagers are not just produced in mass but commercialized too. In terms of the style of beer, most of the beers produced are pale lagers or lager beers (90%). The lager beers are produced by the large breweries or mass producers. Secondly, ales represent about 6%, and stouts represent 0.8%.

17 Usually the combination of import and craft beer segments as defined in this document are called “high end beers”.

18 Classification according to Michael Jackson’s criteria.
Mass-produced beers have lower alcohol by volume (ABV)\textsuperscript{19} with an average level of 4.5%, followed by the import beer with 4.6% ABV, and the craft beers with the highest at 4.9% ABV. Other beer characteristics such as calories, color, some flavors (e.g. malty, bitter, fruity, floral, among other flavors) and consumers ratings are available in the data set for a subsample of beers.

In terms of the socio-demographic variables, the average income and home values for neighborhood surrounding each store, as well as the percentage of black and Hispanic population, the percentage of college graduates, and the average size of the household are observed factors. The socio-economic variables reflect the average values for the neighborhoods surrounding the each store. The average household has almost three members (2.6), an income of almost $43,000 with a home value of approximately $150,000. The percentage of the population around the store who graduated from college is 22%, and the average proportion of blacks and Hispanics living in the community is 15%, see Table 2.

There are significant differences in some consumer characteristics around each store and this is related to beer sales. Average income level is higher by $900 in those neighborhoods in which more craft beers are sold compared to neighborhoods where more mass produced beer is sold. The difference in average income for neighborhoods in which more imported beers are sold is $1,200 compared to neighborhoods that sell more mass produced beer. The same pattern

\textsuperscript{19} Alcohol by volume (ABV) represents the portion of the total volume of liquid that is alcohol. Information on this variable was constructed from different sources like ratebeer.com, beeradvocate.com and Rebecca Hellerstein based on consumer reports.
is present in the house values and other socio-economic variables. It is important to highlight that Dominick’s dataset consumer characteristics does not vary over time. We note that there is a high heterogeneity across the different neighborhoods surrounding the stores in terms of their beer consumption. For example, the share of mass beer by store can be as low as 7.7% and as high as 88%, in the case of craft the range moves from 4% to 40%, and in the case of imported beer the range of the market share moves from 7% to 51%. Different product characteristics might be useful to understand the consumer choices. Using these set of variables together with the consumers’ characteristics we will be able to model the consumer behavior with respect each segment of the market.

4. Modeling Framework

We model the market for beer as an oligopolistic market with differentiated products where each store attends an independent market composed by the neighborhoods surrounding the store, and each brand of beer is considered as a product with a discrete choice framework. The choice of this model allows for the use of aggregate level information, and we can solve the dimensionality problem by projecting the products onto a characteristics space. Discrete choice models also provide a tractable link between consumer theory and econometrics, which allows us to study markets with differentiated products. These models allow for the possibility of prices

20 Differences in the averages for all these variables by type of beer are statistically significant with 99% of confidence.
being correlated with unobserved demand factors.

We assume the utility of consumer $i$ for product $j$ depends on price, product characteristics, and the consumer’s tastes, $U(x_j, \xi_j, p_j, v_i, \theta_d)$, where $x_j$ and $\xi_j$ are the observed and unobserved product characteristics, respectively. The price of each product is represented by $p_j$. The consumer-specific terms affecting utility are $v_i$ and the demand parameters $\theta_d$. Among the observed product characteristics ($x_j$), we account for the size of the bundle (number of units), the alcohol content (ABV), whether the beer type is mass, craft, import; the style (ale, fruit, low alcohol, Oktoberfest, seasonal, smoked, steam, stout, wheat), and the price ($p_j$).

According to Feenstra and Shapiro (2003), one should consider that a seller may maintain prices zones with different pricing strategies according to the presence of other stores in the area. We control for this strategic pricing behavior in the model by including a categorical variable for the pricing zone in which each store is located. The unobserved product characteristics ($\xi_j$) represent all the product attributes that the econometrician cannot measure or observe, but the consumer takes into the account to make their choice. Examples include the quality of the ingredients used in brewing, the freshness of the product, bitterness, sweetness, and all the possible flavors and aromas that can be generated in the brewing process, as well as labels, and bottle shapes.

Consider a random-coefficients specification for utility where the unobserved consumer-specific taste parameters are captured by the error terms:
\[ u_{ij} = x_j \beta_i - \alpha p_j + \xi_j + \epsilon_{ij} \] (1)

In this context, \( \xi \) can be interpreted as the mean of the consumers’ valuations of the unobserved product characteristics, and the error term represents the distribution of the consumers’ preferences around \( \xi \).

We assume a model in which preferences are the same for all the consumers \( (\beta_i = \beta) \) and the error term is independently and identically distributed (i.i.d.) across products and consumers with “extreme value” distributions. We can represent traditional market shares multinomial logit (MNL) model in the usual way as:

\[ S_j = \frac{e^{\delta_j}}{\sum_{k=0}^{l} e^{\delta_k}} \] (2)

where \( \delta_j = x_j \beta - \alpha p_j + \xi_j \) represents the mean utility for product \( j \), and \( k = 0 \) is an outside good that represents the consumer’s expenditure in any other goods but beer. The functional form represented in Equation 2 is a closed form representing the probability of choosing the good \( j \).

Following Berry (1994), by normalizing the mean utility of the outside good to zero and assuming the relationship between observed- and predicted-market shares is invertible, we can represent this relation in a linear form as:
\[ \ln(s_j) - \ln(s_0) = \delta_j = x_j \beta_t - \alpha p_j + \xi_j \] (3)

The problem with this functional form is that the prices are correlated with the unobservable product characteristics, so the explanatory variables are not exogenous to the model, generating an identification problem due to endogeneity. For example, on an average per-unit basis, small breweries use greater quantities and varieties of hops and fewer adjuncts, such as corn or rice but more malted grains, such as barley. The use of higher quality ingredients increases the production costs, thus the prices are positively correlated with factors that are unobservable in our dataset.

The advantage of representing the market shares as Equation 3 is that the functional form is linear, so traditional instrumental variables (IV) can be used to account for the endogeneity of prices. As instruments in this case, we use the prices of the same products in other markets (Hausman, 1996). We assume that product valuations are independent across markets. Consequently, the prices of brand \( j \) in different markets will be correlated due to the common marginal costs, but they will be uncorrelated with the market-specific valuations of the product.

Given the nature of the research question, an important issue is the estimation of a specific parameter for predetermined subsets of the product, i.e. the types of beer (mass, craft, and imports). Therefore, we adjust the MNL model to account for the variability within groups. The nested logit (NL) model relaxes the assumption of the independence of irrelevant alternatives (IIA), allowing for consumer preferences to be correlated by the type of beer. We
can describe the situation with an example: if a consumer wants to buy an American lager, he/she may consider alternatives such as Coors light or Bud Light, but he will not consider an India Pale Ale (IPA). Consequently, removing IPA beers from the choice set will not change the consumer probabilities of choosing a mass-produced beer. Preserving the assumption that consumer tastes are distributed extreme values but allowing them to be correlated across products $j$ in a restricted fashion, we set up the NL model.

According to Berry (1994), we can group the products into exhaustive and mutually exclusive sets $g = 0, 1, 2, 3$ where the outside good $j = 0$ is assumed to be the only member of group 0. If we denote the set of products in group $g$ as $\mathcal{G}_g$, for product $j \in \mathcal{G}_g$, the utility of consumer $i$ can be represented by:

$$u_{ij} = \delta_j + \zeta_{ig} + (1 - \sigma)\epsilon_{ij},$$  \hspace{1cm} (4)

where again $\delta_j = x_j\beta - p_j + \xi_j$ and $\epsilon_{ij}$ is i.i.d. extreme value. For consumer $i$, the variable $\zeta$ is common to all products in group $g$ and has a distribution function that depends on $\sigma$, with $0 \leq \sigma < 1$. Further, $(1 - \sigma)$ is the average correlation between groups of the random utility across products within the same group. We can interpret Equation 4 as a random coefficients model involving random coefficients $\zeta_{ig}$ only on group-specific indicator variables. That is, if $d_{ig}$ is an indicator variable that is equal to one if $j \in \mathcal{G}_g$ and equal to zero otherwise, then we can rewrite Equation 4 as:
Thus, we derive an analytic expression for mean utility levels similar to Equation 3 with one additional term:

\[ u_{ij} = \delta_j + \sum_g d_{ig}\zeta_{ig} + (1 - \sigma)e_{ij} \]  

(5)

Thus, we derive an analytic expression for mean utility levels similar to Equation 3 with one additional term\(^{21}\):

\[ \ln(s_j) - \ln(s_0) = \delta_j \equiv x_j\beta - \alpha p_j + \sigma\ln(\bar{s}_{j/g}) + \xi_j, \]  

(6)

where the additional element compared with Equation 3 is the natural log of the within-group share \((\bar{s}_{j/g})\). However, as in the case of prices, the within-group share is expected to be related with the unobserved characteristics. This is the case because unobserved product characteristics influence the market share within each category. Thus, \(\bar{s}_{j/g}\) is endogenous, suggesting the need for additional exogenous variables that are correlated with the within-group share.

We use product variety as an exogenous variable, indicating the market structure or the degree of competition. The market structure, which is accounted for with the number of products available in each market, is correlated with the within-market share but not with the unobservable product attributes. Economic theory provides support for the use of the number of products within the market as an instrument by framing the situation as a sequential-decision

\(^{21}\) For details refer to Berry (1994).
The decision made by each firm about the number of products is made before the realization of consumer preferences. At this stage, firms do not know consumer preferences. Hence, the number of products is not related with the consumers’ valuations of the unobservable product attributes. Alternatively, the number of products may be considered exogenous because in Illinois, as in most of the United States, brewers are not allowed to sell directly to retailers, configuring the “three-tier system.” Hence, the variety of products available in the market is not an outcome of the market, but a result of distributors’ decisions.22

Thus, in the following section, we present the results of the three estimation approaches: 1) a base-case scenario, where endogeneity problem is completely ignored; 2) a MNL model that uses prices of the same product in other markets as instruments, and 3) an NL model that uses product variety to address the endogeneity of the within market share.

5. Estimation Results

The estimation results of the benchmark model estimated via ordinary least squares (OLS) are presented in column one of Table 3 for comparison purposes. The second column presents the results of the MNL model (Equation 3), which accounts for endogeneity by using the prices of the same products in other markets as instruments. In column three, we present the

22 The three-tier system (producers, distributors, and retailers) was introduced after the prohibition to avoid the contact between producers and retailers.
results of the NL model using the same instrumental variables to account for the endogeneity of prices and within-market shares\textsuperscript{23}.

Using Equation 6, estimates of $\beta$, $\alpha$, and $\sigma$ can be obtained from a linear IV regression of differences in log of market shares on product characteristics, prices, and the log of the within-group share. These results are presented in the column (3) of Table 3.

The explicative power of the model increases once some product heterogeneity is allowed by the nesting strategy. For the base model only 20\% of the variation is explained by the observed product characteristics. In the case of the MNL-IV model the $R^2$ is almost 44\%, this implies that 56 percent of the variance in mean utility levels is due to the unobserved characteristics. For the NL-IV the $R^2$ increases to almost 72\% reducing significantly the percentage of the variance in mean utility levels associated with the unobserved product characteristics.

Even though the coefficient for price in the case of the OLS estimation is statistically significant, the coefficient is very small. On the other hand, the coefficients increase in absolute value once some controls are included to account for the endogeneity. As in Trajtenberg (1989), prices appear to have a positive, or in this case small, effect on consumers due to the existence of

\textsuperscript{23} Similar results to those obtained in Table 3 were observed using a dummy variable to absorb the differences between products, as in (Nevo, 2001), instead of assuming that the error term captures the unobserved product attributes. This alternative strategy can be used because of the richness of the panel data set, for which we were able to estimate an intercept per product.
endogenous regressors.

From the estimation results, it is also possible to see the positive marginal utilities generated by some of the product characteristics such as size and alcohol content. In terms of the household characteristics, marginal utilities also reveal that education level, given by the percentage of college graduates living around the store, affects negatively beer consumption, maybe because substitution effects with other alcoholic beverages such as wine or spirits. The same negative effect was observed in the case of a bigger family. However, in the case of incomes, the effect of consumption is positive on consumption.

Based on the NL estimation, we calculate the price elasticity matrix presented in Table 4. The last two sets of coefficients, for the MNL and NL models, were obtained by using two-stage least squares (2SLS) as an estimation method. Confidence intervals are presented in Table 5.

The demand for beer is highly inelastic with -0.1736 across all types. With respect to other studies, all the estimation results point to inelastic demand, but the variation across estimates is considerable, from -0.142 to -0.889 (see Table 6). Our estimates are close to those in the lower part of the distribution.

Further, within each type, demands for particular types are own-price inelastic, but there is variation across types. Mass produced beer has the lowest own-price elasticity, -0.1238. If the price of a mass produced beer increases by 1%, the quantity demand will fall by 0.1238%. A possible explanation for this insensitivity to price is high brand loyalty among consumers to their particular brand of mass produced beers. Advertising rivalries in the mass produced segment

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have traditionally been intense (Nelson, 2005). The imported beers are also own-price inelastic at (-0.1572). A similar explanation may be that consumers are also traditionally loyal to specific imported brands. Further, stores that sell more imported beers in our data set are surrounded by neighborhoods with higher average incomes, and thus the imported beer consumers may be less sensitive to changes in price. Although craft beers are still inelastic as a category, they are the least inelastic product segment. The own-price elasticity for craft beer is -0.3161, which is more than twice that of the own-price elasticity for mass-produced beer. An explanation for this difference might be that craft beer consumers are more concerned with styles of beers, such as India Pale Ales (IPA), rather than a specific brand. The cross-price elasticity estimates across types of beers are close to zero, suggesting that there is almost no substitution across types of beer. If a consumer wants to buy a six pack of Budweiser, the fact that Sam Adams beer is on sale will likely not affect his choice.

During the first five years of the sample, the number of products available grew at an average annual rate of 14%. However, in the year 1996, the number of products available in the market dropped from 227 to 159, perhaps owing to the change in the concept of the company\textsuperscript{24}. Figure 2 shows the evolution of the elasticity compared with the total number of products available in the market over the years. When the number of products is higher, demand is more

\textsuperscript{24} According to Dominiks website, “In 1996, with the introduction of Dominick’s Fresh Stores, the company initiated a new concept in grocery retailing. Customers’ shopping experiences […] were […] enriched by this European style market […] offering […] restaurant quality carry-out food, specialty bakeries, delis, floral shops, even in-store dining”. (http://www.dominicks.com/ShopStores/Our-Story.page)
elastic. A possible explanation is that the greater number of products implies the presence of substitute products that are closer in product space.

In terms of the income elasticity, we can conclude that beer is a normal good regardless of the type (see Table 4). For the entire data set, the income elasticity is 0.604. Within specific type of beer, the lowest elasticity was imported beer, followed by mass produced, and craft beer has the highest, but they are close in magnitude. Using the current dataset, we were not able to verify the hypothesis that mass produced beer is an inferior good, as suggested by Tremblay and Tremblay (2011). In this sense, the demand for all types of beer increase when positive shocks on income are observed.

The study of the beer market using this simple and, in some way restrictive approach, contrast with the larger computational burden of a BLP model (Berry, et al., 1995). In this case, the Nested Logit modeling approach is preferred since our aim was to model substitution effects as depending on predetermined classes of products (Berry, 1994). We conduct several tests of our model. To verify that the explanatory variables prices and within-market shares are endogenous regressors in the model, after GMM estimation, we calculate the difference-in-Sargan test statistic of exogeneity. Under the null hypothesis that the variables are exogenous, if the test statistic is significant, the variables being tested (prices and the within-market shares) must be treated as endogenous. According to the results of the test, the null hypothesis is rejected with 99% of confidence. Thus, the test statistic is significant and the implication is that they must be treated as endogenous.

As previously described, the variables were used as instruments in order to solve the
endogeneity problem. We evaluated ten variables for prices of the same product in different markets and the variety, given by the number of products available in each market. Since the number of instruments exceeds the parameters to be estimated, we have the case of instrumental variables with over-identified restrictions. For over-identified restrictions, after a GMM estimation, we calculate a Hansen's (1982) J-statistic to test the hypothesis that the instruments are uncorrelated with the error term. According to the results, we cannot reject the idea of these variables being uncorrelated. This statistically non significant result of the test statistic indicates that the instruments may be valid.

Additionally we perform a moment-equation validity test of the unconditional market shares. From the Wald statistic we were able to verify the moment-equation validity with 95% of confidence.

6. Conclusions

In this study, we estimate demand for a differentiated product: beer. Although many researchers have estimated demand for beer and other alcoholic beverages, this article estimates demand for particular styles of beer and identifies the price, cross-price, and income elasticities among craft, imported, and mass produced beers with supermarket scanner data. The results show that beer is a normal good with a demand function that is inelastic to changes in prices and with almost no substitution between categories of beer. Although own-price elasticity is quite inelastic across all types, the category that is the least responsive is mass produced beer. An explanation is that consumers are more loyal to their brand of mass produced beers. In contrast,
consumers are more than twice as responsive to price for the craft beer category. We argue that craft beer consumers are more interested in the style of craft beers than the brand. Further, these consumers may enjoy trying new craft beers.

There are some limitations to this study. The geographical area was limited to the Chicago area, so we cannot generalize the results to draw conclusions that can be used nationwide. However, it is expected that similar or stronger preferences for craft beer can be identified using information for the U.S. Pacific Northwest, given the more developed craft brew culture. A second limitation is the period of study. After the time period covered in the data, the craft beer industry has continued to expand worldwide. A comparison across time periods would be interesting to understand how preferences are changing. The craft beer movement fits a larger trend in food marketing that products are becoming increasingly customized.
7. Chapter References


* In 1991 the tax rate per barrel was increased for big breweries but reduced for small breweries.

**Source:** Brewers Almanac- 2011
Figure 2. Elasticity Dynamics (1991-1997)

Source: Calculations by the authors.
Table 1. Product Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price per unit</td>
<td>$ per single unit</td>
<td>$0.80</td>
<td></td>
</tr>
<tr>
<td>craft</td>
<td></td>
<td>$0.54</td>
<td></td>
</tr>
<tr>
<td>mass</td>
<td></td>
<td>$0.95</td>
<td></td>
</tr>
<tr>
<td>import</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>market share</td>
<td>0.053</td>
<td></td>
</tr>
<tr>
<td>Craft</td>
<td>market share</td>
<td>0.864</td>
<td></td>
</tr>
<tr>
<td>Import</td>
<td>market share</td>
<td>0.082</td>
<td></td>
</tr>
<tr>
<td>Bottle size</td>
<td>In ounces</td>
<td>9.286</td>
<td>6.343</td>
</tr>
<tr>
<td>Alcohol Content</td>
<td>% Alcohol</td>
<td>4.777</td>
<td>0.798</td>
</tr>
<tr>
<td>Ale</td>
<td>1 if ale, 0 otherwise</td>
<td>0.164</td>
<td>0.370</td>
</tr>
<tr>
<td>Fruit</td>
<td>1 if fruit, 0 otherwise</td>
<td>0.023</td>
<td>0.151</td>
</tr>
<tr>
<td>Low Alcohol</td>
<td>1 if low alcohol, 0 otherwise</td>
<td>0.013</td>
<td>0.115</td>
</tr>
<tr>
<td>Oktoberfest</td>
<td>1 if Oktoberfest, 0 otherwise</td>
<td>0.025</td>
<td>0.155</td>
</tr>
<tr>
<td>Seasonal</td>
<td>1 if seasonal, 0 otherwise</td>
<td>0.018</td>
<td>0.135</td>
</tr>
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<td>Smoked</td>
<td>1 if smoked, 0 otherwise</td>
<td>0.026</td>
<td>0.160</td>
</tr>
<tr>
<td>Steam</td>
<td>1 if steam, 0 otherwise</td>
<td>0.001</td>
<td>0.039</td>
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<td>Stout</td>
<td>1 if stout, 0 otherwise</td>
<td>0.020</td>
<td>0.142</td>
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<tr>
<td>Wheat</td>
<td>1 if wheat beer, 0 otherwise</td>
<td>0.016</td>
<td>0.126</td>
</tr>
<tr>
<td>Variable</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Min</td>
</tr>
<tr>
<td>-------------</td>
<td>-------</td>
<td>-----------</td>
<td>------</td>
</tr>
<tr>
<td>Income</td>
<td>42,612</td>
<td>12,652</td>
<td>19,285</td>
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<tr>
<td>House Value</td>
<td>146.694</td>
<td>46.986</td>
<td>64.348</td>
</tr>
<tr>
<td>Household Size</td>
<td>2.680</td>
<td>0.281</td>
<td>1.554</td>
</tr>
<tr>
<td>Education</td>
<td>0.220</td>
<td>0.112</td>
<td>0.050</td>
</tr>
<tr>
<td>Ethnic</td>
<td>0.150</td>
<td>0.179</td>
<td>0.024</td>
</tr>
</tbody>
</table>

*Income* is the average for the sample of the median Income. *House Value* is average house value in thousands of dollars. *Household Size* is the average number of members in each household for the area. *Education* is the average percentage College Graduates. *Ethnic* is the average percentage Blacks & Hispanics.

*Source:* Dominik’s dataset, calculations by the author.
Table 3: Estimation Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>OLS</th>
<th>MNL-IV</th>
<th>NL-IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>-9.61E-06 ***</td>
<td>-0.287 ***</td>
<td>-0.231 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Size</td>
<td>9.07E-06 ***</td>
<td>0.054 ***</td>
<td>0.005 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Alcohol</td>
<td>-2.73E-06 ***</td>
<td>0.028 ***</td>
<td>0.059 ***</td>
</tr>
<tr>
<td></td>
<td>0.006</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>Craft</td>
<td>-1.78E-05 ***</td>
<td>-0.320 ***</td>
<td>-5.302 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Import</td>
<td>-1.75E-05 ***</td>
<td>-0.203 ***</td>
<td>-5.172 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Ethnic</td>
<td>1.20E-05</td>
<td>0.173 ***</td>
<td>0.139 ***</td>
</tr>
<tr>
<td></td>
<td>0.106</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Education</td>
<td>-1.08E-04 ***</td>
<td>-0.557 ***</td>
<td>-1.152 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td>Household Size</td>
<td>-1.13E-05  **</td>
<td>-0.209 ***</td>
<td>-0.130 ***</td>
</tr>
<tr>
<td></td>
<td>0.028</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Incomes</td>
<td>2.60E-07  ***</td>
<td>0.003 ***</td>
<td>0.004 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Price Zone</td>
<td>1.88E-06  ***</td>
<td>0.017 ***</td>
<td>0.023 ***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>σ(Average across g)</td>
<td></td>
<td></td>
<td>0.900 ***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.000</td>
</tr>
</tbody>
</table>

Observations | 12,066 | 12,066 | 12,066 |
R²           | 0.204  | 0.443  | 0.725  |

Legend: * p<.1; ** p<.05; *** p<.01, controlling for dummy by type of beer, flavor and color. P-values
Table 4: Estimated Elasticities

<table>
<thead>
<tr>
<th></th>
<th>Mass</th>
<th>Craft</th>
<th>Import</th>
<th>Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass</td>
<td>-0.1238</td>
<td>0.0004</td>
<td>0.0002</td>
<td>0.597</td>
</tr>
<tr>
<td>Craft</td>
<td>0.0028</td>
<td>-0.3161</td>
<td>0.0013</td>
<td>0.642</td>
</tr>
<tr>
<td>Import</td>
<td>0.0004</td>
<td>0.0008</td>
<td>-0.1572</td>
<td>0.579</td>
</tr>
<tr>
<td>All types</td>
<td>-0.1736</td>
<td></td>
<td></td>
<td>0.604</td>
</tr>
</tbody>
</table>
Table 5. Confidence Intervals for Price Coefficients 95%

<table>
<thead>
<tr>
<th>Type</th>
<th>Price</th>
<th></th>
<th></th>
<th>Price Elasticity</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Coeff.</td>
<td>High</td>
<td>Low</td>
<td>Coeff.</td>
<td>High</td>
</tr>
<tr>
<td>ALL</td>
<td>-0.2796</td>
<td>-0.2310</td>
<td>-0.1776</td>
<td>-0.2228</td>
<td>-0.1736</td>
<td>-0.1204</td>
</tr>
<tr>
<td>MASS</td>
<td>-0.2208</td>
<td>-0.1630</td>
<td>-0.1052</td>
<td>-0.2063</td>
<td>-0.1238</td>
<td>-0.0412</td>
</tr>
<tr>
<td>CRAFT</td>
<td>-0.3356</td>
<td>-0.3010</td>
<td>-0.2664</td>
<td>-0.3566</td>
<td>-0.3161</td>
<td>-0.2756</td>
</tr>
<tr>
<td>IMPORT</td>
<td>-0.3513</td>
<td>-0.2749</td>
<td>-0.1985</td>
<td>-0.2034</td>
<td>-0.1572</td>
<td>-0.1111</td>
</tr>
</tbody>
</table>

**Source:** Estimations from the authors.
Table 6: Results from other Studies

<table>
<thead>
<tr>
<th>Source</th>
<th>Price Elasticity</th>
<th>Income Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hogarty and Elzinga 1972</td>
<td>-0.889</td>
<td>0.430</td>
</tr>
<tr>
<td>Orstein and Hanssens 1985</td>
<td>-0.142</td>
<td>0.011</td>
</tr>
<tr>
<td>Tegene 1990</td>
<td>-0.768</td>
<td>0.731</td>
</tr>
<tr>
<td>Lee and Tremblay 1992</td>
<td>-0.583</td>
<td>0.135</td>
</tr>
<tr>
<td>Gallet and List 1998</td>
<td>-0.730</td>
<td>-0.545</td>
</tr>
<tr>
<td>Nelson 1999</td>
<td>-0.200</td>
<td>0.760</td>
</tr>
<tr>
<td>Nelson 2003</td>
<td>-0.174</td>
<td>-0.032</td>
</tr>
<tr>
<td>This study</td>
<td>-0.173</td>
<td>0.163</td>
</tr>
</tbody>
</table>

Source: Table 2.2. Tremblay and Tremblay (2005).
CHAPTER FOUR

DEMAND FOR GUM: UNOBSERVED FLAVOR QUALITY USING CONTROL FUNCTION APPROACH
IV. Demand for Gum: Unobserved Flavor Quality Using
Control Function Approach

Abstract
This article estimates the demand for mint-flavored gum products using household purchases data and accounting for consumers’ valuation of quality. Unobserved product attributes, such as flavor quality, are important elements to consider when estimating the demand for gum. We use a control function approach in the context of a conditional logit (CL) choice model to estimate the demand for mint flavored gum using disaggregated data on household choices. According to the estimations, evidence exists of improvement of coefficients, reducing their bias once the control function approach is implemented. The results using this method verify the importance of unobserved product characteristics such as quality in the determination prices.

Key Words: Control Function Approach, Quality Differentiation, Unobserved Product Attributes, Demand Estimation, Gum.

1. Introduction

Chewing gum is one of the best performing segments within the confectionery market, and the global market for gum is forecast to reach US$20.7 billion by the year 2015 (GIA, 2011). The industry is characterized by its product innovation, focused on novel and unique flavors, new ingredients, different product shapes, varied colors, and distinctive packaging techniques (GIA, 2011). The production of gum requires ingredients such as a gum base, sweeteners and a variety of flavors. The gum base is usually a standard mix of synthetic latex and natural rubber extracted from the Sapodilla trees. This ingredient is not a source of product differentiation since only two different gum textures are commercialized, chewing and bubble gum, with 83% and 17% of the market share, respectively. The case of sweeteners is similar, just two categories can be identified, sugar and sugar-free gum, with a share of 42% and 58% respectively. Flavor is the major source of product differentiation. This is reflected in the high number of products available in the market with differentiated flavors.

Mint is the flavor that displays the largest market share, accounting for approximately 50%, followed by fruit flavored gum with 19% of total market share (Nielsen, 2005). Mint oil is an important product to the Pacific Northwest (Washington, Oregon, and Idaho), which is responsible for 83% of the United States spearmint production and 50% worldwide. However,

http://www.farwestspearmint.org/history.htm
the share of mint oil supplied by U.S. producers has been falling in recent years. Mint oil imports now account for approximately 25% of this market. Dealers buy cheaper and lower quality oil from China and India and then blend these oils with the more expensive high quality U.S. oil to accommodate each gum manufacturer standard\textsuperscript{26}. From 1993 to 2010, the number of acres harvested dropped 37% and the price per pound dropped 23%\textsuperscript{27}.

The supply chain of mint oil involves three parties: (1) the mint oil producers who sell mint oil to the dealers, (2) the dealers who mix different mint oils to generate the final flavoring oil mixtures, and (3) gum manufacturers who buy the oil mixtures from dealers to produce gum. For each flavor of mint gum (e.g. “doublemint,” mint splash, or cool mint), the gum manufacturer demands a specific mixture of mint oils from the dealer. This specific mint oil mixture is the result of blending mint oils from different qualities, which are measured in terms of the presence of oil components such as limonene, menthone, purene, esthers, among others. The less mixture of oils from different growing regions used in the final product leads to the higher flavor quality which is measured in terms of strength and duration\textsuperscript{28}.

\textsuperscript{26} Based on personal communications with Rod Christensen, President of Far West Spearmint Oil Administrative Committee, August 8, 2010.

\textsuperscript{27} Change from 1993 to 2010. United States Department of Agriculture, National Agricultural Statistics Service.

\textsuperscript{28} Typically, mint oil contains menthofuran. This substance reduces palatability. Oils that contain high levels of menthofuran are considered lower quality, whereas oils with lower level of this substance are considered high quality. Personal communication with mint dealer company representative, August 8 2010.
An investigation of the elasticity of substitution between high quality domestically produced oil and low quality imported oil is important to the U.S. mint oil industry, as their market share has been decreasing with the increase of imports and they have been losing negotiating power with gum manufacturers. However, it is not possible for the researcher to observe or measure differences in the quality of the mint oil mixed to produce each gum flavor, simply because each gum recipe is private information for the manufacturing firms. One alternative is to analyze the consumers’ price elasticity for mint gum accounting for product heterogeneity and unobservable (to the econometrician) product characteristics such as flavor quality.

We assume that consumers have a predetermined ranking of mint flavors based on their previous consumption and their own preferences. Based on the differences in flavor profiles across products, consumers know which flavor delivers the highest utility in consumption. It is necessary to highlight that although the differentiation is purely subjective, the differences in flavor profiles for each gum product are real rather than merely perceived by the consumers. For a discussion of price competition in a setting when product differentiation is purely subjective, see Tremblay, et al., (2002). From the literature on product differentiated oligopolistic models, we know that unobservable product attributes generate endogeneity of prices, leading to biased estimators. The present study considers the control function approach as a strategy for parameter identification using household level data.

Only a few studies have been conducted on brand choice and products using mint oil as flavoring ingredient, such as in gum and other mint flavored products. For toothpaste, previous

The aim of this study is to estimate the demand for mint-flavored gum accounting for the existence of unobservable flavor quality attributes. We postulate that demand for gum can be depicted by a discrete-choice model in an oligopoly context in which prices are endogenously determined by price-setting firms. We also account for the existence of product characteristics unobservable (to the econometrician), but fully considered by gum manufacturers when setting prices and by consumers when purchasing the products. However, unlike in our previous study (Toro-Gonzalez, et al., 2011), we use a different identification strategy known as the control function approach (Petrin, et al., 2009), in the context of a conditional logit (CL) model using household information on gum purchases for the year 2005. Information is arranged in a three-dimensional panel of gum choices and prices for 2,106 counties distributed across the 49 contiguous states (Nielsen, 2005).

The article is organized the following way. In the next section, we describe the utility representation and the control function approach is presented as an identification strategy. Following that, we present the empirical model in the context of mint gum. Next we present some ideas about the specification of the control function. In the subsequent section, the description of the dataset is presented, followed by the estimation results. Finally, implications
are discussed and conclusions are drawn.

2. Empirical Framework

Consider consumer $i$ choosing among $j$ products in market $t$ where the prices are endogenously determined because of the inability of the econometrician to observe all the product attributes. We apply the control function approach using monopoly pricing. The utility that consumer $i$ obtains from product $j$ in market $t$ is specified by:

$$U_{ijt} = V(p_{jt}, x_{j}; \theta_{i}) + \varepsilon_{ijt}$$

$$\varepsilon_{ijt} = \varepsilon_{ijt}^{1} + \varepsilon_{ijt}^{2}$$

Where $p_{jt}$ is the price of product $j$ in market $t$; $x_{j}$ is a vector of observed exogenous variables that affect the utility derived from choice $j$; $\theta_{i}$ are unobserved parameters that represent the tastes of consumer $i$. The error term ($\varepsilon_{ijt}$) in the utility function is divided into two parts, $\varepsilon_{ijt}^{1}$ represent all the unobserved product attributes that are correlated with price, and $\varepsilon_{ijt}^{2}$ is a random term.

Assume the price for each product is correctly specified as a linear function of $z_{jt}$ observed exogenous variables, plus a separable non-observable term $\mu_{jt}$:

$$p_{jt} = \gamma z_{jt} + \mu_{jt}$$

(2)

Where the vector $z_{jt}$ is a set of observable variables that do not enter the utility directly, but that do impact the prices ($p_{jt}$) and the additively separable term ($\mu_{jt}$) represents all the unobserved factors affecting the price of each product, but independent of the error term $\varepsilon_{jt}^2$ in the utility function.

In other words, the idea behind the control function correction is to derive a proxy variable that conditions on the part of $p_{jt}$ that depends on $\varepsilon_{ijt}$, that is $\varepsilon_{jt}^1$. Thus the remaining variation in the endogenous variable will be independent of the error $\varepsilon_{ijt}^2$, and standard estimation approaches will again be consistent (Petrin, et al., 2009). Different to the more traditional instrumental variables (IV) where instruments are used to predict the endogenous variable and replace its observed values by a linear prediction, the control function approach leaves the endogenous variable in the original specification of the model and just add a new term ($\mu_{jt}$) that accounts for the relation between the endogenous variable and the error term.

The benefits of this approach is that in order to obtain consistent estimates we do not have to rely on aggregate data level information, as in the cases of (Berry, 1994), (Berry, et al., 1995), and (Nevo, 2001), when individual or household information is available, allowing for the
possibility of incorporating the consumer heterogeneity into the analysis.

Recall the utility with the control function for all the \( j \) alternatives assuming homogeneous preferences is:

\[
U_{ijt} = V(p_{jt}, x_j, \theta) + \varepsilon_{ijt},
\]

\[
V(p_{jt}, x_j, \theta) = x_j\beta - \alpha p_{jt},
\]

\[
\varepsilon_{ijt} = \lambda \mu_{jt} + \varepsilon_{ijt}^2
\]

Substituting terms we have:

\[
U_{ijt} = x_j\beta - \alpha p_{jt} + \lambda \mu_{jt} + \varepsilon_{ijt}^2
\]  \hfill (3b)

Where \( p_{jt} \) are the prices of the products, \( x_j \) represents the product specific observable characteristics including: flavor, if the product is sugar free, the form of the product, texture, and physical volume or size of the package. Included in the set \( x_j \) we also consider some interactions of the product characteristics with household characteristics such as income, number of members, existence of children and age. \( \mu_{jt} \) are the unobserved terms derived as the error terms of the pricing equation, but with a structural interpretation, that is all the unobserved factors affecting the price of each product. \( \theta = (\beta, \alpha) \) are the unobservable parameters of the observable product characteristics and \( \lambda \) is the parameter that captures the effect of the unobserved product attributes. Assuming \( \varepsilon_{ijt}^2 \) is distributed type I extreme value the model is estimated as a conditional logit (CL) in order to analyze how the characteristics of the different gum products affect the individual probability of being chosen. The scale of the original utility is normalized
by setting the scale of the extreme value distribution for $\varepsilon^2_{ijt}$.

The model is estimated in two stages. First, the price is regressed on observed choice characteristics and the instruments ($z_{jt}$). The residuals of this regression are retained and used as a control variable or control function in the next step. Second, the choice model is estimated with the control function $\mu_{jt}$ entering as an extra variable in the regression.

\[
\begin{align*}
\text{Step 1:} & \quad \hat{\eta} = (z_{jt}'z_{jt})^{-1}z_{jt}'p_{jt} \\
& \quad \hat{\mu}_{jt} = p_{jt} - \hat{\eta}z_{jt} \\
& \quad \text{Step 2:} \quad U_{ijt} = x_j\beta - \alpha p_{jt} + \lambda \hat{\mu}_{jt} + \varepsilon^2_{ijt}
\end{align*}
\]

3. Control Function Specification

It is important to start by highlight that the control function approach relies on the assumption that the price equation is correctly specified. Hence, the appropriate control function and distribution of $\varepsilon^2_{ijt}$ is a specification issue. We rely on economic theory to estimate an alternative equation, the pricing equation containing information on the unobserved demand factor.

Following Tremblay, et al., (1995), these authors use new empirical industrial organization (NEIO) approach for estimating the determinants of a firm’s equilibrium price in an imperfectly competitive setting. To illustrate, assume that the profit maximizing firm $j$ in market
faces the following profit function:

\[
\pi_{jt} = p_{jt}(q_{jt}, Q_{kt})q_{jt} - C_{jt}(q_{jt}),
\]  

(4)

Where \( p_{jt} \) is price, \( q_{jt} \) is firm \( j \)'s output, \( Q_{kt} \) is the total output of firm \( j \)'s rivals (i.e., industry output minus \( q_{jt} \)), and \( C_{jt}(q_{jt}) \) is firm \( j \)'s total cost function. The firm's first order condition of profit maximization is:

\[
\frac{\partial \pi_{jt}}{\partial q_{jt}} = p_{jt} + q_{jt} \left[ \frac{\partial p_{jt}}{\partial q_{jt}} + \left( \frac{\partial p_{jt}}{\partial Q_{kt}} \right) \left( \frac{\partial Q_{kt}}{\partial q_{jt}} \right) \right] - MC_{jt} = 0
\]

(5)

Where \( \frac{\partial Q_{kt}}{\partial q_{jt}} \) is the firm's conjectural variation, and \( MC_{jt} \) is marginal cost. For the purpose of empirical estimation, this condition is normally written as:

\[
p_{jt} = MC_{jt} + \lambda q_{jt}
\]

(6)

\[
\lambda = -\left[ \frac{\partial p_{jt}}{\partial q_{jt}} + \left( \frac{\partial p_{jt}}{\partial Q_{kt}} \right) \left( \frac{\partial Q_{kt}}{\partial q_{jt}} \right) \right]
\]

Where, the parameter \( \lambda \) represents the market power of the firm \( j \) in the market \( t \). This rearranged first order condition, is frequently called the firm's supply relation, and summarizes the actions of the firm under different behavioral assumptions. The market is efficient if price equals marginal cost, which occurs when \( \lambda \) equals zero. Positive and larger values of \( \lambda \) imply a divergence of price from marginal cost and a greater degree of exerted market power or allocative inefficiency. Another way to name the term \( \lambda q_{jt} \) is the markup \( (M_{jt} = \lambda q_{jt} = p_{jt} - \)
\( MC_{jt} \). Hence, the pricing equation can be represented as the sum of the marginal cost \( (MC_{jt}) \) and the markup \( (M_{jt}) \):

\[
p_{jt} = MC_{jt} + M_{jt}
\]

(7)

Because the marginal cost and the markup are both unobservable variables, we follow Tremblay, et al., (1995) by substituting the terms \( MC_{jt} \) and \( M_{jt} \) for functions of their determinants, \( z^1_{jt} \) and \( z^2_{jt} \) respectively.

\[
p_{jt} = \gamma_1 MC_{jt}(z^1_{jt}, v^1_{jt}) + \gamma_2 M_{jt}(z^2_{jt}, v^2_{jt})
\]

(8)

Where \( z_{jt} = [z^1_{jt} \quad z^2_{jt}]' \) and \( v_{jt} = [v^1_{jt} \quad v^2_{jt}]' \) are the observed and unobserved characteristics, and \( \gamma = [\gamma_1 \quad \gamma_2] \) are unobserved parameters. The empirical model for the pricing equation estimation in terms of factors that affect marginal cost and markup is therefore given by Equation 2:

\[
p_{jt} = \gamma z_{jt} + \mu_{jt}
\]

As factors affecting marginal costs \( (z^1_{jt}) \) in each market \( t \) we consider: in-state labor cost, given by the official minimum wage in each state for the year 2005; transportation cost, using distance from the production plants as variable proxy; labor production cost for each product, captured by the official minimum wage in the state where the production of each firm was generated; we use gas prices as a measure of both, transportation costs and input prices; finally,
we use dummy variables for each flavor to capture other differences in the production process for each product.

On the other hand, we include three factors affecting the markups \( (z_{jt}^2) \) in each market \( t \), the number of products in the market as a measure for the competition, and dummy variables per firm and brand in order to capture firms’ ability of maintaining markups and the brand advertisement effect.

4. Data

The data base consists of 106,496 observations of daily household purchases of gum (bubble and chewing) from the AC Nielsen Home-scan survey for the year 2005. The information was collected in 2,106 counties distributed across the 49 contiguous states. On average, each state has 42 counties; however, the distribution varies substantially across counties, from 1 county in Washington D.C. to 100 counties in the case of Kentucky and 167 counties in the state of Texas. More than 98% of the sample corresponds to observations of states with more than 5 counties.

The average number of observations for each county is 368 with a minimum of 1 and the maximum of 1,731. The 96% of the sample correspond to counties with more than 10 observations. Approximately 13% of the sample has two to five households per county, and approximately 83% of the sample is represented by counties with more than 6 participating households.
The overall sample consists of 19,702 participant households with 15 purchases on average during the sample period. The minimum purchases for a household is 1, which occurs in 5% of the cases, and the maximum is 176. Around 24% of the households have between two and five purchases registered in the sample, and approximately 70% of the sample corresponds to households with more than six purchases during the year 2005. In terms of income level, important variation in the income level exists overall and between counties (see Figures 1 and 2), and this variable seems to be slightly related with variety, positive correlation of 22%.

In order to explain the variety, we have to point out that the data base only registers sales, or household purchases. This means we do not have actual information on the product assortment in each market, e.g. products not sold. The data contains only information about the products that were actually sold. In this case, there are 176 counties where the recorded sales belong to just one specific product during all the year, many times even just one sale.

In terms of the choice set this implies that we do not have information on the actual product assortment for each market. Thus, we use the number of products available at the state level as a proxy variable for each county, assuming all the products on the state were also available in all the counties in the state.

Nationwide we have information about 563 different products available, from these, 116 are the total number of mint flavored products. At the state level, the minimum number of products in a given state is 21 and the maximum is 123. However, the actual range of products purchased in a county varies from 1 to 75. From the total of 2,106 counties in the sample, 130 were eliminated because they just report one observation. The number of counties is thus 1,976,
all of them with at least two sample observations. Each observation is a reported sale of a product, and each product is defined as the combination of a brand and a flavor.

On average across counties, under the assumption that the number of products available at the state level is the same as in each county, we have information over 32% of the choices. This percentage is the average observed variety with respect to the state variety. In general, 55% of the total sample is related with counties where the observed number of products with respect to the state variety is lower than 32%, this is 58,665 out of 106,366 total observations. The rest of the 47,701 observations, represent 158 counties around the nation.

On the Figure 3, the solid line in the figure of the left represents the variety of products available statewide and the dots represent the actual number of products observed for each county in the state. On Figure 4, the bars represent the distribution of the county observed product information and the dots represent the actual number of products available in the state.

In terms of brand loyalty, according to the distribution represented in the Figure 5, most of the households (5,616) register just one purchase during the all year. Meanwhile, 1,025 households that made two purchases during all the 2005 year, in both opportunities bought the same brand of the product. Other 2,305 households with only two purchases switch brand between the first and their second purchase. Table 1 presents the descriptive statistics of the main variables in the model.
5. Estimation Results

The first step of the control function approach is to estimate the pricing function to recover the residuals entering the control function in the choice model. The residuals of the initial regression enter the CL without transformation, that is, the control function is the coefficient $\lambda$ times the product-market residual ($\mu_{jt}$).

Two sets of parameters are presented in Table 2. The first column presents the results without the control function variable, this is, not accounting for the omitted product attributes. The second column presents the estimation results using the control function approach. Two different choice models are presented. On the top the consumers choose mint flavored gum among all the available flavors in the market. On the bottom, the consumers choose spearmint flavored gum among all the available mint flavors in the market.

Without the correction, the base price coefficient $\alpha$ is estimated to be 0.59, negative and statistically different from zero (Price coefficient in column one on the top). The inclusion of the control function adjusts the estimated price coefficient in the expected way. This is, the absolute value of the coefficient increases to 1.20. A similar phenomenon is observed in the constrained model for spearmint choice, presented on the bottom of Table 2.

The coefficient of the control function is statistically significant and has the expected positive sign. Specifically, a positive residual occurs when the observed attributes and other observed factors are not enough to explain the price of the product. This result suggests that the product posses desirable attributes that are not included among the observable product
characteristics. Similar results are observed for the spearmint choice model on the bottom of Table 2. Testing the null hypothesis that $\lambda = 0$ is a Hausman (1978) equivalent test for endogeneity, see Imbent (2007). In Table 3 the coefficients of the model are adjusted accordingly.

In general, with the control function approach the correction for omitted variables rice the estimated price coefficients. With the correction, the price coefficient increases, almost double, in absolute value for the mint flavor choice model and increase several times in the spearmint gum flavored model. We also re-estimate the model using aggregate demographics as covariates in the choice model with similar results.

Compared with aggregate data models, the use household level data incorporates more heterogeneity into the estimates. Comparing the results for mint gum flavored market calculated by Toro-Gonzalez, et al., (2011) following Berry’s (1994) “product-market” approach, the price effects under the control function approach are significantly higher. The difference seems to be explained by the nature of the data. In the study following Berry (1994), the model uses information of the market shares, that is, aggregated information over all households in each state. On the other hand, the present study uses disaggregated household level information, increasing the observed heterogeneity. More heterogeneity involves more information about each agent decision, and then more variability that might affect the coefficients. The same phenomena seems to be identifiable in beer studies using disaggregated data. For Hausman, Leonard and Zona (1994), Rojas and Peterson (2008) and Bray, Loomis and Engelen (2009), there is evidence that cross brand price elasticities (in the case of beer) are much more elastic than those obtained.
when overall statistics are calculated.

5.a. Random Coefficients Model

We also estimate a random parameters version of equation (3b):

\[
U_{ijt} = x_j \beta - \alpha_i p_{jt} + \lambda \mu_{jt} + \epsilon^2_{ijt}
\]  

(9)

Assuming the price parameters \( \alpha_i \) are normally distributed. This modeling strategy allowed us to calculate price elasticities by flavor and by product. We pay special attention to spearmint flavored products. The average elasticity obtained for these products is 3.9 with a standard deviation of 2, see Table 4. The results are not statistically significantly different from flavor to flavor, as represented in Figure 6, where all the confidence intervals overlap with each other.

Results for the product price elasticity in the case of spearmint flavored gum are presented in Figure 7. The price elasticity for all sixteen products with spearmint flavoring ranges between 1.7 and 8.1. In all cases the products are price elastic. Figure 8 presents the relation between price elasticity and the estimated unobserved quality. The negative and statistically significant slope means that an increase in quality of 1\%, price elasticity decreases 3\%. This means that more quality is related with less elastic demand of the product, which is a very economically intuitive result.
6. Conclusions

Control function approach provides a simple way to account for endogeneity in choice models. This approach is an alternative to other models such as (Berry, 1994) and (Berry, et al., 1995). As (Petrin, et al., 2009) point out, the control function approach is both easier to implement and is available in situations in which the BLP estimator is not valid, for example in cases where there are zero, one, or just a small number of purchase observations per product, like in this case.

According to the estimations, evidence exists of improvement reducing the bias of the coefficients once the control function approach is implemented. The implementation of this method verifies the importance of unobserved product characteristics such as quality in the determination the price.

We find that more quality products derive in less elastic products. In terms of flavoring substances such as mint as input factor, this implies that there is an incentive for producers to maintain flavor quality in order to maintain product quality perception among consumers.
7. Chapter References


Figure 1. Overall Household Income Distribution

Source: AC Nielsen Data.
Figure 2. Average County Income Distribution

Source: AC Nielsen Data.
Figure 3. Comparison of County Versus State Variety

Source: AC Nielsen Data.
Figure 4. County Variety per County and State

Y axe is the number of products available in each state (X axe). The bar represents the distribution of the actual number of products in each county. The small dot represents the number of products in the state.

Source: AC Nielsen Data.
Figure 5. Household Brand Loyalty Distribution

Source: AC Nielsen Data.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price per Unit</td>
<td>0.821843</td>
<td>0.3422612</td>
<td>0.005</td>
<td>2.89</td>
</tr>
<tr>
<td>Size</td>
<td>17.05476</td>
<td>17.18751</td>
<td>1</td>
<td>360</td>
</tr>
<tr>
<td>Sugar-Free</td>
<td>0.588799</td>
<td>0.492054</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Form</td>
<td>1.584224</td>
<td>0.5986788</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Texture</td>
<td>0.833393</td>
<td>0.372626</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Minimum Wage</td>
<td>5.480025</td>
<td>0.7561899</td>
<td>2.65</td>
<td>7.35</td>
</tr>
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<td>Distance from Plant</td>
<td>800.2669</td>
<td>619.8008</td>
<td>0</td>
<td>2424</td>
</tr>
<tr>
<td>Gas Prices per Gallon</td>
<td>2.177932</td>
<td>0.1567735</td>
<td>1.94</td>
<td>2.61</td>
</tr>
<tr>
<td>Household Income (Rank)</td>
<td>19.41727</td>
<td>5.639261</td>
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<td>27</td>
</tr>
<tr>
<td>Household Size (People)</td>
<td>2.865862</td>
<td>1.446401</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Age</td>
<td>6.480562</td>
<td>1.835281</td>
<td>1</td>
<td>9</td>
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<tr>
<td>Children Under 18</td>
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<td>0.4900011</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total Observations</td>
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<td></td>
<td></td>
<td>105362</td>
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</tbody>
</table>

**Source:** AC Nielsen Data.
Table 2. Estimation results of the Choice Model

<table>
<thead>
<tr>
<th>Mint Flavor Choice</th>
<th>Endogenous Prices</th>
<th>Control Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>-0.5985 *** (0.0000)</td>
<td>-1.2040 *** (0.0000)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.0014 (0.7505)</td>
<td>0.0042 (0.3250)</td>
</tr>
<tr>
<td>Sugar-Free</td>
<td>1.1248 *** (0.0000)</td>
<td>1.2020 *** (0.0000)</td>
</tr>
<tr>
<td>Form</td>
<td>-0.0446 (0.4513)</td>
<td>-0.0748 (0.2083)</td>
</tr>
<tr>
<td>Texture</td>
<td>5.8408 *** (0.0000)</td>
<td>5.8072 *** (0.0000)</td>
</tr>
<tr>
<td>Sugar Free*age</td>
<td>-0.0704 *** (0.0256)</td>
<td>-0.0712 *** (0.0251)</td>
</tr>
<tr>
<td>Texture*age</td>
<td>0.0935 (0.4908)</td>
<td>0.0933 (0.4887)</td>
</tr>
<tr>
<td>Control Function</td>
<td>0.8204 *** (0.0000)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 72515 72515

<table>
<thead>
<tr>
<th>Spearmint Choice</th>
<th>Endogenous Prices</th>
<th>Control Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
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<td>-3.1534 *** (0.0000)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.0545 *** (0.0000)</td>
<td>0.1041 *** (0.0000)</td>
</tr>
<tr>
<td>Sugar-Free</td>
<td>-0.1166 (0.6483)</td>
<td>0.0429 (0.8698)</td>
</tr>
<tr>
<td>Form</td>
<td>0.8952 *** (0.0000)</td>
<td>0.4895 *** (0.0000)</td>
</tr>
<tr>
<td>Texture</td>
<td>23.5120 *** (0.0000)</td>
<td>19.8504 *** (0.0000)</td>
</tr>
<tr>
<td>Sugar Free*age</td>
<td>-0.0497 (0.2108)</td>
<td>-0.0535 * (0.1831)</td>
</tr>
<tr>
<td>Texture*age</td>
<td>0.2708 (0.3089)</td>
<td>-0.0397 (0.8822)</td>
</tr>
<tr>
<td>Control Function (CF)</td>
<td>3.1217 *** (0.0000)</td>
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</tr>
</tbody>
</table>

Observations: 54998 54998

Legend: * p<0.05; ** p<0.01; *** p<0.001 (P-Values)

Source: AC Nielsen Data, calculations by the authors.
Table 3. Scaled Coefficients

<table>
<thead>
<tr>
<th>Mint Choice</th>
<th>Endogenous</th>
<th>Control Function</th>
<th>Nested Logit (IV) †</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>-0.5985 ***</td>
<td>-1.2040 ***</td>
<td>-0.1300 *</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0500</td>
</tr>
<tr>
<td>Size</td>
<td>-0.0014</td>
<td>0.0042</td>
<td>-0.0880 ***</td>
</tr>
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<td></td>
<td>0.7505</td>
<td>0.3250</td>
<td>0.0001</td>
</tr>
<tr>
<td>Sugar-Free</td>
<td>1.1248 ***</td>
<td>1.2020 ***</td>
<td>-0.0240</td>
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</tr>
<tr>
<td>Form</td>
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<td>-0.0748</td>
<td>0.0550</td>
</tr>
<tr>
<td></td>
<td>0.4513</td>
<td>0.2083</td>
<td>0.3851</td>
</tr>
<tr>
<td>Texture</td>
<td>5.8408 ***</td>
<td>5.8072 ***</td>
<td>0.0060</td>
</tr>
<tr>
<td></td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.9246</td>
</tr>
<tr>
<td>Sugar Free*age</td>
<td>-0.0704 ***</td>
<td>-0.0712 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0256</td>
<td>0.0251</td>
<td></td>
</tr>
<tr>
<td>Texture*age</td>
<td>0.0935</td>
<td>0.0933</td>
<td></td>
</tr>
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<td></td>
<td>0.4908</td>
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<tr>
<td>Observations</td>
<td>72515</td>
<td>72515</td>
<td>4403</td>
</tr>
</tbody>
</table>

Legend: * p<0.05; ** p<0.01; *** p<0.001 (P-Values)

Coefficients of the control function are corrected dividing the estimators by $\sqrt{1 + 3\hat{\beta}_\delta^2 \sigma_\delta^2 / \pi^2}$.

since $\sigma_\delta^2 = 0.0000$ the coefficients remain basically the same.

† Nested Logit coefficients from Toro-Gonzalez, et al. (2011)

Source: AC Nielsen Data, calculations by the authors.
## Table 4 Price Elasticities by Flavor

<table>
<thead>
<tr>
<th>Flavor</th>
<th>Price Elasticity</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peppermint</td>
<td>4.60</td>
<td>1.72</td>
</tr>
<tr>
<td>Spearmint</td>
<td>3.93</td>
<td>2.04</td>
</tr>
<tr>
<td>Other mint</td>
<td>3.35</td>
<td>1.12</td>
</tr>
<tr>
<td>Fruit</td>
<td>3.69</td>
<td>1.65</td>
</tr>
<tr>
<td>Spice</td>
<td>3.42</td>
<td>1.56</td>
</tr>
<tr>
<td>Variety</td>
<td>5.22</td>
<td>1.90</td>
</tr>
<tr>
<td>Sour</td>
<td>4.08</td>
<td>1.25</td>
</tr>
<tr>
<td>Other</td>
<td>5.47</td>
<td>2.10</td>
</tr>
</tbody>
</table>

**Source:** AC Nielsen Data, calculations by the authors.
Figure 6 Price Elasticities by Flavor

Triangles represent the mean elasticity, the extremes of the lines represent the minimum and the maximum value for each product.

Source: AC Nielsen Data, calculations by the authors.
Figure 7 Price Elasticity by Product (Spearmint Flavored)

Source: AC Nielsen Data, calculations by the authors.
Figure 8 Quality and Elasticity per Product

Source: AC Nielsen Data, calculations by the authors.