Package-Size Level Demand for Carbonated Soft Drinks and Its Implications on Market Power

by

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ABSTRACT

This study analyzes manufacturer-level carbonated soft drinks (CSDs) demand and market structure at two aggregation levels: brand level and bottle-size level by comparing their findings and implications. We use the BLP (1995) approach to estimate the demand and use the resulting estimates to evaluate market power for CSDs brands. Two pricing conducts, namely Bertrand Nash and joint-profit maximization, are assessed under the two aggregation levels.

Aggregation level changes the implications of CSDs demand estimates. Demand-side empirical results for the bottle-size level do not imply the same directional effects as the brand level for the price, calorie, and caffeine contents when decomposed by income and the number of children in the household. For example, low-income households are less sensitive to CSDs prices at the brand level than middle-income and high-income households. In contrast, at the bottle-size level, high-income households are less price-sensitive than other income categories. In terms of elasticities, the bottle-size level's own-price elasticities are more elastic than those at the brand level. Furthermore, at both levels, cross-price elasticities show consumers have some brand loyalty and are more responsive to the leading brands' changes.

For the pricing conducts, the results suggest the Lerner index, a measure of the market power, is quite sensitive to the price levels. Hence, when we use the demand estimates at the aggregate brand level, the percentage markups are higher than when we use the disaggregated bottle-size level, which is the more realistic one. Hence, the bottle-size level can be more accurate for the estimation because of having more accurate prices. Therefore, the market power assessment might be more accurate when the brands' prices are at the bottle-size level.

Vuong’s (1989) test results indicate that the Coca-Cola Co., PepsiCo, and Dr Pepper Snapple Group compete in Bertrand-Nash's pricing conduct, rejecting the collusive price behavior. The Bertrand-Nash game yields Lerner indices that vary between 40% and 62% at the brand level and 20% and 39% at the bottle-size level. Our results support other authors' conclusion that the high Lerner index is not due to

prices' collusion, but rather an implication of non-price competition, such as product differentiation and advertising.

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LIST OF ABBREVIATIONS

AIDS	Almost Ideal Demand System
BLP	Berry, Levinsohn, and Pakes
CES	Constant Elasticity of Substitution
CO	Company
CSD	Carbonated Soft Drink
CV	Conjectural Variation
DCM	Discrete Choice Model
EASI	Exact Affine Stone Index
FOC	First Order Condition
GEV	Generalized Extreme Value
GME	Generalized Maximum Entropy
GMM	Generalized Method of Moments
IIA	Independence from Irrelevant Alternatives
IID	Independently and Identically Distributed
IO	Industrial Organization
IRI	Information Resources, Inc.
IV	Instrument Variable
LA-AIDS	Linear Approximation Almost Ideal Demand System
MC	Marginal Cost
ML	Maximum Likelihood
MNL	Multinomial Logit
MNP	Multinomial Probit

NEIO	New Empirical Industrial Organization
OZ	Ounce
PCM	Price-Cost Margin
RC	Royal Crown
RTEC	Ready to Eat Cereal
RUM	Random Utility Model
SCPP	Structure Conduct Performance Paradigm
SKU	Stock-Keeping Unit
SSB	Sugar Sweetened Beverage
UPC	Universal Product Code
US	United States
USDA	United States Department of Agriculture

CHAPTER 1

INTRODUCTION

Nowadays, firms produce differentiated products to make their products more attractive in imperfectly competitive markets to increase their sales, gain market power, and increase brand loyalty. Consumer demand for horizontally differentiated products is based on subjective tastes and preferences; thus, these products are imperfect substitutes to each other. One of the typical examples of differentiated products is carbonated soft drinks (CSDs). CSDs are differentiated by flavor, color, sugar content (regular vs. diet), caffeine content, and size.

In 2019, the United States had the highest soft drink industry market revenue globally, with about 247 billion US dollars. Japan, the second country, generated almost five times less market revenue, 53 billion US dollars (Statista (2020)). The carbonated soft drinks market is one of the main components of the US soft drink industry besides bottled water and noncarbonated soft drinks segments (Beverage Digest (2020)).

The US has the second-highest per capita volume sales for CSDs in the world after Mexico (Beverage Digest (2020)). The US retail value of the CSDs increases drastically over time, and the industry has a considerable economic impact on the US economy. For instance, in 2019, total carbonated soft drink volume sales were about 8.46 billion in 192 oz. cases, with a total retail value of around 87.2 billion dollars in the US (Beverage Digest (2020)).

The CSD industry represents oligopolistic competition with highly differentiated products. This is because relatively small numbers of producers produce CSDs, and the industry has a high market concentration. The top three CSD companies, The Coca-Cola Co., PepsiCo, and Dr Pepper Snapple Group, hold more than 85% of the total CSD market share (Beverage Digest (2020)).

The industry's size, the level of consumption of the products, the industry's oligopolistic structure, and the large numbers of highly differentiated products imply the need for an in-depth analysis of the demand for differentiated CSD and its market structure, explicitly pricing conducts.

New Empirical Industrial Organization (NEIO) framework by Bresnahan (1989) makes it possible to examine the degree of competitiveness in the imperfectly competitive markets without observing cost data for estimating different pricing conducts. Only market-level data is sufficient to evaluate the market structure and its price implications. For these kinds of studies, demand estimation is the heart of the study. The seminal work by Berry, Levinsohn, and Pakes (1995, hereafter BLP) makes the discrete choice demand analysis for differentiated goods computable.

Unlike the demand for homogeneous products, the demand for differentiated products presents the difficulty of a large number of brands to analyze, or the dimensionality problem, and the heterogeneity of consumers' tastes and preferences. The traditional demand estimation systems including the Linear Expenditure Model (Stone, 1954), the Rotterdam Model (Theil, 1965; and Barten, 1966), the Translog model (Christen, Jargenson, and Lau, 1975), and the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980) do not solve either of these issues.

BLP's random coefficient logit model solves the dimensionality by projecting the products onto a product characteristics space, hence reducing the number of parameters to be estimated. Moreover, consumer heterogeneity is incorporated by allowing taste parameters to vary across consumers. The inclusion of consumer heterogeneity may prevent misinterpretations of market structure, product targeting, market segments, biased results, and inaccurate inferences concerning market strategies and welfare analysis (Kamakura et al., 1996; Leszczyc and Bass, 1998; Chintagunta, 2001).

Besides dimensionality and consumer heterogeneity, another problem regarding demand estimation is the endogeneity issue. Endogeneity occurs because prices are potentially correlated with the random shocks, especially the omitted unobserved product characteristics observed by the firms and the consumers, but not by the researcher. For instance, firms know what the unobserved product characteristics are, and they set prices according to both observable and unobservable product characteristics, yielding a correlation between prices and unobserved characteristics, and eventually the error terms. The endogeneity of prices requires the instrumental variables (IV) method to avoid inconsistent estimates. Ignoring endogeneity leads to inconsistent parameter estimates (Villas-Boas and Winer 1999). This is a severe problem because inconsistent results change the implications of market and welfare analysis.

Before Berry (1994), the IV method was not applicable in discrete choice models for differentiated good demand estimation. This is because of the presence of nonlinearity of price and unobserved product characteristics. To solve the nonlinearity problem, Berry (1994) suggests inverting market shares' function to make prices and unobserved product characteristics linear.

In sum, the random coefficient logit model is promising because of dealing with the dimensionality problem and including consumer heterogeneity, which provides unrestricted substitution patterns and allowing the use of the IV procedure to solve the endogeneity problem. Furthermore, the random coefficient logit model is used widely in differentiated products' demand estimation studies because it provides more accurate demand estimation and is commonly used to evaluate market power, welfare effects, effects of launching new products, and mergers.

1.1 Motivation

This study attempts to fill the gaps in carbonated soft drink studies and provide a more comprehensive market analysis. There is a lack of information about horizontal price competition and market power for carbonated soft drinks. Previous studies included only two companies: the Coca-Cola Co. and PepsiCo products, while Dr Pepper Snapple Group brands, with high market shares, were ignored in previous studies. Moreover, previous studies include a small number of brands. Gasmi et al. (1992) and Golan et al. (2000) analyze market power for two brands, Coke and Pepsi. Dhar et al. (2005) analyze market power between four CSD brands, Coke, Pepsi, Mountain Dew, and Sprite. However, the carbonated soft drinks market consists of highly differentiated goods and a wide range of brands.

The other side of CSD market power studies analyzes the market vertically such that competition between manufacturers and retailers. For example, Bonnet and Requillart (2013) find that manufacturers have the bargaining power, and retailers do not choose national brands' prices in addition to private label brands do not affect the relationship between manufacturers and retailers. In this study, we assume a horizontal competition between CSDs manufacturers and examine price competition to see whether their behavior is competitive or collusive by considering brands produced by the Coca-Cola Co., PepsiCo, and Dr Pepper Snapple Group.

In terms of carbonated soft drinks, product differentiation can be perceived at different levels. At the manufacturers' level, carbonated soft drinks can be differentiated by the content of the main components: cola, caffeine, sugar, color and flavor, calorie content, and other product characteristics. The CSD products are also differentiated in terms of packaging: type of packaging (glass, plastic, can), size of the unit, and the number of units in a package. The choice of disaggregation level will lead to different estimates of price elasticities, and therefore, different conclusions regarding the pricing conduct and welfare implications.

Treating different brand sizes as separate products is probably more relevant for differentiated goods, specifically for carbonated soft drinks. Chan (2006) states that packaging size significantly impacts the demand for carbonated soft drinks. The effect does not necessarily refer to quantity discount, such that 12 oz. 12 packs of a carbonated soft drink have a higher volume and higher price per ounce than 67.6 oz. single bottle. Furthermore, Hoffmann and Bronnmann (2019) find that 63 % of the consumers have brand loyalty and prefer small bottles over large bottles. The study concludes, "Bottle size matters." Dube (2004) finds that brand loyalty is slightly more apparent than package size loyalty for carbonated soft drinks. For example, consumers are more loyal to Coca-Cola brands than a particular product size of Coca-Cola brands.

Other studies find the inclusion of package size is more relevant for examining differentiated goods. For example, for coffee, Guadagni and Little (1983) claim that from retailer's and consumer's perspectives, different sizes of a brand are distinct.

Consumers have size loyalty and brand loyalty, and retailers' promotions decisions are according to brands' sizes. Kumar and Divakar (1999) find a difference between marketing mix elasticities at the brand-size level and the brand level for potato chips and peanut butter. They suggest that demand for potato chips and peanut butter has a better structure to model idiosyncrasy if the approach is brand-sized rather than aggregate brand level. Consumers have different sensitivity to the price for different package sizes of the same brand. Hence, retailers and manufacturers may offer promotional strategies at the brand-size level to achieve profit maximization.

Moreover, Yonezawa and Richards (2016) emphasize the relevance of the package size and price analysis because consumers can observe both price and size. They find that package size is an essential component of consumer choices for ready-to-eat cereals. Consumers mostly prefer small packages because they evaluate risk and convenience, although heterogeneity in package size decisions exists. They claim these results can explain manufacturers' decision to provide various package sizes instead of just one size. They assert that package size decision does not solely depend on consumer preferences but also manufacturers' strategic reactions arising from competition. Even if manufacturers take advantage of the disconnection between package price and unit price on consumers, this study shows that manufacturers can be better off in terms of profitability when increasing prices rather than changing package size. Moreover, they argue that package size implications are useful for retailers' product assortment decisions because of limited shelf space in the face of the product proliferation (Mantrala et al., 2009; Kim et al., 2002) and consumers seeking greater variety (Lancaster, 1990; Kahn and Lehmann, 1991).

Shreay et al. (2016) assert that in some cases, the reason for quantity surcharges may arise from different package sizes of a particular product because distinct package sizes are imperfect substitutes. Hence, product differentiation exists by package size. Shreay et al. (2016) explain that consumers may view them as imperfect substitutes since different sizes of a product may have different usage and storage options. Therefore, they claim producers or retailers may use package size as a tool besides prices to maximize their profit. Consumers should not expect consistent per-unit prices when package size changes.

This study includes the bottle-size level in the analysis because of its relevance in explaining consumers' choice for carbonated soft drinks. The availability of supermarket scanner data from IRI and AC Nielsen makes the estimation of the demand for differentiated goods possible at very disaggregated levels (e.g., UPC level demand).

To our knowledge, there is a lack of demand and market power/pricing conduct analysis at the bottle/package size level in CSD competition, which is the relevant decision making for consumers. Therefore, two different aggregation level demands are analyzed. Both brand level and bottle-size level carbonated soft drinks demand are estimated, and their implications for market power are compared. The analysis uses Information Resources Inc. (IRI) data from 2006 to 2011 in Dallas, Texas.

The study's relevance stems from the importance of accurately measuring market power by accurately estimating the pricing conduct. We think the disaggregation level of the demand we propose in this study will provide a more accurate substitution pattern and, therefore, a more accurate measure of market power in the carbonated soft drink industry.

Loecker and Eeckhout (2017) argue that firms, who exert market power, can set the prices above the marginal costs, hence produce less output than competitive markets. It affects consumer welfare as well as causes other implications such that lowering factor demand, changing the distribution of economic rent, and business dynamics (i.e., entry and exit, and resource allocation). They find that a rise in market power has some macroeconomic implications. Even if they do not claim market power is the only source for the outcomes, they show that the rise in market power contributes to a decrease in the labor share, in the capital share, in the low skilled wages, in the labor market participation, in labor reallocation and interstate migration rates, and a slowdown in the output and GDP.

1.2 Research Objectives

This study's general objective is to analyze the carbonated soft drinks demand and market structure at both aggregation levels, namely, brand level and bottle- size level. We opt for the menu approach's two-step approach. The demand model is estimated, and demand parameter estimates are used to calculate price-cost margins for alternative competition scenarios, namely Bertrand-Nash and the joint-profit maximization games. Vuong's test (1989) is used to test alternative supply models.

Specific objectives of this study are 1) Using random coefficient logit model, estimate demand for 20 carbonated soft drinks brands in the brand level (i.e., Coke Classic, Diet Pepsi, and 7 Up) and calculate their substitution patterns in Dallas, Texas; 2) Using random coefficient logit model, estimate demand for 42 carbonated soft drinks bottle-size level brands (i.e., Diet Pepsi 12 packs 12 oz. cans, Diet Pepsi 67.6 oz. single plastic bottle, and Coke Classic 6 packs 16.9 oz. plastic bottles) and calculate their substitution patterns in Dallas, Texas; 3) Compare demand estimates in both level of aggregation; 4) Estimate market power of CSD brands at the brand level under Bertrand-Nash and joint-profit maximization; 4) Estimate market power of CSD brands in the bottle-size level under Bertrand-Nash and the joint-profit maximization; 5) Compare the percentage markups in both level of aggregation; 6) Test between alternative supply models, namely Bertrand-Nash and joint-profit maximization at both levels.

1.3 The Outline of the Dissertation

The dissertation is organized as follows. Chapter 2 includes the history and the market structure of the carbonated soft drinks industry and the data. Chapter 3 discusses an analysis of differentiated demand for carbonated soft drinks (CSDs), including the literature review of analyzing demand estimation for differentiated goods, the theoretical framework of random coefficient logit demand, the method and its procedures, and empirical demand results for both brand level and the bottle-size level.

Chapter 4 analyzes the market power of the carbonated soft drinks industry by providing a literature review of market power, theoretical frameworks and methods, and the empirical results of market power and its implications for the carbonated soft drinks industry. Chapter 5 summarizes the findings and concludes the dissertation.

CHAPTER 2

INDUSTRY BACKGROUND AND THE DATA

2.1 Introduction

This chapter describes the carbonated soft drink industry and discusses the data used in this research. Section 2.2 provides a history of the carbonated soft drink and its market structure in the United States. The last section, 2.3, includes a discussion of the data provided by Information Resources Inc. (IRI).

2.2 The Carbonated Soft Drink Industry

2.2.1 History

In the 1760s, carbonated water was invented by simulating natural mineral waters' effervescent nature by developing a carbonation technique using chalk and acid (Riley, 1958). Thomas Henry, a British pharmacist, was the first commercial producer of artificially carbonated water (Riley, 1958). In Europe, the popularity of drinks expanded over time. In 1789, Paul, Schweppe, and Gosse launched a business in Geneva and sold seltzer water. Later, Schweppe moved to London and opened a large-scale production of carbonated drinks (Riley, 1958; Steen and Ashurst, 2006).

The US started importing carbonated drinks from the UK before 1800, and carbonated waters were trendy (Steen and Ashurst, 2006). Benjamin Silliman, a chemistry professor at Yale College, went to the UK to get materials (i.e., books) for the chemistry department. He came across a new growing business in Europe, and he went to London and Edinburgh to learn techniques for producing carbonated water (Riley, 1958). He came back to the US and started a new business in New Haven, CT. He is the first commercial manufacturer for large-scale production in the US (Riley, 1958; Woodroof and Phillips, 1981; Steen and Ashurst, 2006). Besides, Joseph Hawkins produced the first patented artificial mineral water in the US in 1809 (Woodroof and Phillips, 1981).

Flavoring syrups made from fruits and a range of flavors started expanding (Riley, 1958), giving birth to the first effervescent lemonade in 1833 (Emmins, 2000) and Ginger Ale in 1861 (Riley, 1958). With the increasing popularity of flavored carbonated soft drinks, flavored sweet cream production started in 1874. The combined ice cream and soda water and ice cream soda production started taking place (Riley, 1958). Soda fountains were famous in the US. Besides consuming carbonated drinks for refreshment, people were also using them for medicinal purposes, such as quinine tonic water was used to cure malaria. Another popular drink in England around the 1890s was cola (or kola) tonic, a nut from West Africa (Steen and Ashurst, 2006).

The most important discovery in carbonated soft drink history occurred when J.S. Pemberton created Coca-Cola flavor by combining cola nut and coca, an extract from the coca leaf, and sold the drink in soda fountains in his store in Atlanta, Georgia (Steen and Ashurst, 2006). In 1892, A.G Candler acquired all drink rights and launched the Coca-Cola Company in Atlanta, Georgia. The company started an aggressive marketing campaign and advertised the drink as a nutrient beverage and tonic (Riley, 1958; Steen and Ashurst, 2006). Concurrently, R.S Lazenby launched Dr Pepper in 1885 in Waco, Texas. Subsequently, C.D. Bradham launched Pepsi-Cola (took this the name in 1901) in 1898 (Riley, 1958; Steen and Ashurst, 2006).

By the end of the 1800s, most of the available flavors today were already produced (Steen and Ashurst, 2006), including cola, root beer, cream soda, ginger ale, citrus drinks, etc. An advertisement of soda water in 1865 includes these flavors: pineapple, black cherry, strawberry, peach, cherry, grape, apricot, raspberry gooseberry, orange, lemon, apple, pear, melon, and plum (Woodroof and Phillips, 1981).

In London, in 1840, there were about 50 producers (Steen and Ashurst, 2006). During the Great Exhibition, more than 1 million bottles were sold in London in 1851 (Steen and Ashurst, 2006). The industrial revolution promoted the expansion of the carbonated soft drink industry (Steen and Ashurst, 2006). Three hundred trademarks' approval between 1875 and 1881 and over 80 patents in 1885 shows the UK industry's expansion (Steen and Ashurst, 2006). Around the 1850s, thanks to using steam power, manual bottling capacity increased from 100 dozen to 300 dozen per day. In 1900, approximately 70,000 employees and 22,000 horses delivered the 900 million liters produced in the UK (Steen and Ashurst, 2006).

On the other hand, soda fountains were so much popular in the US. As mentioned previously, some drinks were introduced and marketed for medicinal purposes and promising being healthy and nutritious. Soda fountains were the main competitors of the bottled drinks, and during the 1880s and 1890s, more than 70% of the total sales for soft drinks were in soda fountains in the US (Riley, 1958). However, the bottled soft drink industry was in progress.

The US bottled soft drink industry expanded in the 20th century. The US Bureau of Census reported 64 plants of soda bottling in 1850, 123 in 1860, and 387 in 1870 (Woodroof and Phillips, 1981). In 1899, 2763 soft drink bottling plants were in service in the US (Riley, 1958; Steen and Ashurst, 2006). Before the 1929 economic depression, there were 8220 plants, the all-time highest level, but the number decreased to 6000 during the mid-1950s and dropped further to 3000 during the 1980s (Woodroof and Phillips, 1981).

Coca-Cola was distributed as a bottled drink firstly in 1894 in a small-scale bottling in Mississippi (Riley, 1958). The bottling of Coca-Cola had started growing in 1899. The first plant was in Chattanooga, established in 1899, and in 1900, another bottling plant for Coca-Cola was launched in Atlanta (Riley, 1958). After a short time, Coca-Cola had become the leader of the US soft drink industry (Riley, 1958). By 1904, 123 plants bottled Coca-Cola, and the company had sold 1 million gallons of its syrup annually (Riley, 1958). Besides, the Coca-Cola Company spent $100,000 on advertising for its fountain drink in 1901. The following year, Coca-Cola Company advertised its finished bottles in newspapers, and in 1904, the company's advertisements were in general magazines (Riley, 1958).

One of the most popular bottled drinks was ginger ale which Clicquot Club bottled. In 1901, the company started being active in the distribution of its drinks. The company sold the products through wholesale grocery stores. It started firstly in New England, and later on, it reached New York, New Jersey, the middle Atlantic States, and the Pacific coast (Riley, 1958). Additionally, in these years, Dr Pepper and Pepsi-Cola were popular, and their lines had extended in the bottling and the distribution.

Per capita consumption of carbonated drinks has increased dramatically over time, parallel to the increase in bottled drinks production. In 1899, 2763 plants produced approximately 39 million bottled drinks annually, corresponding to 12 bottles of per capita consumption annually. In 1920, bottled drinks' annual production reached 175 million cases, corresponding to 38 bottled drinks per person per year. These figures rose to 272 million cases, increasing the yearly per capita consumption to 53 bottles in 1929. After the depression, in 1932, the annual production of bottled drinks decreased to 141 million cases. At the end of the 30s, the production reached the 500 million case mark, and per capita consumption was approximately 100 bottles annually. After the war, between 1949 to 1950, the production has increased drastically to 1 billion cases annually and 158 bottles of per capita consumption (Riley, 1958).

In the 1950s, the franchised bottlers of Coca-Cola were more than 1000, Pepsi-Cola and Seven-Up had more than 500 bottlers, and Dr Pepper had over 400 franchised bottlers for distribution (Riley, 1958). Other brands like Canada Dry, Orange Crush, Squirt, and many others had hundreds of franchised bottlers (Riley, 1958).

In the second half of the twentieth century, the soft drink industry had continued to expand thanks to technological improvements, such as the introduction of cans and plastic bottles and the mass production with high-speed packaging and extensive distribution systems (Steen and Ashurst, 2006). Glass bottles were the unique form of packaging for carbonated soft drinks until other kinds were invented (Steen and Ashurst, 2006). Aluminum cans were introduced in 1957, and by 1965 canned soft drinks were started to be sold in vending machines. In 1970, plastic bottles were produced for soft drinks, and in 1973 the pet bottles were created.

From 1950 to 1970, The US soft drink market had doubled its share of the commercial beverage market (Katz, 1978). In 1970, annual per capita consumption was 388.1 8-oz containers, with a wholesale value of $5.3 billion (Katz, 1978). The consumption of soft drinks increased from 36 million 8-oz servings in 1950 to about 72 billion 8-oz servings in 1970 (Woodroof and Phillips, 1981).

Woodroof and Phillips (1981) report that in the US, in 1978, the consumption of soft drinks (by excluding bottled water, tea, and coffee consumption) was about 7,601 billion gallons with 34.8 gallons average per capita; beer consumption was 5,137 billion gallons with 34.9 (legal age) per capita. It was 1,912 billion gallons with 8.71 gallons average per capita for drink mixes, while for fruit juices, it was 1,411 billion gallons with 6.43 gallons per capita. Finally, in the same year, for spirits, the consumption was 449 million gallons with 3.9 gallons per capita, and wine consumption was 413 million gallons with 2.8 gallons per capita consumption.

The second half of the century was also a good time for product development besides packaging and distribution developments (Steen and Ashurst, 2006). The first diet carbonated soft drink, a ginger ale called No-Cal, was produced in 1952. Coca-Cola Co. extended its production in 1954 by making its packaged products larger, using different materials, such as cans (Woodroof and Phillips, 1981). In conjunction with varied packaging, the Coca-Cola Co. added new drinks to its portfolio. In 1960, they launched a line of citrus-flavored drinks, Fanta, which is one of the top-selling products globally in today's world. Afterward, in 1961, the company added another successful brand to its line, Sprite, a lemon-lime drink (Woodroof and Phillips, 1981). From then to now, Sprite has a solid position in its segment. In 1963, the company introduced Tab, its first low-calorie beverage. In 1982, they launched Diet Coke. On the other hand, in 1964, PepsiCo introduced Diet Pepsi-Cola, one of the most successful carbonated soft drink products. In the same year, PepsiCo added Mountain Dew to its line following its acquisition from Barney and Ally Hartman bottlers.

Originating from being successful producers of carbonated soft drinks, the Coca-Cola Co. and PepsiCo became two leading companies in other beverage industry areas. The Coca-Cola Co. purchased The Minute Maid Company in 1960 and became the world's largest citrus products producer (Woodroof and Phillips, 1981). PepsiCo has been an active producer for beverages and in the snack industry with PepsiCo and Frito-Lay's merger in 1965 and the Tropicana acquisition in 1998. Additionally, PepsiCo purchased Quaker Oats and then Gatorade. Besides, the Coca-Cola Co. and PepsiCo, Dr Pepper Company has been extended. In 1994, Cadbury Schweppes acquired Dr Pepper and 7-Up companies, and the Royal Crown Cola (RC Cola) in 2000.

Woodroof and Phillips (1981) emphasize that one of the reasons for the popularity of carbonated soft drinks in the US is their availability. They can be found in grocery stores, supermarkets, department stores, restaurants, gas stations, and vending machines. Another reason for their convenience is that they have an extensive range of packaging: from glass bottles to aluminum cans and plastic bottles, and from single packaging to multiple packs. They also come under various types: regular and flavored, diet or non-diet, and caffeinated or non-caffeinated options. Woodroof and Phillips (1981) point out that their availability arises from the competition in the market. They highlight that most of the drinks are produced under franchise agreements. The companies carry their right to the formulas of drinks and the trademarks. The franchised companies make their syrup and flavor concentrate. There are about 200 national brands and hundreds of private brands that are sold locally and regionally in the US.

All of the carbonated soft drinks include the same few ingredients and their unique component, or their proportions make the difference and provide the variety on the shelves (Shachman, 2005). Carbonated soft drinks consist of water, sweetener, acidulant, flavor, color, and carbon dioxide gas (Shachman, 2005). 87 to 92 % of the beverage is water, and 8 to 12 of the beverage masses come from sweeteners (natural or artificial) (Shachman, 2005). Almost all carbonated soft drinks include acidulant to add sourness to the soft drink, while a flavor or combination of flavors gives its unique characteristics. Also, color is used for the visual effect of the soft drink, and the carbon dioxide gas provides the fizziness of the beverages (Shachman, 2005).

Effervescence refers to the technical term of fizziness known for sparkling and bubbling (Shachman, 2005). Carbonated soft drinks are called with various names, such as soda, soda water, soda pop, and pop (Woodroof and Phillips, 1981). Soda pop is commonly used in the US. It is probably extracted from sodium bicarbonate, which makes the drinks fizzy and carbon dioxide, making the carbonated beverages popping (Shachman, 2005).

2.2.2 Market Structure

Soft drinks, also known as liquid refreshment beverages (LRB), refer to nonalcoholic beverages consumed cold, unlike hot beverages such as tea and coffee. The soft drink industry includes carbonated soft drinks, bottled water, fruit beverages, ready-to-drink tea and coffee, energy drinks, and sports beverages. Figure 2.1 shows the soft drinks market revenues worldwide by country in 2019. The US is by far the first country with total revenue of about 247.5 billion dollars.

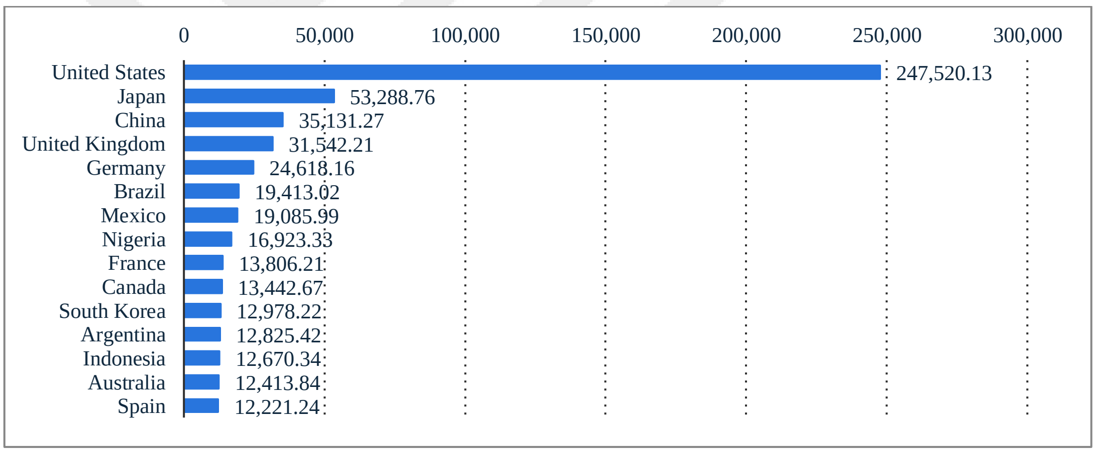

Figure 2. 1: Revenue of the soft drinks market worldwide by country in 2019 (million US dollars)

Source: Statista 2020

Carbonated soft drinks are one of the major component of the soft drink market in the US. Figure 2.2 illustrates the per capita consumption of CSDs in 2019 for the ten most populated countries worldwide. Mexicans have the highest CSDs consumption in the ten most populated countries with 634 8-oz. servings per capita. The US is in second place with 618 8-oz. servings per capita in 2019.

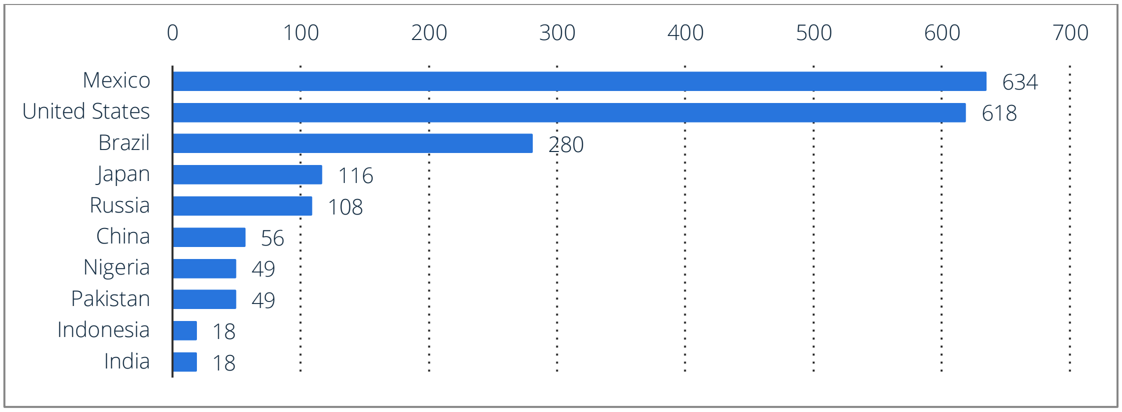

Figure 2. 2: Per capita consumption of carbonated soft drinks in 2019 in the ten most populated countries worldwide (in 8-ounce servings)

Source: Beverage Digest 2020

Figure 2.3 illustrates the consumption share of beverages in the US by segment, including alcoholic and nonalcoholic drinks. The highest consumption share of beverages for Americans is bottled water. CSDs are the second most consumed beverages among all drinks.

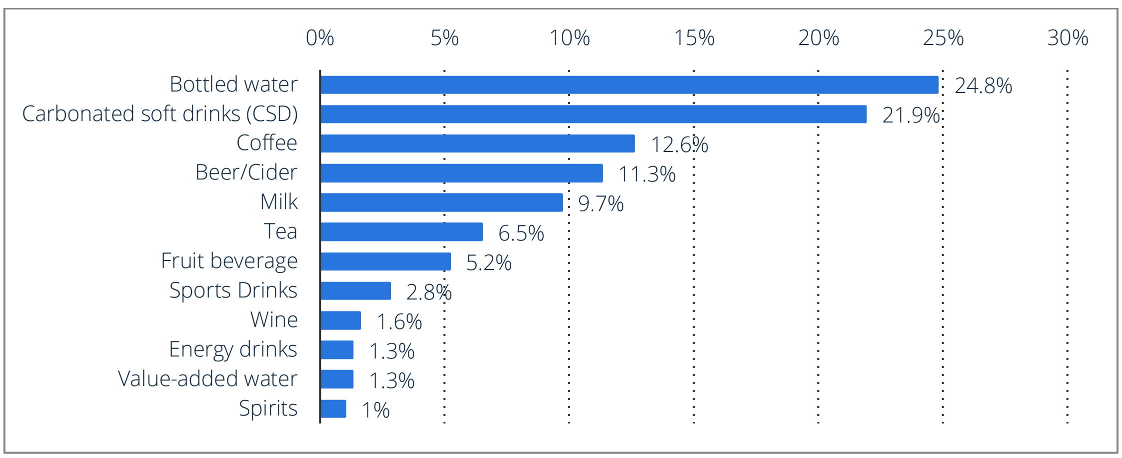

Figure 2. 3: Consumption share of beverages in the United States in 2018, by segment

Source: International Bottled Water Association 2019

Even if bottled water consumption is higher than carbonated soft drink consumption in the US, Figure 2.4 shows that CSDs brands are the leading brands in liquid refreshment bevereges. Coke Classic controls approximately 12% of the total volume sales at the brand level, with Pepsi, Mountain Dew, and Dr pepper trailing behind with 4.9%, 3.5%, and 3.4%, respectively. Gatorade, a sports drink, controls approximately 3.5%, while the bottled water brands Dasani and Aquafina control 2% and 1.7% of total volume sales, respectively (Figure 2.4).

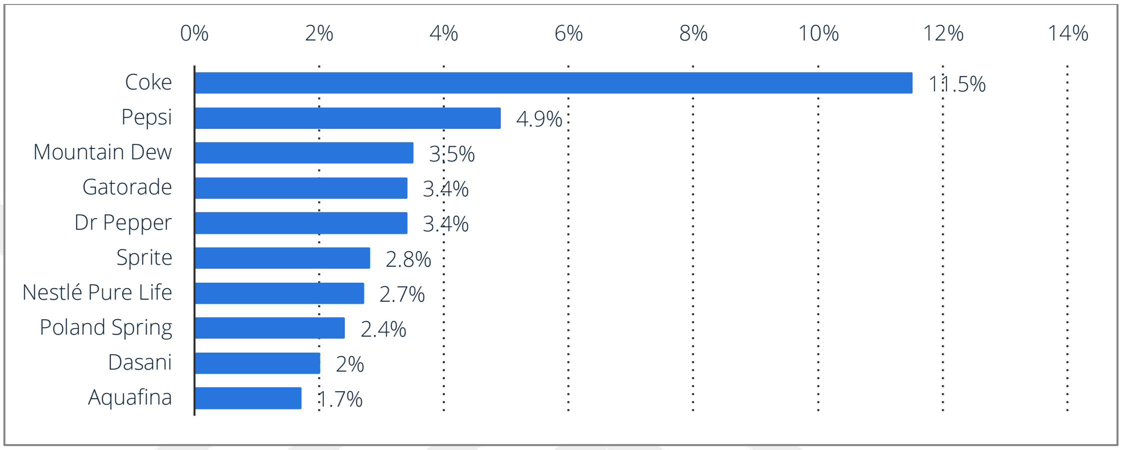

Figure 2. 4: Leading liquid refreshment beverage (LRB) brands in the United States in 2019, based on volume share

Source: Beverage Digest 2020

Howard et al. (2010) offer an interesting perspective of the soft drink industry by visualizing the soft drink industry's brand owners. They create a cluster diagram that includes soft drink brands and their varieties besides their ownership and licensing connections (See Figure 2.5 and Figure 2.6). The study consists of drinks sold in refrigerator cases and 94 Lansing, Michigan metropolitan area retailers that are limited to sell fresh produce in March 2008. The authors exclude non-refrigerated beverages, 100 % juice, 100 % water, and dairy products. The variety of soft drinks includes six categories that are soda, energy drink, sports drink, water, tea, and juice/punch.

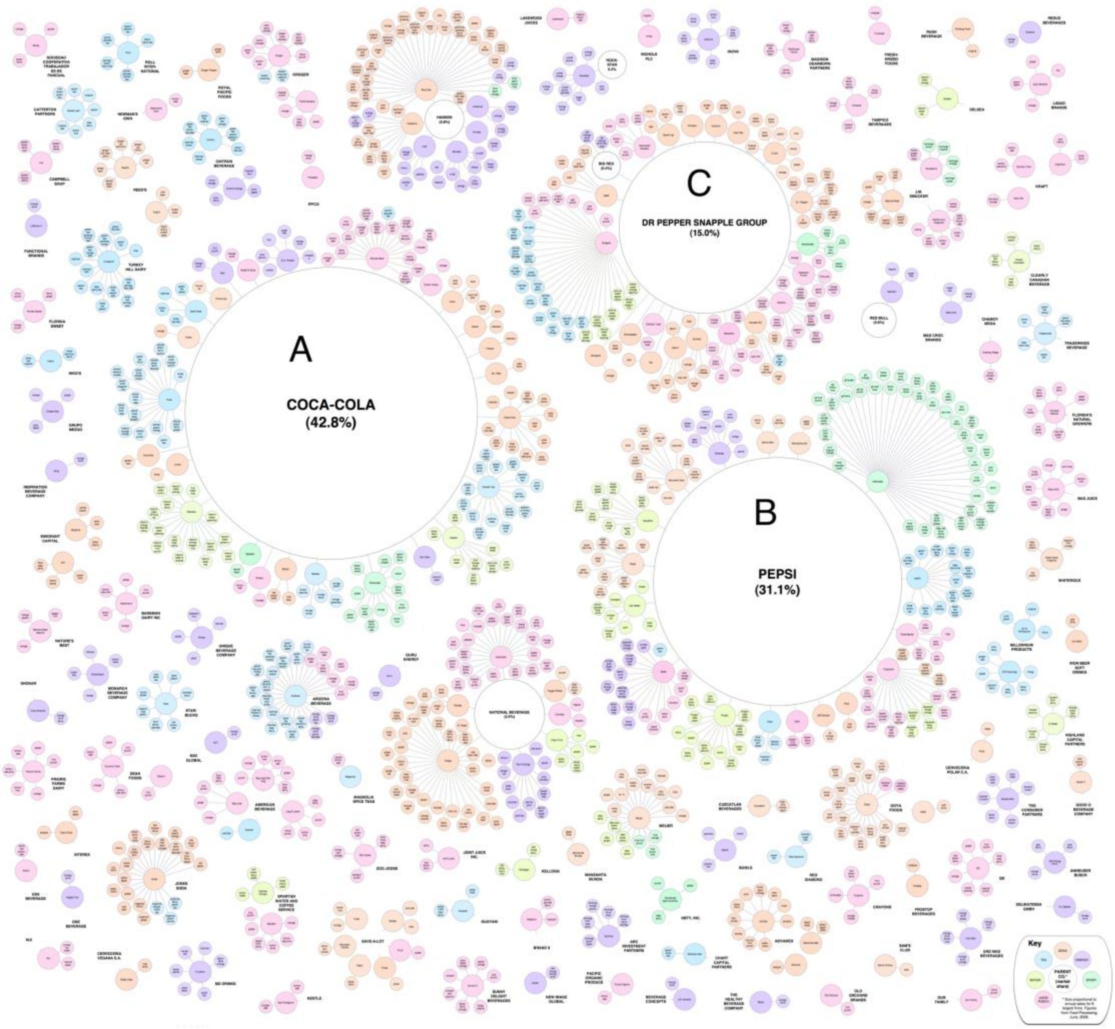

Figure 2. 5: Visualizing the Soft Drink Industry Structure, 2008

Notes: A: Coca-Cola Co., B: PepsiCo., C: Dr Pepper Snapple Group. See Appendix A for a closer look.

Source: Modified and adopted from Howard et al. (2010)

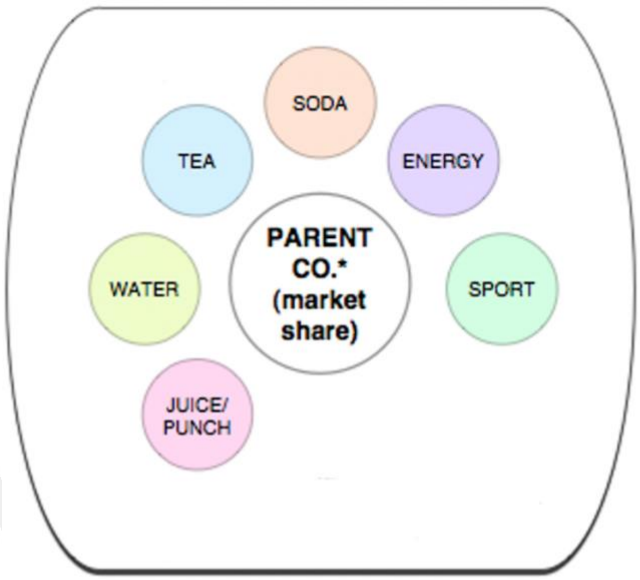

Figure 2. 6: Key for the Cluster Diagrams of Visualizing Soft Drink Market, 2008

Source: Modified and Adopted from Howard et al. (2010)

Howard et al. (2010) data consist of 101 parent companies with 195 brands, offered under 993 varieties. The authors find that Coca-Cola, Pepsi, and Dr Pepper Snapple Group have 407 varieties, with Coca-Cola owning 42.8 % of the drinks with 25 brands and 133 varieties. Pepsi has 31.1 % of the beverages with 17 brands and 161 varieties. Finally, Dr Pepper Snapple Group has 15 % of the drinks with 21 brands and 113 varieties. The authors find that the top 50 varieties are owned by 8 firms and are sold in more than half of the stores.

On the other hand, more than 300 varieties are available in only one store each. They note that less dominant companies either produce cheaper brands in only specific retailers or compete in newer categories such as teas, energy drinks, and flavored waters instead of carbonated soft drinks. They point out successful competitors may eventually be acquired by leading companies, such as the acquisition of Glaceau/Vitamin water by Coca-Cola in 2007. Consequently, even if soft drinks are produced by using primarily water and sweeteners, there is an illusion of diversity in the soft drink industry arising from obscuring ownership.

One aspect worth noting is the declining trend in the US per capita CSD consumption. As illustrated in Figure 2.7, the CSD consumption decreased from 728 8-oz servings in 2010 to 618 8-oz servings in 2019, a 15% decline in ten years. This decline may be explained by the association of obesity prevalence and the consumption of calorie-rich foods, such as carbonated soft drinks.

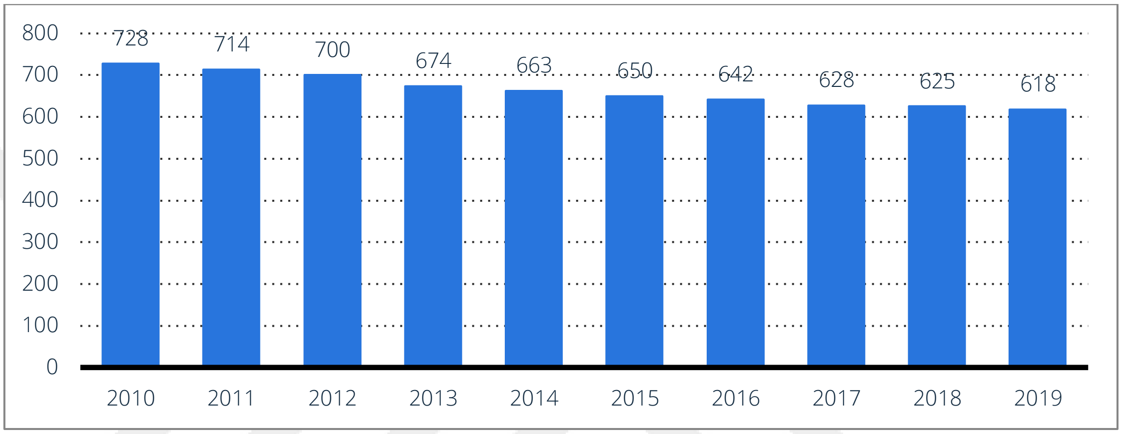

Figure 2. 7: Per capita consumption of carbonated soft drinks (CSD) in the United States from 2010 to 2019 in 8-oz servings

Source: Beverage Digest 2020

Table 2.1 represents volume sales in billion cases (192-oz.) of carbonated soft drinks from 1997 to 2004, and it shows that there was positive growth in volume sales of CSD during the years. According to Fuhram (2006), the US's first decline in volume sales occurred in 2005. As showed in Figure 2.8, the drop in sales volume has continued in the next decade. Figure 2.9 shows the negative growth in the CSD industry's volume sales. The highest decline in sales was in 2013. However, the retail value of carbonated soft drinks has increased between 2010 and 2019 (except for 2013), as shown in Figures 2.10 and 2.11. The retail value of carbonated soft drinks in 2019 was approximately 87.2 billion US dollars.

Table 2. 1: US Carbonated Soft Drink Market Volume Sales and Volume Growth from 1997 to 2004

Year	Millions of Cases (192-oz.)	% Change
1997	9,571.4	-
1998	9,894.0	3.4%
1999	9,953.3	0.6%
2000	10,003.3	0.5%
2001	10,053.3	0.5%
2002	10,134.7	0.8%
2003	10,172.3	0.4%
2004	10,244.8	0.7%

Source: Beverage Marketing Corporation, merged from The Food Institute Report (2003) and Rodwan (2005)

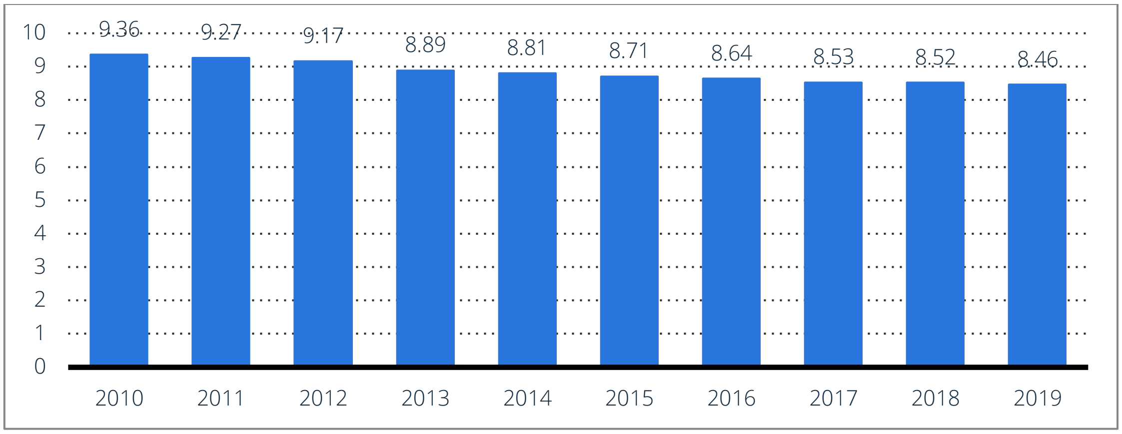

Figure 2. 8: Carbonated soft drink all-channel sales volume in the United States, 2010-2019, volume in billion 192-oz cases

Source: Beverage Digest 2020

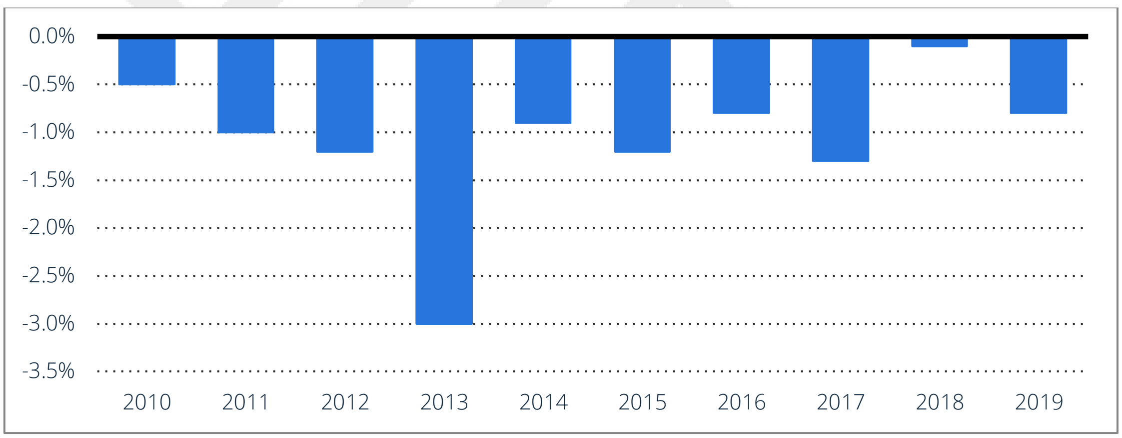

Figure 2. 9: Carbonated soft drink all-channel sales volume growth in the United States, 2010-2019

Source: Beverage Digest 2020

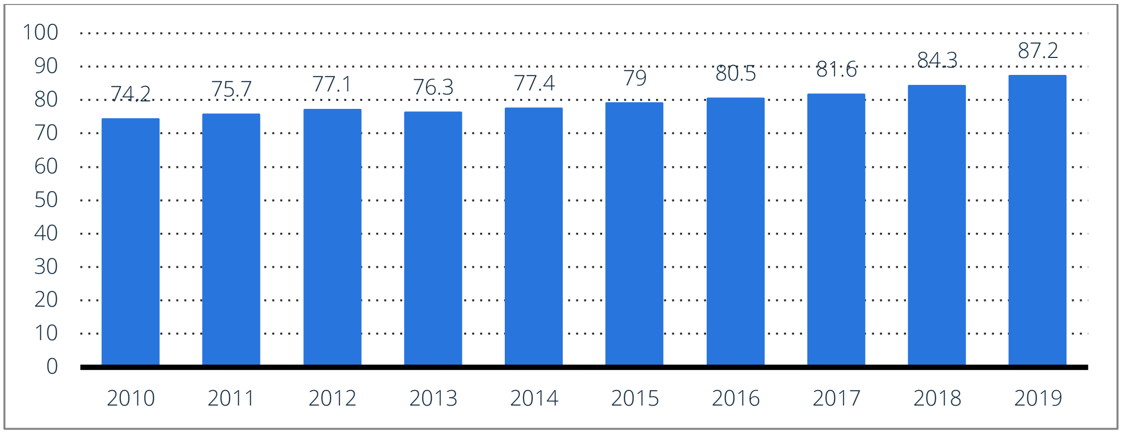

Figure 2. 10: Retail value of carbonated soft drinks in the United States from 2010 to 2019 (in billion US dollars)

Source: Beverage Digest 2020

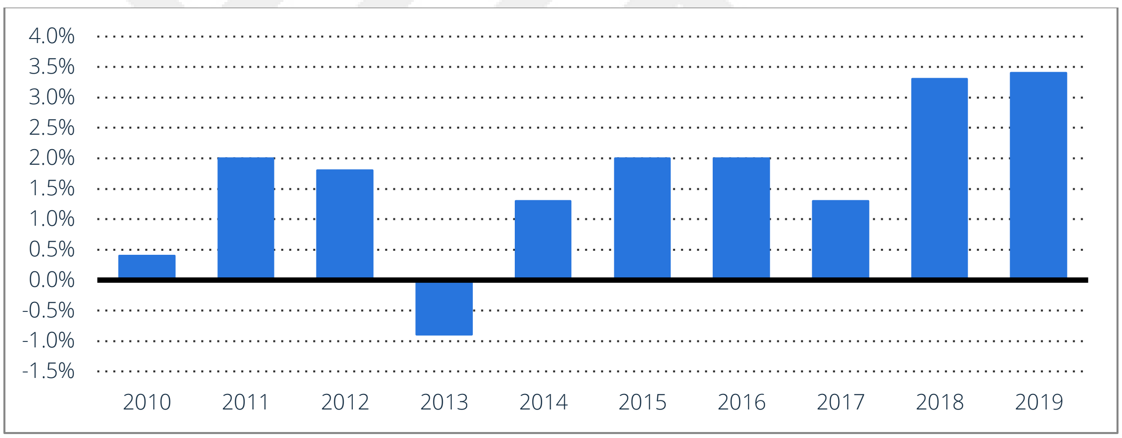

Figure 2. 11: Retail value growth of carbonated soft drinks in the United States, 2010-2019

Source: Beverage Digest 2020

The US CSD market offers 74% of its soft drinks under regular form and 26% under diet form (Figure 2.12). The Cola flavor dominates the CSD market with 50.6% of the volume sales, followed by the heavy citrus-flavored, the lemon lime-flavored, and the pepper-flavored CSD, with 11.3%, 10.3%, and 10.2% of the total volume sales, respectively (Figure 2.13).

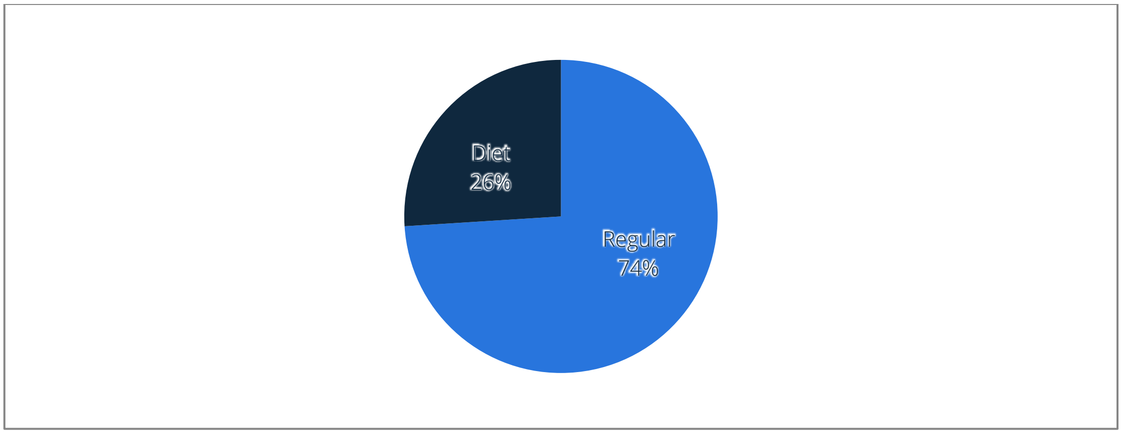

Figure 2. 12: Regular and diet carbonated soft drink (CSD) market volume share in the United States in 2018

Source: Beverage Industry Magazine 2020

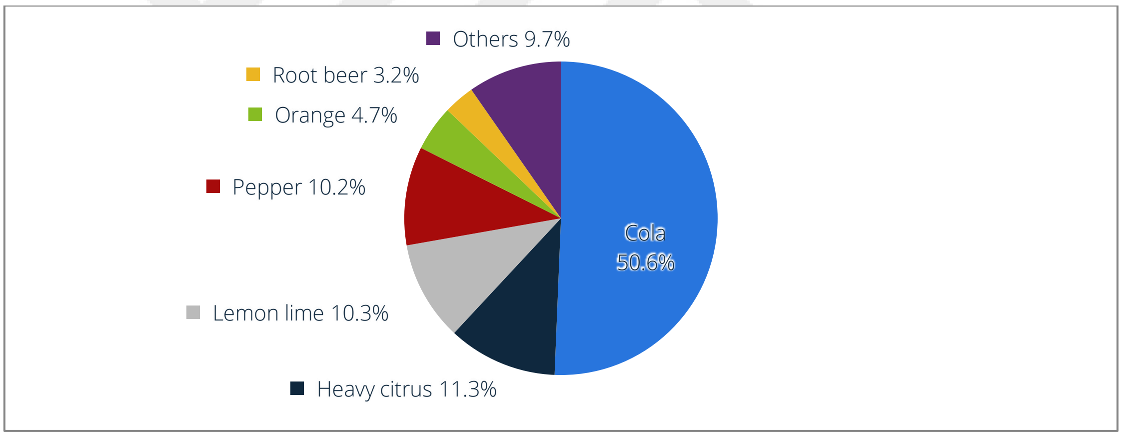

Figure 2. 13: Share of carbonated soft drink sales volume in the United States in 2018, by flavor

Source: Beverage Industry Magazine 2020

While cola dominates the market as flavor, Coca-Cola Co. dominates the market as a company (see Figure 2.14). The industry has a high concentration ratio, so that the first three companies have more than 85% of the market share. In fact, the Coca-Cola Co. brands control approximately 43% of the US CSD market share, with PepsiCo holding about 25% and Dr Pepper holding around 20%.

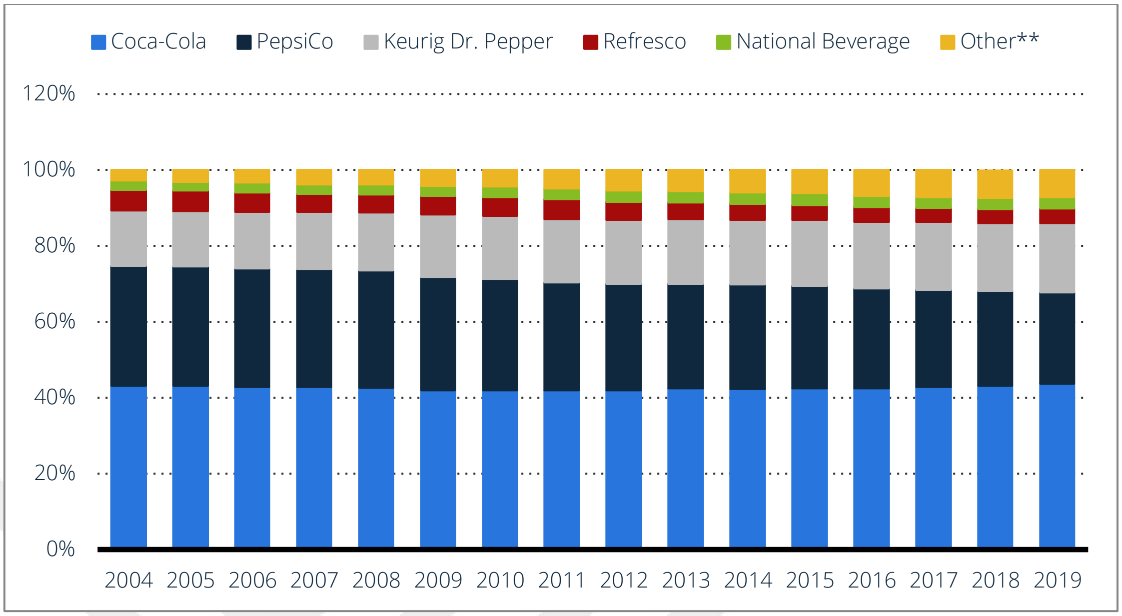

Figure 2. 14: Market share of leading carbonated soft drink companies in the United States from 2004 to 2019

Source: Beverage Digest 2020

Figure 2.15 demonstrates that the Coca-Cola Co. holds its market share slightly similar during the years from 2004 to 2019. On the other hand, the market share of PepsiCo in carbonated soft drinks has been declined over the years. From 2004 to 2019 the market share decreased 31.7% to 24.9% (see Figure 2.16). Finally, Keurig-Dr Pepper, which has the third place of the leading CSD companies, has increased its market share by 25% from 2004 to 2019 (see Figure 2.17).

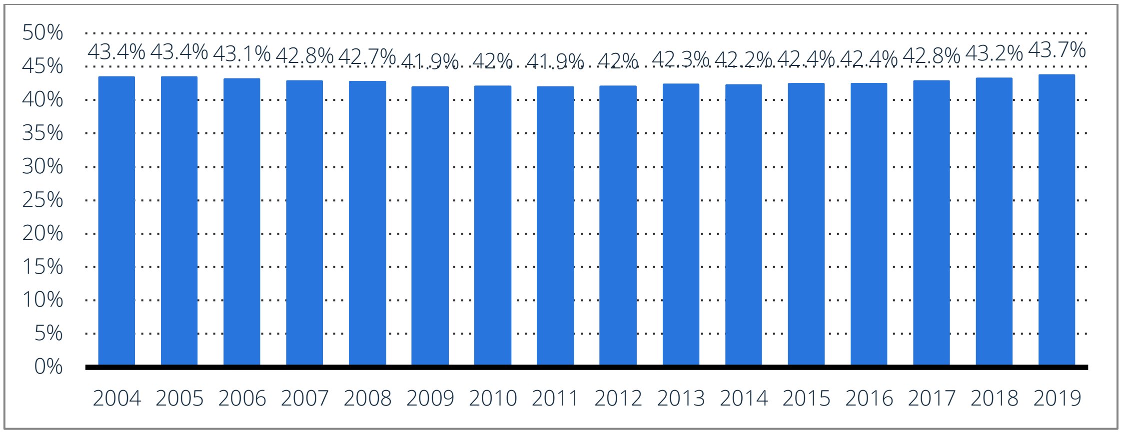

Figure 2. 15: Coca-Cola Company's market share in the United States from 2004 to 2019

Source: Beverage Digest 2020

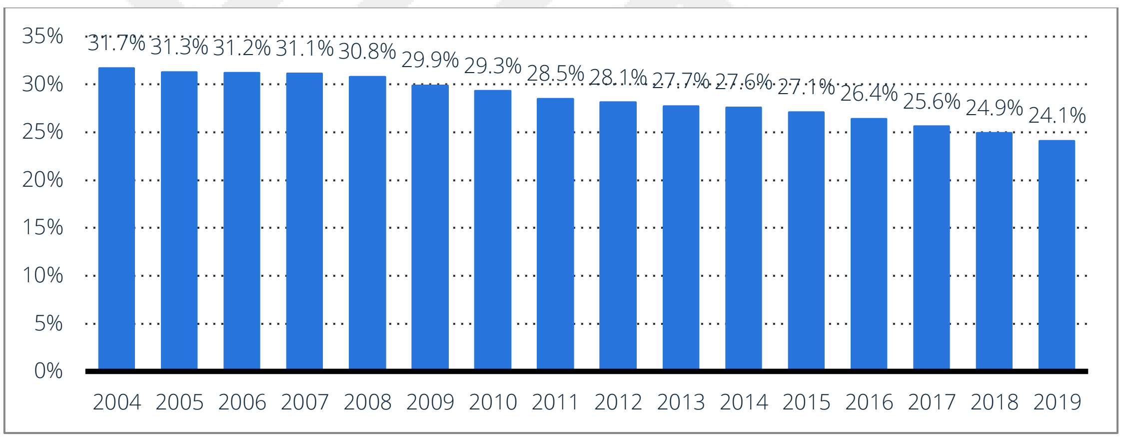

Figure 2. 16: PepsiCo company's market share in the United States from 2004 to 2019

Source: Beverage Digest 2020

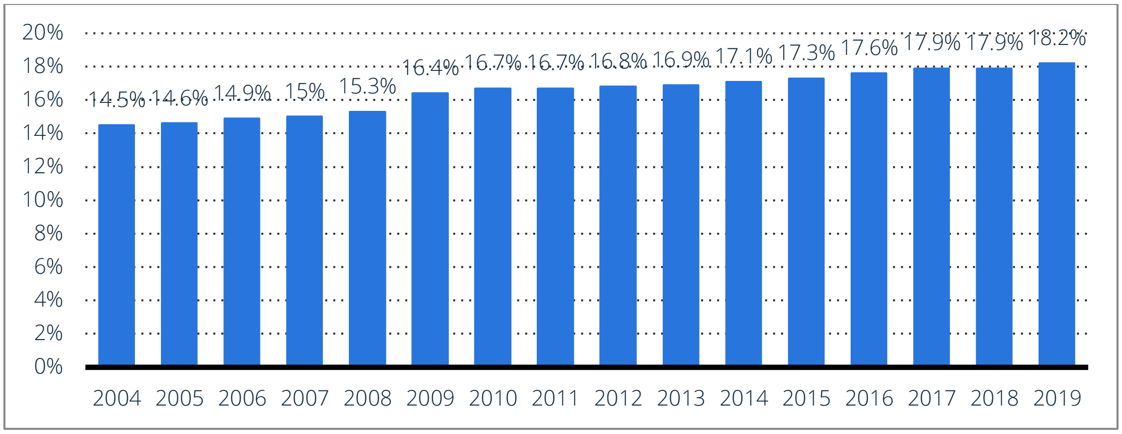

Figure 2. 17: Keurig Dr Pepper company's market share in the United States from 2004 to 2019

Source: Beverage Digest 2020

Figure 2.18 shows leading CSD brands in the US in 2019 according to their volume share. Five of the leading brands, namely Coke Classic, Diet Coke, Sprite, Fanta, and Coke Zero Sugar, belong to the Coca-Cola Co. PepsiCo owns four of the top brands: Pepsi-Cola, Diet Pepsi, Mountain Dew, and Diet Mountain Dew, while Keurig-Dr Pepper Company has just one brand, Dr Pepper, in the leading ten brands. Coca-Cola[1] brand by far leads the top ten brands in volume share, with approximately 18 % of the total market. This market share is more than double the 7.8% Pepsi Cola market share and the 7.2% Dr Pepper share. In 2019, the second to the fifth leading brands have more than 7% volume shares each. Besides, five of the ten top brands have cola flavor, and three of them have citrus-lime flavor. Finally, there is one in pepper flavor and one in fruit flavor.

[1] Coca-Cola, Coke Classic, and Coke are used interchangeably and refer to the same product.

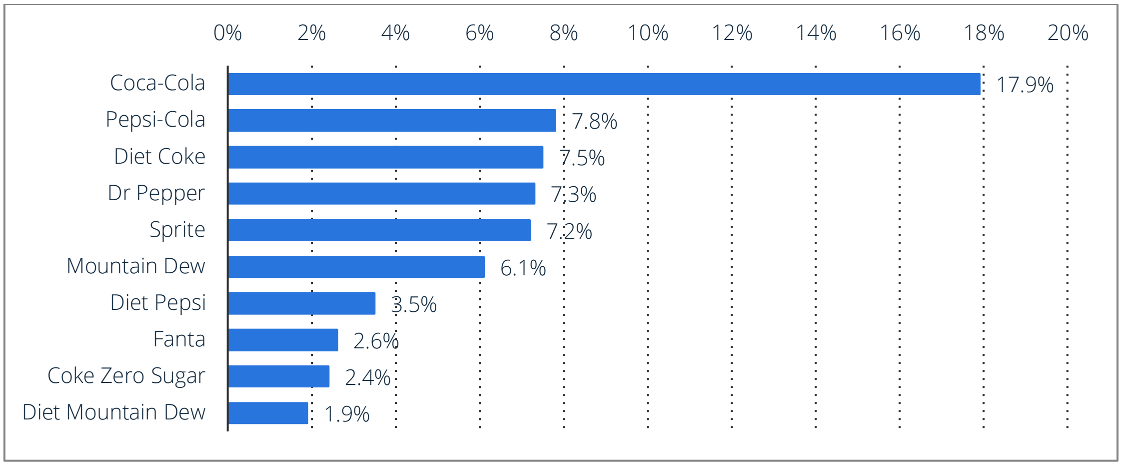

Figure 2. 18: Leading carbonated soft drink brands in the United States in 2019, based on volume share

Source: Beverage Digest 2020

Figure 2.19 shows the market share of the Coke Classic brand from 2004 to 2019. Coke Classic has protected its market share over the years. However, Diet Coke's market share showed in Figure 2.20, increased from 2004 to 2008, and from 2009 to 2019, its market share decreased by about 24%.

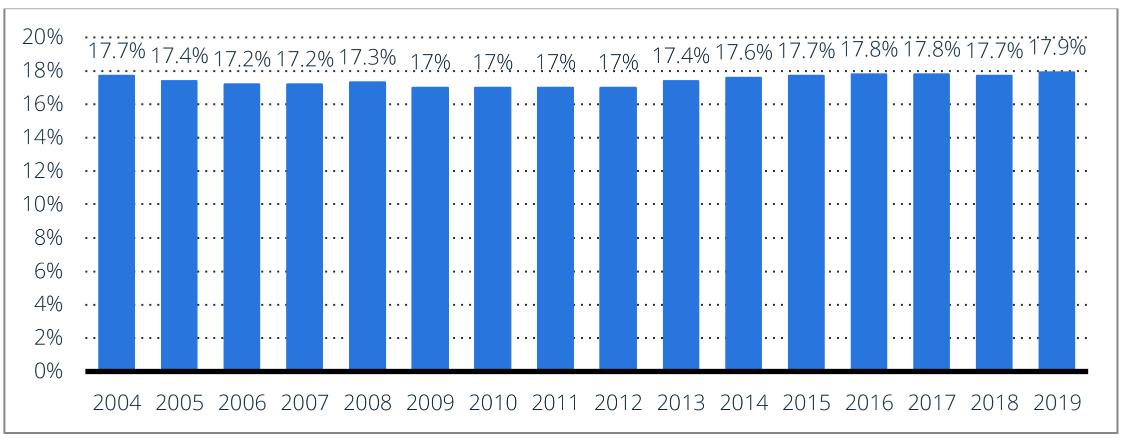

Figure 2. 19: Market share of the Coke Classic brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

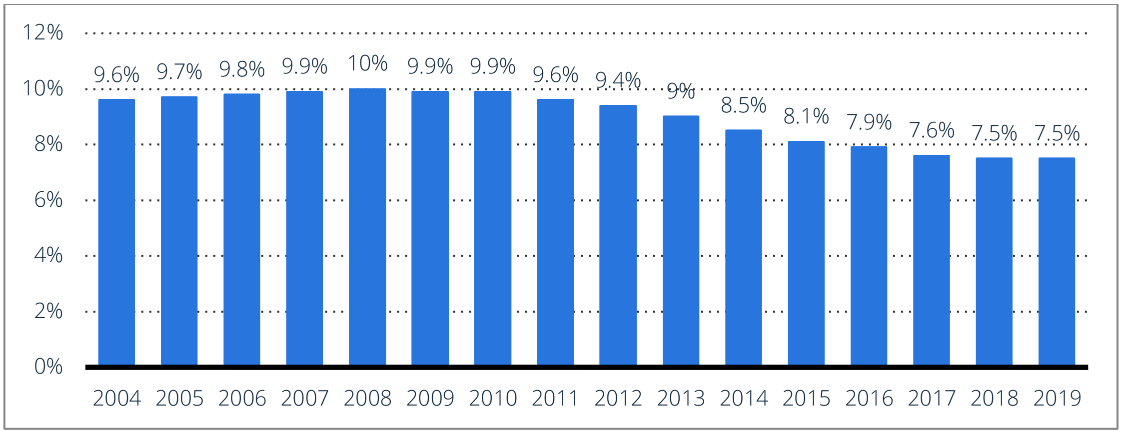

Figure 2. 20: Market share of the Diet Coke brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

From 2004 to 2018, the Fanta brand's market share, one of the leading five brands of the Coca-Cola Co, has tended to increase. It raised from 1.3% to 2.7%, and in 2019, it declined to 2.6% (see Figure 2.21). On the other hand, from 2004 to 2008, Sprite's market share remained the same, 5.6%, and from 2012 to 2019, it increased from 5.7% to 7.2% (see Figure 2.22).

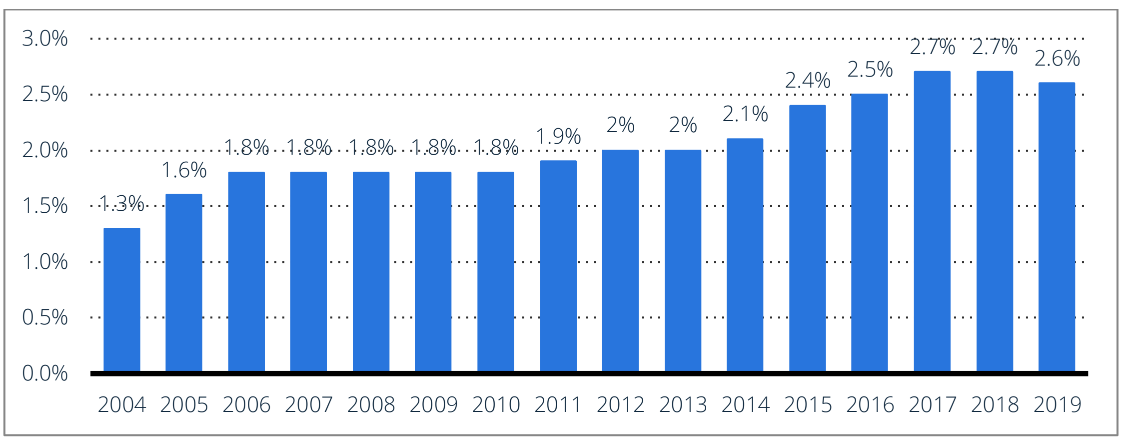

Figure 2. 21: Market share of the Fanta brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

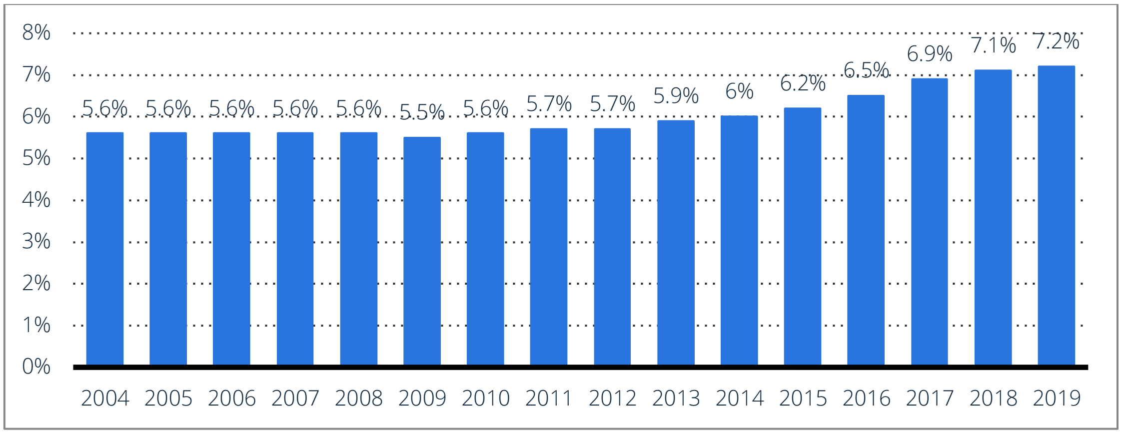

Figure 2. 22: Market share of the Sprite brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

As shown in Figure 2.23 and Figure 2.24, Pepsi Cola's and Diet Pepsi's market shares tend to decrease over the years. For Pepsi-Cola, the market share was 11.4% in 2004, and it declined to 7.9% in 2019. Similarly, Diet Pepsi's market share decline from 6% to 3.5% between 2004 to 2019.

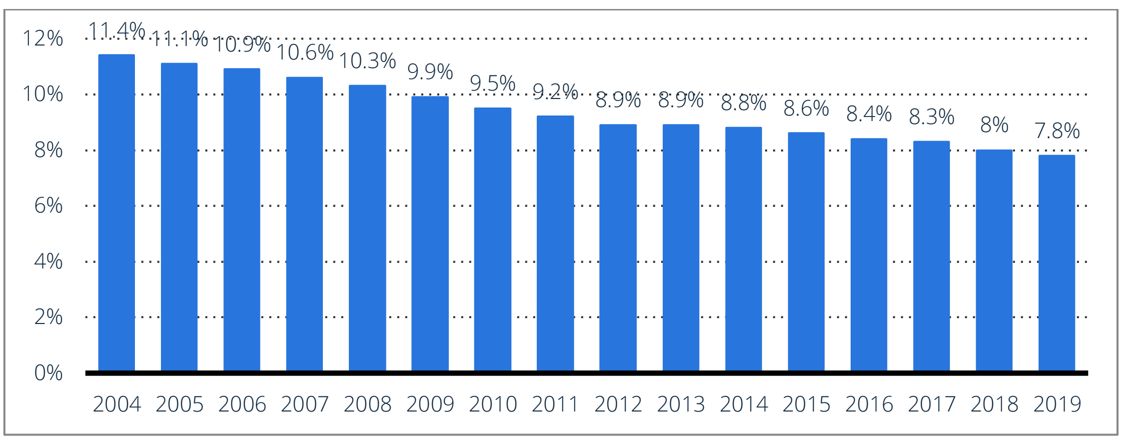

Figure 2. 23: Market share of the Pepsi-Cola brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

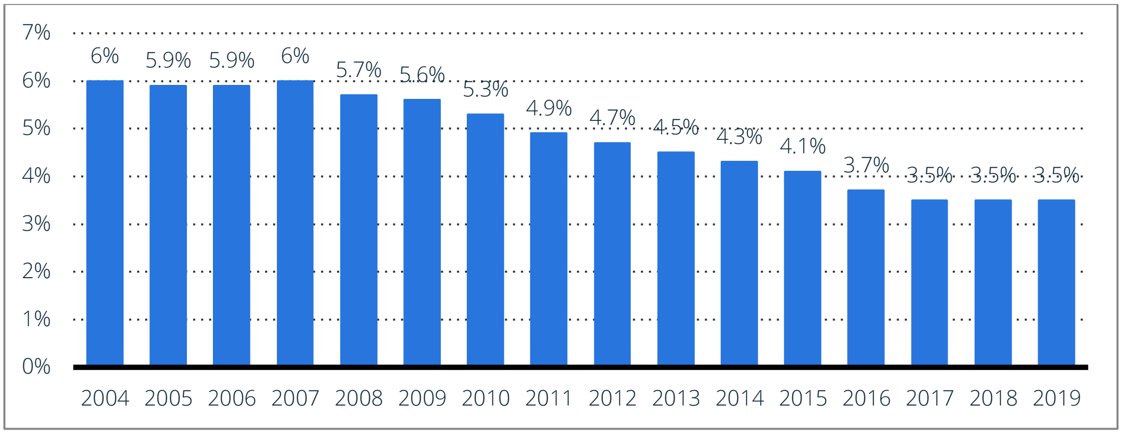

Figure 2. 24: Market share of the Diet Pepsi brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

Mountain Dew is one of PepsiCo's solid brands, and its market share increased from 6.2% to 6.8% from 2004 to 2008 (See Figure 2.25). In 2013 and 2014, it reached its highest volume share, 6.9%. After 2014, its share had started decreasing, and in 2019 it had 6.1%, which is its lowest market share over the last 15 years.

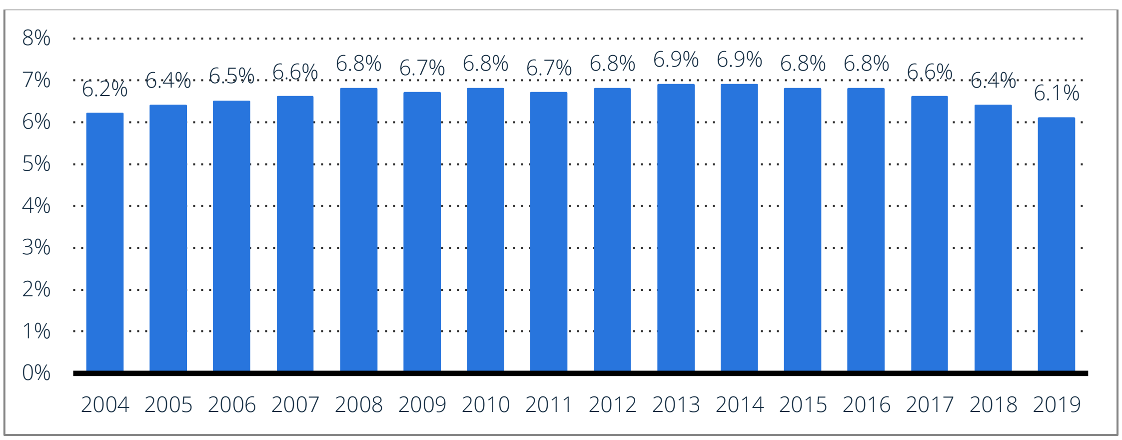

Figure 2. 25: Market share of the Mountain Dew brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

Furthermore, Figure 2.26 shows that Dr Pepper's market share has an increasing trend over the years. Its market share increased from 5.5% to 7.3% between 2004 to 2019. Diet Dr Pepper's market share ranged between 1.5% to 1.7% from 2006 to 2019 (see Figure 2.27).

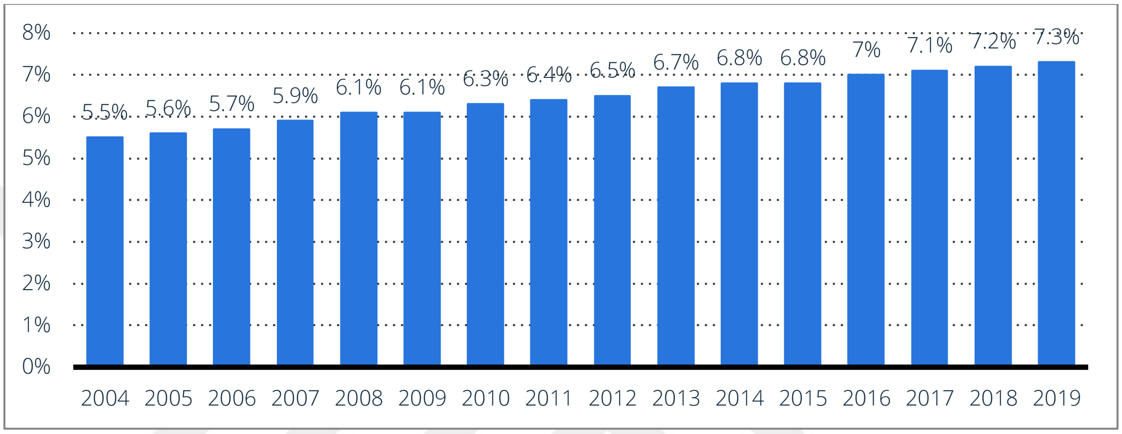

Figure 2. 26: Market share of the Dr Pepper brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

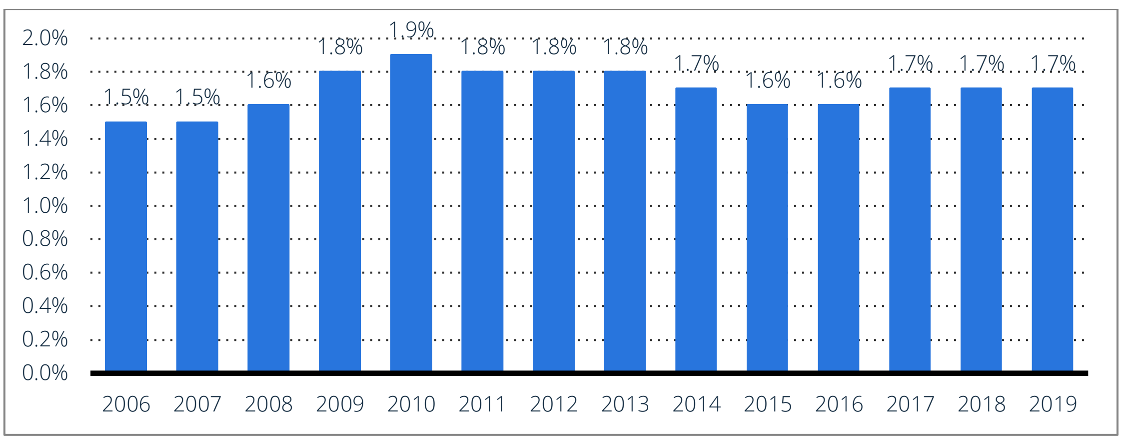

Figure 2. 27: Market share of the Diet Dr Pepper brand in the United States from 2004 to 2019

Source: Beverage Digest 2020

To sum up, The US soft drink industry generates about 247 US billion dollars total revenue in 2019 (Figure 2.1). The carbonated soft drinks category is a significant part of the soft drink industry. For instance, in 2019, total carbonated soft drink volume sales were about 8.46 billion in 192 oz. cases, with a total retail value of around 87.2 billion dollars in the US (Beverage Digest (2020)).The first three CSD companies hold more than 85% of the market share (Figure 2.15). CSDs are produced by relatively small numbers of producers, which corresponds to an oligopolistic market structure. CSDs are highly differentiated products, and they are differentiated by flavor, size, color, sugar content (regular vs. diet), and caffeine content. Therefore, the CSD industry represents oligopolistic competition with highly differentiated products.

2.3 The Data

2.3.1 Data Description

This research uses scanner data provided by Information Resources, Inc. (IRI) that includes weekly sales of carbonated soft drinks from January 2006 to December 2011. The data set includes dollar sales, unit sales, volume equivalents, and universal product codes (UPC) for each brand across major geographical areas in the United States. Current Population Survey by US Census provides demographic variables used for consumer heterogeneity.

In this research, Dallas, Texas is chosen as a geographical area arbitrarily, believing that carbonated soft drink demand is independent across geographical regions. Besanko et al. (2004) define close substitutes as having the same or similar product performance characteristics, the same or similar occasions to use, and the same geographical areas. Therefore, the same products may not be considered substitutes across different geographical areas.

The sample includes two different aggregation levels, which correspond to two different demand estimations. One estimation is performed at the brand level and contains 20 carbonated soft drinks, such as Dr Pepper, Sunkist, Pepsi, Diet Coke, Coke Classic, and Diet Pepsi. The second estimation is performed at the UPC level or bottle-size or package-size level. This research considers different package sizes as separate brands. For instance, Diet Coke 67.6 oz. single plastic bottle is not the same as Diet Coke 12 oz. 12 cans, or Diet Coke 16.9 oz. 6 plastic bottles. We consider 42 bottle-size brands, which come from the twenty brands with varying package sizes and materials. The brands are chosen according to their weekly volume sales.

We aggregate the weekly IRI data into four-week to keep the number of observations computationally manageable. The resulting sample has 78 four-weekly periods, spanning from January 2006 to December 2011. In the industrial organizations' framework, each period is a market; hence, the sample includes 78 markets.

The IRI data does not provide volume sales, but it includes unit sales and the volume equivalent for each unit. Volume sales are computed by multiplying unit sales with their volume equivalents. Each carbonated soft drink brand's price is calculated by dividing each brand's aggregated dollar sales by each brand's aggregated volume sales for each market. Since ounce is used as the volume equivalent unit, prices are per ounce for each brand.

The market share of each carbonated soft drink brand is obtained by dividing each brand's volume sales by the potential market size. The potential market size is computed by multiplying the Dallas, Texas population, obtained from The Census Bureau, by per the capita four-week consumption of carbonated soft drinks. The outside good's market share is calculated by subtracting the sum of the brands' market shares in the choice set from one.

The sample at the brand level consists of twenty choices in every period or market, leading to a balanced panel sample. There are 78 markets with 20 brands, implying 1560 (78x20) observations. On the other hand, not all 42 bottle-size level brands appear in every period, generating unbalanced panel data. Of the 42 choices, 35 appear in every market, while seven are irregularly absent in some markets. There are 3122 observations for the unbalanced panel data.

Data for product characteristics of each brand comes from its nutritional fact labels provided by each company's website. Calories and caffeine content are collected as product characteristics and it is assumed that these characteristics remain the same during the data period. Sugar content is excluded from the analysis because it gives similar information with calories (they are nearly proportional). Since volume equivalent is taken as one ounce, prices are per ounce, calorie and caffeine variables represent calorie per ounce and caffeine per ounce.

Private label brands are excluded from this study because their product characteristics are unknown to the researcher. Private label brands exist in the IRI data, and they belong to various supermarket chains. In the IRI data, the chains are masked/hidden for the researcher who cannot distinguish between two retail chains' private labels for the nutritional facts.

To allow for consumer heterogeneity, demographic variables are collected from the Current Population Survey, and for each market, 500 random draws are obtained. The demographics used in this research are the household income and the number of households under 15 years old. In addition to observed demographics, households' unobserved characteristics are randomly generated (500 draws) from the standard normal distribution for each market. There are 78 markets and 500 draws for each market; hence, 39000 simulated households.

Table 2.2 represents the market shares and prices at the brand level in the Dallas metropolitan area. Coke Classic holds the highest market share with 16.4% of the total sales. The second leading brand in this market is Dr Pepper, with 13.5% of the market share. The most expensive brand is Coke Zero, while the least expensive one is Royal Crown Cola. The sample consists of 20 brands; 7 belong to The Coca-Cola Co., PepsiCo. produces 3, and 10 belong to Dr Pepper Snapple Group. The Coca-Cola Co. brands have 33.09% of the market shares, PepsiCo has 9.07%, and Dr Pepper Snapple Group's brands have 27.32% of the market shares.

Table 2. 2: Market Shares and Prices for the Brands in the Brand Level

Brand	Brand Description	Manufacturer	Market Share	Price ($/oz.)
1	COKE CLASSIC	The Coca-Cola Co.	16.4468%	0.0240
2	DR PEPPER	Dr Pepper Snapple Group	13.5843%	0.0226
3	DIET COKE	The Coca-Cola Co.	7.3686%	0.0250
4	PEPSI	PepsiCo	5.5919%	0.0210
5	SPRITE	The Coca-Cola Co.	4.3788%	0.0245
6	DIET DR PEPPER	Dr Pepper Snapple Group	4.3275%	0.0229
7	7 UP	Dr Pepper Snapple Group	2.6348%	0.0216
8	SUNKIST	Dr Pepper Snapple Group	2.3649%	0.0220
9	DIET PEPSI	PepsiCo	1.9315%	0.0223
10	COKE ZERO	The Coca-Cola Co.	1.6455%	0.0266
11	MOUNTAIN DEW	PepsiCo	1.5480%	0.0238
12	CAFFEINE FREE DIET COKE	The Coca-Cola Co.	1.4939%	0.0238
13	A & W ROOT BEER	Dr Pepper Snapple Group	1.4507%	0.0223
14	SPRITE ZERO	The Coca-Cola Co.	0.9235%	0.0237
15	FANTA	The Coca-Cola Co.	0.8294%	0.0230
16	DIET 7 UP	Dr Pepper Snapple Group	0.7601%	0.0211
17	CAFFEINE FREE DIET DR PEPPER	Dr Pepper Snapple Group	0.7516%	0.0207
18	ROYAL CROWN COLA	Dr Pepper Snapple Group	0.6534%	0.0200
19	CANADA DRY	Dr Pepper Snapple Group	0.5386%	0.0230
20	A & W CREAM SODA	Dr Pepper Snapple Group	0.2587%	0.0221

Table 2.3 provides the bottle-size level brands' market shares and prices. Coke Classic 12-oz-12-cans captures the highest market share, 8.1% of the total Dallas market. Dr Pepper's, Diet Coke's, and Pepsi's 12-oz-12-cans are the following leading brands. The top four brands have the same package size, 12-oz-12-cans. Moreover, Coke Classic's 2 liters plastic bottle is the fifth leading brand according to its market share, 2.8%.

The data at hand show that Coke Zero's 16.9-oz-6-packs sells for the highest price (Table 2.3), while 7-Up-2-liters single plastic bottle item sells for the lowest price during the period of study. The 16.9-oz-6-packs of plastic bottles sell for higher prices across all brands than the 2-liters single plastic bottles. In the data by bottle-size, there are 17 brands from The Coca-Cola Co., nine brands from PepsiCo, and 16 brands from Dr Pepper Snapple Group. The Coca-Cola Co. brands hold 27.22% of the market share, PepsiCo brands have 7.53%, and Dr Pepper, Snapple Group brands, have 20.93% of the market shares in the IRI data.

Table 2. 3: Market Shares and Prices for the Brands in the Bottle-Size Level

Brand	Brand Description	Manufacturer	Market Share	Price ($/oz.)
1	COKE CLASSIC 12-OZ 12 CANS	The Coca-Cola Co.	8.1280%	0.0229
2	DR PEPPER 12-OZ 12 CANS	Dr Pepper Snapple Group	8.0649%	0.0209
3	DIET COKE 12-OZ 12 CANS	The Coca-Cola Co.	3.7212%	0.0233
4	PEPSI 12-OZ 12 CANS	PepsiCo	3.2718%	0.0207
5	COKE CLASSIC 67.6-OZ (2-LT) PLASTIC	The Coca-Cola Co.	2.8557%	0.0187
6	DIET DR PEPPER 12-OZ 12 CANS	Dr Pepper Snapple Group	2.4515%	0.0210
7	SPRITE 12-OZ 12 CANS	The Coca-Cola Co.	2.1657%	0.0225
8	DR PEPPER 67.6-OZ (2-LT) PLASTIC	Dr Pepper Snapple Group	2.0990%	0.0172
9	COKE CLASSIC 12-OZ 24 CANS	The Coca-Cola Co.	2.0193%	0.0213
10	SUNKIST 12-OZ 12 CANS	Dr Pepper Snapple Group	1.5729%	0.0202
11	7 UP 12-OZ 12 CANS	Dr Pepper Snapple Group	1.5553%	0.0203
12	COKE CLASSIC 16.9-OZ 6 PACKS PLASTIC	The Coca-Cola Co.	1.3923%	0.0247
13	DIET COKE 67.6-OZ (2-LT) PLASTIC	The Coca-Cola Co.	1.0816%	0.0188
14	PEPSI 67.6-OZ (2-LT) PLASTIC	PepsiCo	1.0763%	0.0174
15	SPRITE 67.6-OZ (2-LT) PLASTIC	The Coca-Cola Co.	0.9822%	0.0183
16	DIET COKE 12-OZ 24 CANS	The Coca-Cola Co.	0.9769%	0.0219
17	DIET PEPSI 12-OZ 12 CANS	PepsiCo	0.9576%	0.0213
18	A&W ROOT BEER 12-OZ 12 CANS	Dr Pepper Snapple Group	0.9259%	0.0208
19	COKE ZERO 12-OZ 12 CANS	The Coca-Cola Co.	0.8451%	0.0238
20	MOUNTAIN DEW 12-OZ 12 CANS	PepsiCo	0.8208%	0.0213
21	CAFFEINE FREE DIET COKE 12-OZ 12 CANS	The Coca-Cola Co.	0.7609%	0.0234
22	DIET COKE 16.9-OZ 6 PACKS PLASTIC	The Coca-Cola Co.	0.7109%	0.0269
23	DR PEPPER 16.9-OZ 6 PACKS PLASTIC	Dr Pepper Snapple Group	0.6847%	0.0250
24	DIET DR PEPPER 67.6-OZ (2-LT) PLASTIC	Dr Pepper Snapple Group	0.5743%	0.0169
25	7 UP 67.6-OZ (2-LT) PLASTIC	Dr Pepper Snapple Group	0.5609%	0.0167

Table 2.3. Continued

Brand	Brand Description	Manufacturer	Market Share	Price ($/oz.)
26	SPRITE ZERO 12-OZ 12 CANS	The Coca-Cola Co.	0.5540%	0.0239
27	PEPSI 12-OZ 24 CANS	PepsiCo	0.5311%	0.0184
28	CAFFEINE FREE DIET DR PEPPER 12-OZ 12 CANS	Dr Pepper Snapple Group	0.5275%	0.0217
29	FANTA 12-OZ 12 CANS	The Coca-Cola Co.	0.5200%	0.0222
30	DIET 7 UP 12-OZ 12 CANS	Dr Pepper Snapple Group	0.4448%	0.0217
31	ROYAL CROWN COLA 12-OZ 12 CANS	Dr Pepper Snapple Group	0.4171%	0.0207
32	DIET DR PEPPER 16.9-OZ 6 PACKS PLASTIC	Dr Pepper Snapple Group	0.3511%	0.0255
33	DIET PEPSI 67.6-OZ (2-LT) PLASTIC	PepsiCo	0.3470%	0.0170
34	CANADA DRY 12-OZ 12 CANS	Dr Pepper Snapple Group	0.2633%	0.0232
35	MOUNTAIN DEW 67.6-OZ (2-LT) PLASTIC	PepsiCo	0.2580%	0.0175
36	COKE ZERO 67.6-OZ (2-LT) PLASTIC	The Coca-Cola Co.	0.2431%	0.0193
37	CANADA DRY 67.6-OZ (2-LT) PLASTIC	Dr Pepper Snapple Group	0.2423%	0.0180
38	A&W CREAM SODA 12-OZ 12 CANS	Dr Pepper Snapple Group	0.1925%	0.0219
39	PEPSI 16.9-OZ 6 PACKS PLASTIC	PepsiCo	0.1751%	0.0241
40	COKE ZERO 12-OZ 24 CANS	The Coca-Cola Co.	0.1584%	0.0224
41	COKE ZERO 16.9-OZ 6 PACKS PLASTIC	The Coca-Cola Co.	0.1016%	0.0279
42	DIET PEPSI 16.9-OZ 6 PACKS PLASTIC	PepsiCo	0.0961%	0.0248

Table 2.4 and Table 2.5 present the summary statistics of product characteristics and demographics in the brand level and the bottle-size level, respectively. The average calorie content of 12-oz drinks for brand level is 93.1 while it is 87.38 for the bottle-size level. The average caffeine content at the brand level is 54.6 mg, while for the bottle-size level, the average caffeine content is 54 mg for a 12-oz drink.

For both aggregation levels, we obtain random draws, and we end up with 39,000 simulated households at each level. For the brand level, the average income is about $81,554. For the bottle-size level demand, the average income is approximately $83,047. Moreover, in both levels, households have less than one person under 15 years old, on average.

The average price for the bottle-size level is $0.0218 per oz., which is less than the brand level average price of $0.0231 per oz. For the minimum price, it is smaller when CSDs are considered at the bottle-size level, while we observe the opposite behavior for the maximum price. This is because the bottle-size level includes more disaggregated brands, so more realistic prices. At the brand level, when the price is calculated, all sizes of drinks (i.e., 20 oz. single plastic bottle, 12-oz 12 cans, 12 oz. 24 cans, and 2-liter single plastic bottle) are taken into account, implying a move away from their actual prices.

Table 2. 4: Summary Statistics for the Brands in the Brand Level

Description	Mean	Min	Max	Std. Dev.
Price per oz.	0.0231	0.0161	0.0309	0.0025
Calories in 12-oz.	93.1	0	174	76.6861
Caffeine (mg) in 12-oz.	19.221	0	54.6	20.2261
Income	81,554.99	5,200	759,951	71,068.96
No. of kids	0.8794	0	5	1.1376

Table 2. 5: Summary Statistics for Brands in the Bottle-Size Level

Description	Mean	Min	Max	Std. Dev.
Price per oz.	0.0218	0.0123	0.0346	0.0035
Calories in 12-oz.	87.3803	0	170	74.7160
Caffeine (mg) in 12-oz.	26.4417	0	54	19.2167
Income	83,047.73	5,001	1,139,999	81,616.7
No. of kids	0.8295	0	7	1.0988

The last piece of the data is for instrumental variables discussed in the next chapter explicitly. Prices are potentially correlated with unobserved product characteristics, causing an endogeneity problem. The use of an instrumental variable method (IVs) is necessary to provide consistent parameter estimates. This study uses brand-specific dummy variables and input prices as instrumental variables for the price. Input prices include sugar prices, dextrose prices, the federal funds rate, producer price indices, employment cost index related to soft drink manufacturing, and gasoline prices from 2006 to 2011. Sugar and dextrose prices are obtained from the United States, Department of Agriculture (USDA), gasoline price is gathered from the US Energy Information Administration, producer price indices and employment cost index for soft drinks, and the federal funds rate retrieved from The Federal Reserve Bank of St. Louis.

CHAPTER 3

DIFFERENTIATED DEMAND ANALYSIS FOR CARBONATED SOFT DRINKS

3.1 Introduction

This chapter includes an analysis of differentiated demand for carbonated soft drinks (CSDs) at the brand and bottle-size levels. In section 3.2, the literature review of analyzing demand estimation for differentiated goods is discussed. Section 3.3 includes the theoretical framework of random coefficient logit demand, and section 3.4 describes its method and procedures. Section 3.5 presents the empirical results of the demand models estimation. Section 3.6 discusses the findings.

3.2 Analyzing Demand for Differentiated Products

Firms produce horizontally differentiated products in imperfectly competitive markets to gain market power and gain brand loyalty. These products represent heterogeneous goods, and they are imperfect substitutes to each other. Consumer demand for differentiated goods is based on subjective tastes and preferences. Salty snacks (e.g., Lays Original, Pringles Sour Cream and Onion, and Doritos Nacho Cheese), ready to eat cereals (e.g., Multigrain Cheerios, Kellogg's Frosted Flakes, and Cookie Crisp Chocolate Chip Cookie Flavored Cereal), and carbonated soft drinks (e.g., Sprite, Mountain Dew, Dr Pepper, Diet Coke, Pepsi Cola, and Sunkist) are a few examples of horizontally differentiated goods. In this section, we discuss issues for empirical demand estimation for differentiated goods.

The most commonly used demand systems for differentiated goods can be categorized into two broad approaches. These are the representative consumer model (non-address branch) and spatial or location models (address branch) (Eaton and Lipsey, 1989; Carlton and Perloff, 2005).

In the representative consumer model, we assume that typical consumers consider a set of brands as equally good substitutes for each other. In these kinds of models, consumer heterogeneity is generally ignored. Either a representative consumer is used for capturing the aggregated demand for differentiated products, or even if it can be assumed that consumer preferences differ, with symmetry assumption, all products are treated as equal in competition with all other products (Eaton and Lipsey, 1989). For example, Coca-Cola is an equally good substitute for Pepsi Cola, and also it is for Sprite. When there is a slight change in price in any product, it leads to a slight change in demand for other products.

In spatial or location models, consumers perceive some brands as closer substitutes than others. Unlike the representative consumer model, location models include consumer heterogeneity in tastes and preferences. Consumers view the products as having a location or characteristics space, and the closer products in terms of location or characteristics space are better substitutes than others (Carlton and Perloff, 2005). Therefore, different consumers have different preferred locations or characteristics (Eaton and Lipsey, 1989). One example is that two mid-size cars are closer substitutes than a full-size car. Another example is that one consumer may think Coca-Cola Classic is a better substitute for Pepsi Cola than Sprite. A product's demand may be independent of some other products' prices since they are not close substitutes (Carlton and Perloff, 2005).

Suppose we need to estimate the demand for J differentiated products. Under the traditional approach, the consumer demand model can be written in an aggregate demand system of the form

$$q = D(p, x, \varepsilon) \tag{3.1}$$

where q is a $J \times 1$ vector of quantities demanded, p is a $J \times 1$ vector of prices, x is a vector of demand shifters, ε is a $J \times 1$ vector of random shocks. Examples of the traditional demand estimation systems include the Linear Expenditure Model (Stone, 1954), the Rotterdam Model (Theil, 1965; and Barten, 1966), the Translog model (Christen, Jargenson, and Lau, 1975), and the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980). These models' main concern is to specify a functional form that is flexible and consistent with economic theory (Nevo, 2010).

One of the studies of the traditional demand approaches which deal with carbonated soft drinks (CSDs) is Cotterill et al. (1996). The authors analyze the carbonated soft drink industry's market power by including nine CSDs brands: Coke, Pepsi, Royal Crown Cola (RC Cola), Dr Pepper, Mountain Dew, Sprite, 7 Up, private label, and all other brands as one category. They found market power is mainly arising from product differentiation, does not due to collusion.

Dhar et al. (2005) also analyze four major brands from PepsiCo and Coca-Cola Company: Coke, Pepsi, Mountain Dew, and Sprite. They specify a brand-level flexible nonlinear AIDS model and examine the market structure of non-diet soft drinks. They found that Mountain Dew has unique positioning. This is because even if Sprite and Mountain Dew's tastes are similar, thanks to Mountain Dew's caffeine content, it is positioned also closer to Coke.

Another study by Langan and Cotterill (1994) estimates the brand-level demand elasticities using the linear approximation almost ideal demand system (LA-AIDS) of Deaton and Muelbauer (1980) and use them to measure the market power in that specific market. Their study includes nine regular carbonated soft drinks brands: Coca-Cola, Pepsi, RC Cola, Sprite, 7 Up, Dr Pepper, Mountain Dew, combined with all other brands and private labels. They found Coke's and Pepsi's prices are highly correlated, but they do not affirm collusive pricing.

Other categories of studies examine sugar-sweetened beverages (SSBs) demand and its taxing implications. For instance, Chacon et al. (2018) examine the demand for milk, soft drinks, packaged juice, and bottled water using the Guatemalan household survey and employ the AIDS model. Using the LA-AIDS, Guerrero-Lopez et al. (2017) and Colchero et al. (2015) examine the demand for soft drinks, other sugar-sweetened beverages, and high energy-dense foods in Chile and Mexico, respectively. These studies use the resulting own-price and cross-price elasticities to estimate the effect of tax on SSB consumption. All three studies found evidence that soft drink demand is elastic; hence, a price change (i.e., tax) would reduce soft drink consumption. Additionally, Colchero et al. (2015) found that individuals consume more high-quality products such as water and milk if soft drink prices increase.

Besides, Zhen et al. (2011) use a dynamic extension of the AIDS model and examine the demand for nine non-alcoholic SSB. The results indicate that as a consequence of habit formation, tax revenues rising from SSBs will be 15 to 20% smaller in the long-run than in the short-run. Additionally, they found low-income households have less elastic own-price elasticities than high-income households. However, high-income households evaluate beverages to be more substitutable than low-income households.

Additionally, Zhen et al. (2014) use the Exact Affine Stone Index (EASI) demand system, which carries the properties of the AIDS model and some additional advantages. The authors examine the demand for twenty-three packaged foods and beverages to gain more insight into the effect of taxes on these particular products' consumption. They found that an increase in SSB prices causes a decline in total calories taken from the 23 goods, but it induces more sodium and fat because of product substitution. The estimated drop in calories taken is higher for low-income households than high-income households. However, welfare loss is also higher for low-income households.

Studies using the traditional approach in demand estimations either examine the products at a highly aggregated level; hence, they ignore product differentiation that characterizes most industries or examine the limited number of products. Differentiated goods include a large number of products. Including only a limited number of products may create a problem because they ignore other brands.

Under the traditional approach, analyzing demand for differentiated products presents some issues and challenges. First of all, since a large number of products are analyzed, it creates the dimensionality problem. There is an exponential increase in parameters to be estimated. For example, if there are 60 brands to be analyzed, at least 3600 ($60^2 = 3600$) parameters need to be estimated. Even if imposing symmetry, homogeneity, and adding up restrictions, there would still be too many parameters to estimate.

Second, the traditional approach ignores consumer heterogeneity. In representative consumer models, only aggregate demand for a product can be gathered. In some cases, the aim is to explicitly model and estimate consumer behavior (Nevo, 2010). Consumer heterogeneity plays a vital role in estimating horizontally differentiated products because their demand depends on subjective taste and preferences. Omitting consumer heterogeneity leads to misinterpretations of market structure, product targeting, market segments, biased results, and wrong inferences concerning market strategies (Kamakura et al., 1996; Leszczyc and Bass, 1998; Chintagunta, 2001).

One way to solve the dimensionality problem is aggregation. However, in this case, the substitution between different products cannot be estimated because of the individuals' aggregation. In terms of the Industrial Organization (IO) approach, the substitution between products is the heart of any study. Nevo (2010) points out that nearly all demand studies include some level of aggregation. Depending on the study's focus, the researcher must decide on the aggregation level and whether the aggregation solves dimensionality.

Another way to solve the dimensionality problem is to impose symmetry. Spence (1976) and Dixit and Stiglitz (1976) proposed the constant elasticity of substitution (CES) demand model. The utility from consumption of the J products is given by

$$u(q_1, \ldots, q_J) = \left(\prod_{i=1}^{J} q_i^{\rho} \right)^{1/\rho} \tag{3.2}$$

where ρ is a constant parameter. The representative consumer's demand can be obtained from the above utility function, using the following expression

$$q_k = \frac{p_k^{-1/(1-\rho)}}{\sum_{i=1}^{J} p_i^{-1/(1-\rho)}} M \qquad i = 1, \ldots, J \tag{3.3}$$

where M is the income of the representative consumer. The dimensionality problem is solved by imposing symmetry between different products. This implies

$$\frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i} = \frac{\partial q_j}{\partial p_i} \frac{p_i}{q_j} \tag{3.4}$$

for all i, k, j. It implies that the cross-price elasticities of product i and the product k with respect to the price of j are restricted to be equal, with other conditions remaining the same and ignoring how close substitutes the products are (Nevo, 2010). Imposing symmetry necessitates strong assumptions, and the proposed models with symmetry restriction generally yield an appropriate fit for trade and macroeconomics data (Nevo, 2010). However, in IO, the study of interest is to know the substitution between products, and with symmetry assumption, it is highly restricted.

Another way to solve the dimensionality problem is to split the brands into smaller groups and use a flexible, functional form for demand estimation within each group. The consumer categorizes expenditure into broad groups, and later the expenditure of a group is allocated to sub-groups of products. Each stage of allocation depends on the total expenditure and prices of goods in a particular group (Nevo, 2010). Hausman, Leonard, and Zona (1994) and Hausman (1996) use multistage budgeting by dividing the demand into a three-stage system for differentiated products in the case of beer and ready-to-eat cereals (RTEC), respectively. The authors use a similar structure where the top stage includes total demand for a particular product. In the middle stage, the interest is on estimating the demand for specific segments. Finally, in the lower level, the demand for specific brands is captured for a given segment. One of the problems with this approach is the difficulty of dividing the categories into particular segments. For example, Cotterill (1994), Ma (1997), and Cotterill and Haller (1997) divide RTEC demand into four categories (all family, taste enhanced wholesome, simple health, and children cereal), while Hausman (1996) divides the breakfast cereal brands into three groups (family, kids, adults). The difficulty of segmentation arises because some products may be multilayered, and it may require a priori information about products.

Another approach of analyzing the demand for differentiated products is to view a brand or choice in characteristic space rather than product space (Lancaster, 1966; Gorman, 1980). As mentioned earlier, in location (or spatial) models, some products are better substitutes than others. Therefore, a bundle of product attributes is used for a substitutability measure instead of its number. Discrete choice models (hereafter DCMs), such as logit, probit, nested logit, multinomial logit, multinomial probit, and mixed logit, are some applications for location models, and they can be used to estimate the demand for differentiated goods in characteristics space. The dimensionality problem, arising from analyzing many products, is solved by projecting the products onto a characteristic space instead of squaring the number of products, reducing the number of estimated parameters.

DCMs are highly prevalent in estimating the demand for differentiated goods. The literature abounds of the applications of discrete choice models, notably the automobile industry (Berry et al., 1995; Verboven, 1996), the ready to eat cereal industry (Nevo, 2001; Chidmi and Lopez, 2007; Zhu et al., 2016), the yogurt market (Villas-Boas, 2007a; Bonnet and Bouamra-Mechemache, 2019), the coffee market (Guadagni and Little, 1983; 1998; Villas-Boas, 2007b; Draganska et al., 2010; Bonnet et al., 2013; Bonnet and Villas-Boas 2016), the fluid milk industry (Chidmi and Murova, 2011; Hirsch et al., 2018; Lopez and Lopez, 2009; Li et al., 2018; Bonanno and Lopez, 2009; Bonnet and Bouamra-Mechemache, 2015), the beer industry (Rojas and Peterson, 2008; Toro-Gonzales et al., 2014; Lopez and Matschke, 2012), the smartphone industry (Hiller et al., 2018), butter and margarine (Griffith et al., 2010), and the carbonated soft drink industry (Mariuzzo et al., 2003; 2010; Dube, 2004; Bonnet and Requillart, 2013; Lopez and Fantuzzi, 2012; Lopez et al., 2015; Liu and Lopez, 2016).

The discrete choice analysis was proposed by McFadden (1974; 1981; 1984). The starting point of the discrete choice models is the choice set, consisting of a set of alternatives and fulfilling three requirements. The choice set has finite alternatives, the alternatives are mutually exclusive, and they are exhaustive. It means that the decision-maker needs to choose only one alternative from the choice set, and the choice set includes all possible alternatives, which have to be finite. The decision maker's choice is related to the characteristics of the alternatives. One chooses the alternative that maximizes his utility.

The discrete choice analysis is based on utility theory through the random utility model. The seminal paper, "Law of Comparative Judgement," by Thurstone

(1927) in the psychophysiology field, asserts that an alternative j with correct stimulus level V_j is perceived with an error, that is $V_j + e_j$. Marschak (1960) applies this perspective to economics, and the perceived stimulus level is interpreted as a utility with random elements. Marschak (1960) calls this process a random utility maximization (RUM) model. The random utility concept inspires McFadden to produce a series of seminal papers (see, for example, 1974; 1981; 1984), giving birth to the discrete choice analysis.

One of the discrete choice models used for demand estimation is the multinomial logit model (MNL). MNL is a model where a decision-maker faces more than two alternatives in the choice set. Each alternative has its characteristics; hence dimensionality problem is solved by projecting product onto characteristics space. However, two issues arise from analyzing differentiated goods demand analysis using the multinomial logit model.

Firstly, because the own-price elasticities are proportional to the goods' price, the lower price leads to the lower elasticities in absolute value. Consequently, it causes lower price brands to have a higher markup, which is the case if only a brand has a lower marginal cost, which is not necessarily true for some brands (Nevo, 2000a). Besides, Nevo (2000a) emphasizes that the functional form of price designates patterns of own-price elasticity. For instance, if the price enters the indirect utility function in a logarithmic form, then own-price elasticities will be nearly constant. In MNL, being proportional to the prices makes own-price elasticities depend on the functional form, which is undesirable.

The second problem with the multinomial logit model is the cross-price elasticities pattern implied by assuming the independence of irrelevant alternatives or IIA. Under this assumption, if the price of an alternative changes, the market share of all other alternatives will change equally, regardless of whether the alternatives are close in characteristics space or not. For instance, if Diet Coke's price increases, under the IIA assumption, the market shares of Diet Pepsi (a closer substitute) and Sprite (not a close substitute) will be affected equally, holding all else the same.

The IIA problem arises because of the identically and independently distributed (*i.i.d*) structure of the random shocks (Nevo, 2000a). In the case of price increase of a product, which is some consumers' first preference, some of these consumers' decisions shift to the next alternative in the choice set. Because heterogeneity across consumers enters only through the i.i.d. random shocks, the likelihood of switching to other alternatives is the same (Nevo, 2000a). However, intuitively, their options are more likely to depend on the products' characteristics and similarity rather than the average consumer preference (Nevo, 2010).

To solve the independence of irrelevant alternatives, there is a need for the variation around the mean utility that diverges systematically across options (Nevo, 2010). There are two ways to achieve this. The first is to generate the correlation allowing ε_{ijt} to be correlated across brands. The second is to generate the correlation by allowing heterogeneity in taste and preferences (Nevo, 2010). While the first brings on the nested logit model, the second leads to the mixed logit model.

The generalized extreme value (GEV) model proposed by McFadden (1978) caries out relationships between options through correlation in $\varepsilon_{\mathrm{ijt}}$ and the nested logit model is one of the cases of the GEV model. In the nested logit model, we group the brands in the choice set into mutually exclusive sets (or nests), and $\varepsilon_{\mathrm{ijt}}$ consists of random *i.i.d*. shocks and a group-specific component. This grouping implies the correlation between brands within the same group is higher than across groups. It also implies a higher chance for the first and the second option being in the same group in the case of shifting options in a price increase.

The nested logit model has a closed-form solution like the multinomial logit model, which is one of the advantages of this model since it simplifies the estimation process alongside solving the IIA problem. On the other hand, one of its disadvantages is distinguishing segmentation or groups for brands in the choice set. To divide brands into segments, the researcher requires prior knowledge, similar to the case of multistage budgeting, as mentioned earlier. Sometimes a prior knowledge does not help because, in some industries, products are multilayered. Another disadvantage is that, within a nest or group, the IIA property still holds.

An alternative to logit-based models is the multinomial probit model, which does not carry undesired IIA properties. The probit model's errors follow a normal distribution with non-zeros in the off-diagonal covariance matrix to allow correlation across brands, with some restrictions to guarantee identification (Cameron and Trivedi, 2005). On the other hand, the multinomial probit model has no closed-form solution, which creates difficulty in the estimation process. Furthermore, the model requires that if the choice set includes J brands, we need to solve (J-1) integrals (Cameron and Trivedi, 2005). This estimation issue is another cost of having the dimensionality problem.

The mixed logit model, also known as the random coefficient (or random parameter) logit model proposed by Berry, Levinsohn, and Pakes (1995), has unrestrictive substitution patterns. The random shock ε_{ijt} still follow Type I extreme value distribution. However, having a free substitution pattern is achieved by considering consumer heterogeneity, which ensures the choice set alternatives correlate across brands. This is done by allowing consumers' taste over product attributes to vary across observed and unobserved consumer characteristics.

In the random coefficient model, own-price elasticities are not defined by only functional form as in the case of multinomial and nested logit; in other words, market shares are not solely specified by a single parameter. Every consumer has a different price sensitivity for different products. According to Nevo (2010), if a product has a lower price and captivates more price-sensitive consumers, its average price sensitivity will be higher, implying a lower equilibrium markup, unlike in MNL, lower price brands always have higher markups. Briefly, own-price elasticities depend on the functional form and the differences in the price sensitivity between consumers.

The random coefficient model does not only solve the problem with own-price elasticities but also cross-price elasticities. Cross-price elasticities do not suffer from the IIA property anymore. Additionally, there is no need to know a priori segmentation. Indeed, a dummy variable for segmentation as a product characteristic may capture the definition of the particular industry's segmentation (Nevo, 2000a).

Although providing unrestrictive substitution patterns, the random coefficient model comes at a computational cost since it does not have a closed-form solution and needs to be solved by numerical simulation. Additionally, consumer heterogeneity requires more information in terms of additional consumer demographic data and assumptions about the distribution of the unobserved consumer characteristics. However, observing individual purchase decisions is not compulsory. Using distributions from The Census Data and Current Population Survey, one can gather consumer demographics for different cities in the United States (Nevo, 2000a).

Even if there is a need for additional sources for consumer heterogeneity, it provides a more robust estimation thanks to including more information in the model. Especially for the differentiated-good industry, it is crucial to know consumer behavior's inner vision for companies and policymakers because of the need to make some decisions, such as launching new products, setting promotions, and imposing taxes. As mentioned earlier, the inclusion of consumer heterogeneity may prevent misinterpretations of market structure, product targeting, market segments, biased results, and inaccurate inferences concerning market strategies and welfare analysis (Kamakura et al., 1996; Leszczyc and Bass, 1998; Chintagunta, 2001).

Besides dimensionality and consumer heterogeneity, another problem regarding demand estimation is the endogeneity issue. Endogeneity may arise from omitted variables and measurement errors. Omitted variable bias may occur because of the unavailability of data since some variables are unquantifiable and unobservable. Demand shocks, unobserved consumer heterogeneity, and unobserved product characteristics such as shelf space and location, feature and display of the product, weekly brand-specific characteristics, advertisements, store coupons, unobserved promotional activities, and brand equity are some of the examples for the reasons of omitted variables (Nevo, 2000a; Chintagunta, 2001; Chintagunta et al., 2005). Further, unobserved product characteristics violate the assumption that all consumers face the same product characteristics, leading to average prices in the analysis that creates endogeneity because of measurement error (Nevo, 2000a).

Endogeneity occurs because prices may be correlated with the random shocks, especially the omitted unobserved product characteristics observed by the firms and the consumers, but not by the researcher. For instance, firms know what the unobserved product characteristics are. They set prices according to both observable and unobservable product characteristics, yielding a correlation between prices and unobserved characteristics and the error terms. The endogeneity of prices requires the instrumental variables (IV) method to avoid inconsistent estimates.

Ignoring endogeneity leads to inconsistent parameter estimates (Villas-Boas and Winer 1999). This is a severe problem because inconsistent results change the implications of market and welfare analysis. For example, Miller and Alberini (2016) estimate energy-electric demand and find that tackling issues, such as endogeneity and consumer heterogeneity, may change the elasticities by varying between 50 and 100%. Moreover, Zhen et al. (2014) show that the effect of calorie reduction on consumer choices is overestimated by ignoring price endogeneity.

Chintagunta (2001) states that ignoring endogeneity causes biased price elasticities more than ignoring consumer heterogeneity. Additionally, Chintagunta et al. (2005) find that unmeasured brand characteristics cause overstated variances in the distribution of heterogeneity in household preferences and the distribution of price sensitiveness and endogeneity. In conclusion, ignoring endogeneity is more likely to cause inconsistent estimates and consequently inaccurate inference regarding the study's implications.

Before Berry (1994), the IV method was not applicable in discrete choice models for differentiated good demand estimation. This is because of the presence of nonlinearity of price and unobserved product characteristics in the demand equation. To solve the nonlinearity problem, Berry (1994) suggests inverting market shares' function to make prices and unobserved product characteristics linear.

To sum up, the random coefficient logit model by Berry, Levinsohn, and Pakes (1995, hereafter BLP) is a promising model because of dealing with dimensionality problem, as well as including consumer heterogeneity, and allowing the use of IV procedure to solve endogeneity problem. It gives unrestricted substitution patterns, unlike other methods discussed earlier. The random coefficient logit model is used widely in differentiated products' demand estimation studies because it provides a more accurate estimation of the own- and cross-price elasticities, commonly used to evaluate market power, welfare effects, effects of launching new products, mergers, and vertical relationships between manufacturers and retailers.

Several studies use random coefficient demand models to evaluate industries' market power. For example, Nevo (2001) and Chidmi and Lopez (2007) estimate a differentiated random coefficient demand model and use the results to evaluate the market power in the ready-to-eat breakfast cereal industry. Other studies include Chidmi and Murova (2011), Hirsch et al. (2018), and Li et al. (2018) for fluid milk, Berry et al. (1995) for the automobile industry. Besides, Griffith et al. (2010) use the random coefficient logit model to evaluate the welfare effect of taxes in the margarine and butter markets. Berry et al. (1999) use the same modeling approach to assess the impacts of exporting restraints in the automobile industry. Other examples include the effects of the introduction of new goods by Petrin (2002) for the case of the minivan market; and the effects of mergers by Nevo (2000b) for the case of breakfast cereals and Bonnet and Schain (2017) for the case of dairy desserts. Some other studies use the random coefficient demand model to analyze the vertical relationships between manufacturers and retailers. Examples include the coffee industry (Villas-Boas 2007; Draganska et al., 2010; Bonnet and Villas-Boas, 2013; and Bonnet et al., 2013); the fluid milk and dairy industry (Bonnet et al., 2013; Bonnet and Bouamra-Mechrache, 2015); Villas-Boas, 2007); and the bottled water industry (Bonnet and Dubois, 2010).

In the carbonated soft drink (CSD) industry, Lopez and Fantuzzi (2012) estimate the demand for carbonated soft drinks using the random coefficient logit model on quarterly scanned data consisting of 26 brands in 20 US cities. The authors use the results to investigate issues related to obesity. Their findings indicate that taxes on CSDs could reduce their consumption, but soft drinks consumption has little impact on obesity.

Further, Lopez et al. (2015) analyze the spillover effects of TV advertisements on CSD companies and private labels using demand parameters resulting from estimating the random coefficient logit model. The authors use two data sets: advertising data and household (home scan) panel data. The advertising data set consists of weekly brand-level advertising expenditures and weekly brand level gross rating points of national and local TV networks in five designated market areas (DMA): New York, Atlanta, Washington DC, Seattle, and Detroit, between 2006 to 2008. The household panel includes 13,985 households' weekly CSD purchase records from grocery stores, drugstores, vending machines, and online shopping in these five DMA. The analysis consists of 22 brands, consisting of 18 national brands and two Walmart private labels.

The authors use the price, sugar, sodium, and caffeine contents as product characteristics and CSD TV and company ads in specifying the indirect utility. The authors find that advertising for a brand increases the demand for that particular brand as expected. Moreover, even if the advertising decreases the demand for other CSD brands, interestingly, it increases the demand for the private label of carbonated soft drinks. Another finding is that if there is a decrease in the CSD drinks' advertisements, it will decrease aggregate CSD sales, and consumer demand would move to other beverages.

Moreover, Liu and Lopez (2016) evaluate the impact of social media conversations on demand for CSD by adding conversations as a variable to the random coefficient logit model to contribute to public health policies and firms' decisions about promotion and product designs. The analysis includes monthly CSD sales for 12 DMA and 18 CSD brands in the US and social media conversations on Facebook, Twitter, and YouTube from April 2011 to October 2012. The authors use sugar, sodium, and caffeine contents of drinks as product characteristics besides prices and social media conversations on brands. The results show that there is a significant effect of social media conversations on the consumers' brand choices as well as on their nutritional perspective. The article supports that social media can be used as a strategic tool for brand promotions and public health policies.

Bonnet and Requillart (2011) and Bonnet and Requillart (2012) analyze vertical relationships between retailers and manufacturers in the soft drink industry by simulating the effect of an excise tax and excise and ad valorem taxes on sugar, respectively. The two studies use the same data, consisting of a French representative survey of 19000 households for three years (2003-2005) for non-alcoholic beverages, including carbonated soft drinks, iced tea, and fruit drinks. Both studies use the random coefficient logit model, and the findings indicate that imposing an excise tax on soft drinks' sugar content reduces their consumption effectively. Besides, the results show that firms strategically price their products in response to the sugar tax.

Additionally, Bonnet and Requillart (2013a; 2013b) study the impact of cost shocks on consumer prices through taxes on sugar; and the tax incidence with strategic firms' pricing. Both studies approach the French soft drink market as a vertically related market and opt for the random coefficient logit model. They exclude fruit drinks from the analyses and analyze CSD and iced tea drinks. By analyzing the pass-through rate of input cost changes or the pass-through rate of taxes, the first study shows that consumers are exposed to over-shifts of cost changes or excise tax by the industry. The second study finds that pass-through for an excise tax and ad valorem tax have different impacts on consumer prices. While excise tax is over-shifted to consumers, an ad valorem tax is under-shifted. Another finding is that imposing an excise tax is the most efficient tool for decreasing soft drink consumption according to its sugar content.

Moreover, Bonnet and Requillart (2016) analyze taxation's effect on the individual consumption of sugar-sweetened beverages (SSBs). SSBs include regular CSD, iced tea, other soft drinks, fruit juice, and nectar. The authors use the random coefficient logit model as the tool for demand analysis. Empirical results indicate that there is a high level of heterogeneity in the consumption of SSBs. Adults consume more SSBs than children. A 0.20 cents per 1 Euro tax on SSBs would reduce sugar consumption from SSBs by 0.8 kg on average for adults, and for 5% of adults, it may decrease the consumption by 2 kg annually. The rates are higher for obese adults.

Similarly, for the children, sugar consumption from SSBs may reduce by 0.25 kg on average, and for 5% of children, it decreases by 0.6 kg per year in France.

Some carbonated soft drinks' studies take into account the package sizes in their analysis. For instance, Dube (2004) analyzes the carbonated soft drinks market's demand at the universal product code (UPC) level. The author follows Hendel (1999), who assumes multiple discreteness and multiple-unit purchases for a particular product category. Dube estimates the demand for soft drinks at the package size level by considering different product package sizes as distinct choices. The author distinguishes between fixed attributes and time-varying attributes in the analysis. The fixed features consist of total calories, total carbs, sodium, caffeine, phosphoric acid, citric acid, caramel color, and clean color. The author also includes package size indicators as fixed explanatory variables, namely the 6 packs of 12 oz. cans, the 12 packs of 12 oz. cans, and the 6 packs of 16 oz. bottle indicators, while the 67.6 oz. bottle being the left-out category to avoid dummy trap. The time-varying attributes consist of shelf prices and marketing mix variables. The analysis examines brand loyalty (e.g., Coke vs. Pepsi) besides product size loyalty (e.g., 6 packs of Coke vs. 12 packs of Coke). Twenty-six products are examined, including Pepsi, Coca-Cola, and Dr Pepper Snapple Group products in varying sizes.

The study finds that brand loyalty is slightly more apparent than package size loyalty. For example, consumers are more loyal to Coca-Cola brands than a particular product size of Coca-Cola brands. It is highlighted that the effect of package size is considerably small, and it can be explained by consumers' decisions made according to their preferences rather than habits. Another finding of Dube's study is that larger households tend to prefer larger package sizes (e.g., 12 packs). Besides, advertising and displaying a product impact 67.6 oz. single bottle product than 6 packs of cans and bottles. Further, 6 packs of caffeine-free Diet Pepsi and 6 packs of Diet Pepsi are substitutes for each other. Additionally, the author emphasizes that the study does not find Sprite and 7UP to be substitute products, as one would expect, because the two brands do not have comparable sizes in the choice set.

Chan (2006) estimates a continuous hedonic choice model for CSD. The study allows multiple-product, multiple-unit purchasing behavior. The author states that packaging size has a significant impact on demand. The effect does not necessarily refer to quantity discount, such that 12 packs of a soft drink have a higher volume and higher price per ounce than 2-liter bottles. The study categorizes package size into two categories: large bottles (larger than 32 oz.) and packed units (more than one unit). The study points out different package sizes may have other purposes of consumption, such that when a bottle is opened, it loses its fizz quickly. Hence, packs are more suitable for individual use, and larger bottles may be practical for prominent families and some events.

The author uses package sizes as product characteristics and larger bottles and packed unit indicators to capture their effects on the demand. The data includes stock-keeping units (SKU) and provides information about retail prices and features and displays each week. It distinguishes different package sizes of a product. The analysis uses eight dummy variables as product characteristics: cola, flavored soda, mixer/club soda, diet (or regular), Coca-Cola, Pepsi, large bottle, and packed. Using these eight categories, all possible SKU combinations are aggregated, and it makes 23 categories of soft drinks. Therefore, the analysis is not at the SKU level because it is aggregated SKU level. This is different from UPC level demand (e.g., Dube (2004)) estimation because each UPC is unique for each type of product, and it is highly disaggregated. Still, every category for aggregated SKU is not unique and includes different categories itself. For example, one of the 23 products is "Large bottle Regular Flavors," which consists of 2 liters Sprite and 2 liters 7UP (Coca-Cola Company produces Sprite while Dr Pepper-Snapple Group produces 7UP in the US).

The study finds some of the soft drinks are substitutes, and some are complements. Complementarity exists when their flavor and package sizes are different. For example, a 2-liter bottle of Sprite is a complement for 12 packs of Regular Coke (Large Bottle Regular Flavor and Pack Regular Coke are complements). The author emphasizes that consumers' variety-seeking behavior in flavor and package size is a plausible complementarity explanation.

Bronnmann and Hoffmann (2018) estimate a hedonic price model to analyze the effect of different product characteristics on price, including traditional brands and private labels in the German soft drink market. Product attributes are brand dummy variables, such as Coca-Cola and private label Aldi, retail format (discounter, hypermarket, supermarket, and others), flavor (cola, orange, mix, lemon, and others), bottle-size in ml (<500, 500-1000, 1001-1500, 1501-2000, and >2000), sugar content (regular and diet), and promotional and regular price. The study finds that drinks with 1001-1500 ml are the most preferred bottle-size. The authors attribute the importance of bottle-size to the higher prices of smaller size drinks than large-sized ones.

Furthermore, Hoffmann and Bronnmann (2019) analyze the demand for CSD in the German market using the random coefficient logit model. The authors use the price, brand dummy variables, the bottle-size category (five categories: <500, 500-1000, 1001-1500, 1501-2000, and >2000), and brand loyalty as product characteristics. The authors use income, household size, age, and marital status of the household head for consumers' characteristics. The study uses household scanner data, consisting of 720 households and 22 carbonated soft drinks brands, for 24 months period, between 2009 and 2010. The study estimates brand loyalty by measuring if a consumer continues to buy a particular product during the study time using household scan panel data. The study finds that 63 % of the consumers have brand loyalty and prefer small bottles over large bottles. The study concludes, "Bottle-size matters."

Other studies include different package sizes of some other products. Montgomery (1997) estimates fruit juices demand at the store level to develop micro marketing pricing strategies. The analysis includes different brands with varying sizes, such as Tropicana Premium 64 oz., Minute Maid 96 oz., and Dominicks 128 oz. Silva-Risso et al. (1999) evaluate a decision support system to develop a promotional decision routine and the marketing efficiency to measure the manufacturer's sales promotion calendar. They apply the analysis to the tomato sauces market. The probability of an individual visiting a store in the market area is calculated and conditional on the individual's visit. She chooses whether to buy the target category. Finally, the individual decides the brand size.

Bronnmann and Asche (2016) analyze German frozen seafood by using a hedonic price function. Package size is one of the product attributes in the analysis, and the study finds small package sizes are more preferred than large packages in the seafood market. Kim (2008) also includes package size and material in the demand analysis. The US margarine industry has been examined by estimating the industry's random coefficient logit and market power. The study finds that they are essential elements for the margarine demand in terms of package size and material.

Chintagunta (1992) uses the multinomial probit model to analyze the demand for ketchup with varying sizes. The study considers Heinz 28 oz., Heinz 32 oz., Heinz 40 oz., Heinz 64 oz., Hunts 32 oz., and Del Monte 32 oz. It is noted that Heinz 28 oz. and 32oz. compete with each other, and also Heinz 40 oz., according to results from the correlation matrix. Elasticities show changes in Heinz 28 oz.'s prices, Heinz 32 oz., and Del Monte 32 oz. carry significant impacts on the purchase probabilities of the remaining three brands.

Fader and Hardie (1996) assert that most choice models' unit analysis is brand level. Still, consumers, manufacturers, and retailers make their choices according to SKU level and its attributes, not only the brand name. SKU level is not directly observable by consumers, but they observe SKU attributes such as brand name, package size, type, and form. For example, toothpaste's SKU attributes can be brand, package size and type, product form, formula, and flavor, and they tell brand and package size are common for all product categories. Their analysis includes 56 unique SKUs for fabric softeners, and they emphasize instead of using 56 SKUs, they can use 22 attribute levels. They are ten brand names (nine national brands and one private label), four size attributes (small, medium, large, extra-large), four forms of the products (sheets, concentrated, refill, liquid), and four formulas (regular, unscented, light, stain guard). They conclude that including these attributes in the analysis may be useful for managerial decisions (i.e., deciding to drop a particular formula or a particular package size).

Guadagni and Little (1983) discuss that consumers chose alternatives, and the alternatives' aggregation level is not precise, and which one is relevant for the analysis is not certain. They ask that various flavors, colors, and sizes should be accepted as different products or all aggregated in brand names. Even if there is no obvious answer to this question, they treat different brand sizes as separate products. Their preliminary analysis shows no hierarchical order between brand and size (i.e., choosing brand first and then product size). They claim that from retailer's and consumer's perspectives, different sizes of a brand are distinct. Consumers have size loyalty, and retailers' promotions decisions are according to brands' sizes. They estimate the demand for coffee in popular sizes (one pound and three-pound), and they find consumers exhibit brand loyalty and size loyalty.

The reason for nonlinear pricing can be either quantity discounts (second-degree price discrimination) or quantity surcharges. Quantity surcharges are the opposite of quantity discounts. When larger packages are expensive than smaller packages, it is called a quantity surcharge. Shreay et al. (2016) assert that in some cases, the reason for quantity surcharges may arise from different package sizes of a particular product are imperfect substitutes, so product differentiation exists by package size.

Shreay et al. (2016) estimate the random coefficient logit model to obtain demand elasticities of canned tuna, and it has three product attributes: canning medium (oil or water), meat type (albacore or chunk light), and size (6.12 oz. or 12.5 oz.). They discuss two 6 oz. cans of tuna may not be evaluated equally with one 12 oz. can of tuna. This is because consumers may view them as imperfect substitutes since different product sizes may have different usage and storage options. Therefore, they claim producers or retailers may use package size as a tool besides prices to maximize their profit. Consumers should not expect consistent per-unit prices when package size changes. However, they conclude, these results depend on some particular products. Other goods may not be perceived as differentiated, and they exhibit the same perception in either large or small sizes.

Granger and Billson (1972) examine characteristics of consumers' effects on package size and package price decision. They discuss that it can be categorized as three steps for purchasing a product: whether buy or not to buy a product, which brands to buy, which package size to buy, and these decisions vary with consumer characteristics. They find that when consumers have information of a product unit price, and if there is a quantity discount, they most likely choose larger product sizes. If the unit price is not provided, consumers are more likely not to distinguish the product's relative value. Similarly, Russo (1977) states that consumers can adjust their decisions according to unit price when the unit price is provided.

On the other hand, Wansink (1996) and Nason and Bitta (1983) find that even if the unit price is provided, consumers do not necessarily adjust their purchasing decision due to unit price. Some consumers believe larger sizes have lower unit prices even if it is not the case (i.e., quantity surcharge). This misconception may arise because of having limited time and information costs (Binkley and Bejnarowicz (2003)).

Kumar and Divakar (1999) analyze the demand for potato chips and peanut butter using the Rotterdam model. The study finds a difference between marketing mix elasticities at the brand-size level and the brand level. They suggest that demand for potato chips and peanut butter has a better structure to model idiosyncrasy if the approach is brand-sized rather than aggregate brand level. Consumers have different price sensitivity for different package sizes of the same brand. Hence, retailers and manufacturers may offer promotional strategies at the brand-size level to achieve profit maximization.

Cakir and Balagtas (2014) estimate a random coefficient model for bulk ice cream to evaluate consumers' reactions to downsizing packages. Package downsizing implies that a product's package size decreases, and the price remains the same as the previous size. Compared to price sensitiveness, the study finds that consumers are less sensitive to package size changes by finding the elasticity of package sizes being one-fourth of the price elasticity. Also, estimations results show that working households are less responsive to changing package sizes. Their finding is consistent with Binkley and Bejnarowicz's (2003) findings, which propose that time-constraint consumers are less careful to unit prices; hence, similarly, the consumers can have the inability to realize package downsizing because of having limited time.

Another finding of Cakir and Balagtas (2014) is that higher-income households have less responsiveness to package downsizing while larger households are more sensitive to downsizing. They emphasize that these findings can be useful for decision-makers by targeting specific demographics for package downsizing decisions. Additionally, the study's findings imply that package downsizing can be another tool for manufacturers' profitability rather than price competition. When there is a cost increase, they assert that it is possible to maintain margins by downsizing.

On the other hand, Yonezawa and Richards (2016) examine manufacturer's package size and unit price decisions on Consumer Package goods (CPGs) for consumer preferences, production and distribution cost, and strategic responses between manufacturers. They emphasize the package size and price analysis because consumers can observe both price and size. They propose a structural model that consists of interactions between consumers, retailers, and manufacturers. In the model, consumers decide between differentiated products' discrete choices, manufacturers simultaneously set prices and package sizes, and retailers set retail prices under pass-through of manufacturers' package size decision, consumer demand, and manufacturer and retailer costs. To estimate the model, they use supermarket scanner data for RTEC in two US metropolitan areas.

They find that package size is an essential component of consumer choices for RTEC. Consumers mostly prefer small packages because they evaluate risk and convenience, although heterogeneity in package size decisions exists. They claim these results can explain manufacturers' decision to provide various package sizes instead of just one size. They assert that package size decision does not solely depend on consumer preferences but also manufacturers' strategic reactions arising from competition. Even if manufacturers take advantage of the disconnection between package price and unit price on consumers, this study shows that manufacturers can be better off in terms of profitability when increasing prices rather than changing package size. Although package downsizing (increasing unit price) relaxes the effect of price increase, other manufacturers react to decrease wholesale prices due to downsizing.

Yonezawa and Richards (2016) also provide effects of package size changes on retailers' costs, profits, and the decision of pricing and product assortments. They assert that retailers may charge higher prices for a downsized product since the demand results show consumers prefer smaller packages to larger ones. Furthermore, even if package downsizing comes with higher unit prices and causes an increase in retail costs, increasing-price competition between manufacturers by the result of package downsizing gives the opportunity of obtaining lower costs for retailers. Moreover, they argue that package size implications are useful for retailers' product assortment decisions because there are a limited shelf space and proliferation of CPGs industry products (Mantrala et al., 2009; Kim et al., 2002), consumers seek higher variety (Lancaster, 1990; Kahn and Lehmann, 1991). On the other hand, it is crucial because when too many products are available, consumers may have difficulty making decisions since extra effort may be required when choosing between large numbers of alternatives (Huffmann and Kahn, 1998; Chernev, 2003).

Consequently, in terms of carbonated soft drinks, product differentiation can be perceived at different levels. At the manufacturers' level, carbonated soft drinks can be differentiated by the content of the main components: cola, caffeine, sugar, color and flavor, calorie content, and other product characteristics. The CSD products are also differentiated in terms of packaging: type of packaging (glass, plastic, can), size of the unit, and the number of units in a package. The disaggregation level choice will lead to different estimates of price elasticities, and therefore different conclusions regarding the pricing conduct and welfare implications (i.e., tax).

This study includes bottle-sizes in the analysis because it is the relevant choice point. The availability of supermarket scanner data from IRI and AC Nielsen estimates the demand for differentiated goods possible at very disaggregated levels (e.g., UPC level demand). We opt for the random coefficient logit model that provides unrestrictive substitution patterns and solves the dimensionality by projecting the products onto a product characteristics space, reducing the number of parameters to be estimated. Consumer heterogeneity is incorporated by allowing taste parameters to vary across consumers. However, to our knowledge, there is a lack of demand analysis at the bottle/package size level in CSD competition, which is the relevant decision making for consumers. Two different aggregation level demands are analyzed. Both brand level and bottle-size level carbonated soft drinks demand are estimated, and their implications are compared. The analysis uses Information Resources Inc. (IRI) data from 2006 to 2011 in Dallas, Texas.

3.3 Theoretical Framework

In the BLP's random coefficient model (summarized here for exposition purposes), a consumer chooses a brand from competing products that maximizes her utility. The consumer's decision on a selected brand is due to the observed and unobserved brand and consumer characteristics.

The indirect utility of consumer i, $i = 1, \dots, n$, from purchasing one unit of brand j, $j = 1, \dots, J$, in market t, $t = 1, \dots, T$, is given by

$$U_{ijt} = \alpha_i p_{jt} + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt} \tag{3.5}$$

where p_{jt} is the price of product j at market t, x_{jt} is a K-dimensional vector of observed product characteristics, ξ_{jt} is the unobserved product characteristics for the econometrician but observed by the firms and the consumers, α_i and β_i are the parameters to be estimated, and ε_{ijt} is a mean zero stochastic term with distribution $P_\varepsilon^*(\varepsilon)$.

α_i and β_i are assumed to be random coefficients and can be decomposed into deterministic and random components. That is,

$$\begin{pmatrix}\alpha_i\\ \beta_i\end{pmatrix} = \begin{pmatrix}\alpha\\ \beta\end{pmatrix} + \Gamma D_i + \Sigma v_i$$

$$\begin{pmatrix}\alpha_i\\ \beta_i\end{pmatrix} = \begin{pmatrix}\alpha\\ \beta\end{pmatrix} + \begin{pmatrix}\Gamma_\alpha\\ \Gamma_\beta\end{pmatrix} D_i + \begin{pmatrix}\Sigma_\alpha\\ \Sigma_\beta\end{pmatrix} v_i \tag{3.6}$$

where D_i is a $dx1$ vector of observed consumer characteristics (demographics) with either parametric or nonparametric distribution $P_D^*(D)$, Γ is a $(K+1)\ x\ d$ matrix of coefficients that measure how the taste characteristics vary with demographics, v_i is a vector of unobserved consumer attributes with parametric distribution $P_v^*(v)$, and Σ is a $(K+1)\ x\ (K+1)$ matrix of parameters for the unobserved characteristics.

Substituting equation (3.6) into (3.5) yields:

$$U_{ijt} = (\alpha + \Gamma_\alpha D_i + \Sigma_\alpha v_i)\, p_{jt} + x_{jt}(\beta + \Gamma_\beta D_i + \Sigma_\beta v_i) + \xi_{jt} + \varepsilon_{ijt}$$

$$= \alpha p_{jt} + \Gamma_\alpha D_i p_{jt} + \Sigma_\alpha v_i p_{jt} + \beta x_{jt} + \Gamma_\beta D_i x_{jt} + \Sigma_\beta v_i x_{jt} + \xi_{jt} + \varepsilon_{ijt}$$

Rearranging:

$$U_{ijt} = \alpha p_{jt} + \beta x_{jt} + \xi_{jt} + \Gamma_\alpha D_i p_{jt} + \Sigma_\alpha v_i p_{jt} + \Gamma_\beta D_i x_{jt} + \Sigma_\beta v_i x_{jt} + \varepsilon_{ijt} \tag{3.7}$$

Equation (3.7) consist of two parts:

1) $\delta_{jt} = \alpha p_{jt} + \beta x_{jt} + \xi_{jt}$

2) $\mu_{ijt} = \Gamma_\alpha D_i p_{jt} + \Sigma_\alpha v_i p_{jt} + \Gamma_\beta D_i x_{jt} + \Sigma_\beta v_i x_{jt} + \varepsilon_{ijt}$

where δ_{jt} is the mean utility from brand j, that is, common to all consumers; and μ_{ijt} is a consumer-specific deviation from that mean, which captures the effects of the unobserved characteristics.

Following Nevo (2000a), the indirect utility can be rewritten as

$$U_{ijt} = \delta_{jt}\left(p_{jt}, x_{jt}, \xi_{jt};\ \theta_1\right) + \mu_{ijt}\left(p_{jt}, x_{jt}, D_i, v_i;\ \theta_2\right) + \varepsilon_{ijt} \tag{3.8}$$

and θ_1 and θ_2 are the parameters to be estimated where $\theta_1 = (\alpha, \beta)$ and $\theta_2 = (\Gamma, \Sigma)$.

To complete the demand system, an outside good has to be included in the model. With the outside good, there is a possibility that consumer i does not choose one of the j brands $(j = 1, \dots, J)$ in the choice set. The consumer may select the outside good, which is denoted by $j = 0$. For example, if there are 25 carbonated soft drinks brands, the outside good includes all the remaining brands in the sample. The utility for the consumer who decides to purchase an outside good is normalized to zero.

Define the set of consumer choices by

$$S_{jt}\left(p_{jt}, x_{jt},\ \xi_{jt}; \theta\right) = \{\left(D_i, v_i, \varepsilon_{ijt}\ \right) : U_{ijt} \geq U_{ikt}\ \forall k =\ 0,1, \dots, J\ \} \tag{3.9}$$

where θ is a vector of all parameters in the model.

The consumer i buys one unit of a product j in the market t that gives the highest utility within the choices set. Aggregating the consumers' choice, the market share of the product j in the market t corresponds to the probability of the jth product being chosen. That is,

$$s_{jt}\left(p_{jt},\ x_{jt}\ , \delta_{jt}; \theta\right) = \iiint I\left[\left(D_i, v_i, \varepsilon_{ijt}\right) : U_{ijt}\ \geq U_{ikt} \forall k = 0,1, \dots, J\right] dP_{\varepsilon}^{*}(\varepsilon) dP_{v}^{*}(v) d\hat{P}_{D}^{*}(D) \tag{3.10}$$

Due to the different assumptions for distributions of D, v, and ε, the integrals in equation (3.10) will either have a closed-form solution or not. Hence, the integral is computed either analytically or numerically. The integral has a closed-form solution, and it can analytically be solved when we assume that consumer heterogeneity enters the model through only the error term ε_{ijt}. On the other hand, when the consumer heterogeneity forms a part of the deviation from the mean utility, μ_{ijt}, the integrals do not have a closed-form solution, and they should be solved numerically (BLP, 1995; Nevo, 2000a).

3.4 Methods and Procedures

The estimation process is done by computing the integral in equation (3.10). Depending on consumer characteristics' assumptions, the integrals' solution differs; it will either have a closed-form solution or not, leading to either the multinomial logit model or the random coefficient logit model. In this study, we opt for the random coefficient logit model by BLP (1995) for demand estimation. This choice imposes itself because the model has advantages over the traditional methods (i.e., AIDS, Rotterdam, and Linear Expenditure model), the multinomial logit model, and the nested logit model. The random coefficient model does not suffer from dimensionality problems arising from the number of brands considered; it solves the endogeneity problem using an instrumental variable approach (generalized method of moments). Besides, it considers consumer heterogeneity and solves the independence from irrelevant alternatives (IIA) by yielding richer substitution patterns.

The multinomial logit model is discussed and demonstrated for comparison purposes because it is involved in the random coefficient logit model as a starting point for the mean valuation utility. The multinomial logit model raises when consumer heterogeneity enters the model only through the error term ε_{ijt}. Therefore, the integral in equation (3.10) has a closed-form solution in the multinomial logit model. It can be solved analytically under the assumption that the error terms follow the type I extreme value distribution. In the random coefficient model, consumer heterogeneity is modeled as a deviation from the mean utility, μ_{ijt} Furthermore, the integral does not have a closed-form solution, and it is solved by numerical simulation.

3.4.1 The Multinomial Logit

In the multinomial logit (MNL) case, it is assumed that Γ=0 and Σ=0, implying $\alpha_i = \alpha$ and $\beta_i = \beta$. It means that consumer heterogeneity enters the model only through the error term ε_{ijt}. Therefore, with the MNL, the indirect utility function becomes

$$U_{ijt} = \delta_{jt}\left(p_{jt}, x_{jt}, \xi_{jt};\ \theta_1\right) + \varepsilon_{ijt} \tag{3.11}$$

where ε_{ijt} is $i.i.d$ with type I extreme value density and $\theta_1 = (\alpha, \beta)$

The integral in equation (3.10) has a closed-form solution given by:

$$s_{jt} = \frac{\exp\,(\delta_{jt})}{\exp(\delta_{0t}) + \sum_{k=1}^{J} \exp\,(\delta_{kt})} = \frac{exp\,(\delta_j)}{1 + \sum_{k=1}^{J} exp\,(\delta_k)}$$
$$= \frac{\exp\,(\alpha p_{jt} + \beta x_{jt} + \xi_{jt})}{1 + \sum_{k=1}^{J} \exp\,(\alpha p_{kt} + \beta x_{kt} + \xi_{jt})} \tag{3.12}$$

where s_{jt} is the market share of the product j in the market t.

As stated above, the market share of the product j in the market t corresponds to the probability that the jth product is chosen. The market share in equation (3.12) is also known as the predicted market share function, and the aim is to estimate the model parameters α and β. The data contains observed shares, that is $\hat{s}_{jt}$, $j = 1, \dots, J$ and parameters α and β need to be estimated by matching the observed shares to the predicted shares so that the distance between $\hat{s}_{jt}$ and s_{jt} is the minimum possible. That is,

$$\min_{\alpha,\beta} \hat{s}_{jt} - s_{jt}\left(\delta_{1t}, \dots, \delta_{jt}\right), \text{ for } j = 1,2, \dots, J \tag{3.13}$$

where $\hat{s}_{jt}$ is the observed market share and s_{jt} is the predicted market share. Note that the share of outside good is defined by $\hat{s}_{0t} = 1 - \sum_{j=1}^{J} \hat{s}_{jt}$.

Recall equation (3.11) that is the indirect utility function in the MNL case given by

$$\begin{aligned} U_{ijt} &= \delta_{jt}\left(p_{jt}, x_{jt}, \xi_{jt}; \theta_1\right) + \varepsilon_{ijt} \\ &= \alpha p_{jt} + \beta x_{jt} + \xi_{jt} + \varepsilon_{ijt} \end{aligned}$$

where p_{jt} is the price of product j at market t, x_{jt} is a K-dimensional vector of observed product characteristics, ξ_{jt} is the unobserved product characteristics for the econometrician but observed by the firms and consumers, α and β are parameters to be estimated, and ε_{ijt} is a mean zero stochastic term with distribution $P_{\varepsilon}^{*}(\varepsilon)$.

ε_{ijt} is potentially correlated with the price and product characteristics. However, for the study period, we assume the product characteristics, such as sugar content, for example, are kept constant[2]. To tackle the endogeneity problem, we use the instrumental variable (IV) method. Following Berry (1994), we invert the market share equation and solve the main valuation utility.

[2] Usually, when manufacturers alter the product characteristics, a new brand is developed. We rule out this case in our data.

When the observes shares $\hat{s}_{jt}$ is equated to the predicted shares s_{jt}, which is functions of $\delta_{1t}, \ldots, \delta_{jt}$, there will be $J + 1$ nonlinear equations with $J + 1$ unknowns that are $\delta_{0t}, \delta_{1t}, \ldots, \delta_{jt}$. That is,

$$\hat{s}_{0t} = s_{0t}(\delta_{0t}, \ldots, \delta_{jt})$$
$$\hat{s}_{1t} = s_{1t}(\delta_{0t}, \ldots, \delta_{jt})$$
$$\vdots$$
$$\hat{s}_{jt} = s_{jt}(\delta_{0t}, \ldots, \delta_{jt})$$

(3.14)

Since $\sum_{j=0}^{J} \hat{s}_{jt}$ corresponds to the sum of all probabilities, it is equal to one, that is $\sum_{j=0}^{J} \hat{s}_{jt} = 1$, with $j = 0$ for the outside good. This requirement implies the equations are linearly dependent and creates a need to normalize the mean utility from outside good; that is $\delta_{0t} = 0$. Hence, there will remain J equations from $\hat{s}_{1t}$ to $\hat{s}_{jt}$. Now, this system of equations can be inverted to solve $\delta_{1t}, \ldots, \delta_{jt}$ as functions of the observed market shares $\hat{s}_{0t}, \ldots, \hat{s}_{jt}$, such that

$$\hat{\delta}_{jt} = \delta_{jt}(\hat{s}_{0t}, \ldots, \hat{s}_{jt})$$

(3.15)

Recall the equation (3.12) that is the predicted shares in the MNL case

$$s_{jt} = \frac{exp\,(\delta_j)}{1 + \sum_{k=1}^{J} exp\,(\delta_k)}$$

With equating the observed shares to the predicted shares, the system of equations becomes

$$\hat{s}_{0t} = \frac{1}{1 + \sum_{k=1}^{J} exp\,(\delta_{kt})}$$
$$\hat{s}_{1t} = \frac{exp\,(\delta_{1t})}{1 + \sum_{k=1}^{J} exp\,(\delta_{kt})}$$
$$\vdots$$
$$\hat{s}_{jt} = \frac{exp\,(\delta_{jt})}{1 + \sum_{k=1}^{J} exp\,(\delta_{kt})}$$

(3.16)

Taking the natural log of both sides, we get a system of linear equations given by

$$ln\, \hat{s}_{0t} = 0 - ln\,(1 + \sum_{k=1}^{J} exp(\delta_{kt}))$$

$$ln\, \hat{s}_{1t} = \delta_{1t} - ln\,(1 + \sum_{k=1}^{J} exp(\delta_{kt}))$$

$$\vdots$$

$$ln\, \hat{s}_{Jt} = \delta_{J} - ln\,(1 + \sum_{k=1}^{J} exp(\delta_{kt}))$$

(3.17)

Rearranging these equations yields:

$$ln\, \hat{s}_{1t} - ln\, \hat{s}_{0t} = \delta_{1t}$$

$$ln\, \hat{s}_{2t} - ln\, \hat{s}_{0t} = \delta_{2t}$$

$$\vdots$$

$$ln\, \hat{s}_{jt} - ln\, \hat{s}_{0t} = \delta_{jt}$$

(3.18)

Therefore, the inversion gives $\delta_{jt}\,'s$ as functions of observed shares $\hat{s}_{0t}$,…, $\hat{s}_{jt}$. Using the indirect utility function, $\delta_{jt} = \alpha p_{jt} + \beta x_{jt} + \xi_{jt}$, it can be finally written as

$$ln\, \hat{s}_{jt} - ln\, \hat{s}_{0t} = \alpha p_{jt} + \beta x_{jt} + \xi_{jt}$$

(3.19)

Now, the system consists of linear equations, and it is plausible to apply the linear two-stage method to estimate alpha and beta consistently.

The price elasticities, implied by the multinomial logit model, are given by

$$\eta_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} \alpha p_{jt}(1 - s_{jt}) & if\ j = k \\ -\alpha p_{kt} s_{kt} & if\ j \neq k \end{cases}$$

(3.20)

The cross-price elasticities in equation (3.20) do not depend on the other products. For example, the cross-price elasticity of good 2 with respect to good 1, the cross-price elasticity of good 3 with respect to good 1, and the cross-price elasticity of any good j with respect to good 1 are identical. That is,

$$\begin{gathered} \eta_{21} = -\alpha p_{1t} s_{1t} \\ \eta_{31} = -\alpha p_{1t} s_{1t} \\ \vdots \\ \eta_{j1} = -\alpha p_{1t} s_{1t} \end{gathered} \tag{3.21}$$

This is the independence from irrelevant alternatives (IIA) problem, previously mentioned. Because of the IIA problem, the cross-price elasticities are not realistic. Another problem with the multinomial logit elasticities is that own-price elasticities are proportional to own prices. It implies lower prices correspond to lower elasticities in absolute value. Inaccurate own-price and cross-price elasticities change the implications of market and welfare analysis. The random coefficient logit model deals with these problems.

3.4.2 The Random Coefficient Logit Model

Recall the indirect utility function from equation (3.8) which is given by

$$U_{ijt} = \delta_{jt}\left(p_{jt}, x_{jt}, \xi_{jt};\ \theta_1\right) + \mu_{ijt}\left(p_{jt}, x_{jt}, D_i, v_i;\ \theta_2\right) + \varepsilon_{ijt}$$

where δ_{jt} is the mean utility from brand j, that is, common to all consumers; and μ_{ijt} is a consumer-specific deviation from that mean, which captures the effects of the unobserved characteristics.

In the multinomial logit (MNL) case, $\Gamma = 0$ and $\Sigma = 0$, and it means that consumer heterogeneity enters the model only through the error term ε_{ijt}. However, in the random coefficient logit model, consumer characteristics such as income, age, and the number of children are taken into account. Consumer heterogeneity enters the model through μ_{ijt}. In this case, the price elasticity of demand is given by

$$\eta_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} \frac{\mathrm{p_j}}{s_j}\iint \alpha_i s_{ij}\left(1 - s_{ij}\right) dP_v^*(v)\, d\hat{P}_D^*(\mathrm{D}) & if\ j = k \\ \frac{\mathrm{p_k}}{s_j}\iint \alpha_i s_{ij}\, s_{ik}\, dP_v^*(v)\, d\hat{P}_D^*(\mathrm{D}) & if\ j \neq k \end{cases}$$

(3.22)

where

$$s_{ij} = \frac{\exp\left(\delta_j + \mu_{ij}\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_k + \mu_{ik}\right)}$$

(3.23)

The cross-price elasticities of the random coefficient model do not suffer from the IIA problem anymore. Also, unlike multinomial logit, own-price elasticities are not defined solely by a single parameter, and every consumer has their own-price sensitivity.

In the random coefficient logit model, the predicted market share is a function of the mean valuation utility and the consumer-specific deviation from that mean. For the J goods in the choice set, the algorithm proceeds by finding the parameters theta1 and theta two that equate the observed market shares to the predicted ones. The difference is the inversion discussed above involves nonlinear equations. To tackle the nonlinearity issue, BLP (1995) suggest constructing a mapping procedure for the inversion. Their algorithm uses the generalized method of moments (GMM) to estimate the unknown parameters that minimize the distance between the predicted market shares, provided by the integrals' solution in equation (6), and the observed market shares. That is,

$$Min_{\theta}\ ||\mathrm{s}\left(p_j, x_j, \delta_j; \theta\right) - \hat{s}||$$

(3.24)

where $s(\,.\,)$ is the predicted market share and $\hat{s}$ is the observed market shares.

We follow the inversion suggested by Berry (1994) to "extract" the mean utility valuation δ that equates the predicted market shares to the observed market shares. That is,

$$\hat{s}_{jt} = s_{jt}(\delta_{jt}\,;\ \theta_2)$$

(3.25)

where θ_2 represents the parameters that enter the indirect utility function in a nonlinear fashion.

The obtained mean utility δ is then regressed on the price and product characteristics, using the sample moments defined by the interaction of the instrumental variables and the error term given by

$$\delta_{jt}\left(s_{jt}\,;\,\theta_2\right) = \alpha p_{jt} + \beta x_{jt} + \zeta_{jt} \tag{3.26}$$

The error term is interacted with instruments, denoted Z, to form the objective function to minimize using the GMM estimation. The estimation is based on the assumption that the instruments are not correlated with errors, that is $E[\,Z\,\zeta\,] = 0$. The GMM objective function to be minimized is given by

$$min_{\theta} Q(\theta) \;=\; \zeta(\theta)' Z W^{-1} Z' \,\zeta(\theta) \tag{3.27}$$

where W is a consistent estimate of $\mathrm{E}[\,\mathrm{Z}\,'\zeta\,\zeta\,'\mathrm{Z}]$, and θ is the vector of parameters to be estimated.

Nevo (2000a) suggests four steps to compute the parameter estimates. It is emphasized that preparing the data is an essential step for the estimation. The data includes two parts. The first one is the market-level data, and the second one is the draws from the distribution of D and v that enter the random part of the indirect utility function. There will be pairs of (D_i, v_i) for $i = 1, \ldots, ns$; where ns is the number of draws from the distribution of D and v given by the distributions $\hat{P}_D^*(\mathrm{D})$ and $P_v^*(v)$.

Step 1: Draw *ns* observations from the distributions of demographic variables, D and unobserved consumer characteristics, v. Using starting values of theta2, compute the predicted market shares according to the following smooth simulator suggested by Nevo (2000a) and assuming the error term follows the extreme value distribution of $f(\varepsilon)$ to integrate ε's analytically:

$$s_{jt}\left(p_{jt}, x_{jt}, \delta_{jt}, \hat{P}_D^*(\mathrm{D}), P_v^*(v); \theta_2\right) = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijt} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp\,(\delta_j + \mu_{ij})}{1 + \sum_{k=1}^{J} \exp\,(\delta_k + \mu_{ik})} \tag{3.28}$$

Step 2: Using Berry's inversion (1994), compute the mean valuation utility, δ that equates the predicted market shares with the observed market shares.

$$s_{jt}{}^{-1} = (\hat{s}_{jt};\ \theta_2) = \delta_{jt} \tag{3.29}$$

This inversion can be solved using a construction map proposed by BLP (1995). The solution uses numerical estimation with starting values of δ_{jt} by iteration, according to the following algorithm:

$$\delta_{jt}{}^{new} = \delta_{jt}{}^{old} + \ln(\hat{s}_{jt}) - \ln\left(s\left(p_{jt}, x_{jt}, \delta_{jt}{}^{old}, \hat{P}_D^*(\mathrm{D}), P_v^*(v); \theta_2\right)\right) \tag{3.30}$$

where $s(\,.\,)$ is the predicted market share computed in step 1.

Step 3: With the mean valuation utility delta at hand, estimate the vector of parameters theta2 by interacting with the error terms $\zeta_{jt} = \delta_{jt}\left(s_{jt}\,;\ \theta_2\right) - (\alpha p_{jt} + \beta x_{jt})$, with the instruments Z to form the objective function as:

$$min_{\,\theta}\ Q(\theta)\ =\ \left(\delta_{jt}\,(\theta_2) - (X\theta_1)\right)' ZW^{-1}Z' \left(\delta_{jt}\,(\theta_2) - (X\theta_1)\right) \tag{3.31}$$

where $X = [x, p]$ and W is a consistent estimate variance matrix of the sample moment conditions, $E\left[\,Z\,'\zeta(\hat{\theta})\ \zeta(\hat{\theta})\ 'Z\right]$.

Step 4: Find the values of θ_2 that minimize the GMM objective function. Nevo (2000a) suggests that expressing θ_1 as a function of θ_2 will speed up the process. θ_1 represents the parameters that enter the indirect utility linearly. Therefore, the nonlinear part of the objective function can be searched. This is done by taking the first-order conditions with respect to θ_1:

$$-X'ZW^{-1}Z'\left(\delta_{jt}\,(\theta_2) - X\hat{\theta}_1\right) = 0 \tag{3.32}$$

Solving for $\hat{\theta}_1$ yields the following:

$$\hat{\theta}_1 = (X'ZW^{-1}Z'X)^{-1}X'ZW^{-1}Z'\delta(\theta_2) \tag{3.33}$$

The minimization is now with respect to nonlinear parameters of θ_2. Nevo (2000a) suggests using the Quasi-Newton method using an analytic gradient to find the minimum of the GMM objective function.

3.5 Empirical Results

3.5.1 Brand Level Analysis

This section presents the empirical results of the brand level random coefficient logit demand models. Table 3.1 shows BLP's random coefficient logit demand parameter estimates at the brand level. The second column gives the mean utility parameter estimates representing consumers' mean tastes about product characteristics, namely price, calorie, and caffeine contents. These parameters enter the indirect utility function linearly. The third and the fourth columns represent the interaction of product characteristics with household income and the number of persons in the household with age under 15 years. Finally, the last column gives the interaction of product characteristics and unobserved consumer characteristics.

The price parameter is negative, as expected, and statistically significant at the 1% level in the mean utility. The caffeine parameter estimate is positive and statistically significant at the 1% level. In contrast, the calorie variable has a negative but not statistically significant effect on the mean utility. Signs of mean utility parameter estimates indicate that consumers prefer carbonated soft drink (CSD) brands with low price, high caffeine, and low calorie on average. These estimates are for the mean utility, and they do not include interactions between consumer and product characteristics. When interactions are included, price, calorie, and caffeine parameters vary by consumer observed and unobserved characteristics. For example, one consumer may perceive higher calories better, while for another, lower calories may be more favorable.

Table 3. 1: Demand Parameter Estimates at the Brand Level

	Mean Utility	Interactions		
Variables		Income	Children	Unobserved
Constant	-5.4554***	0.0764	-0.0566	-0.0956
	(-13.3319)	(0.0802)	(-0.0404)	(-1.3528)
Price	-33.9148***	-0.8521	-0.5507	0.3389
	(-2.1999)	(-0.0626)	(-0.0269)	(0.1188)
Calorie	-0.1632	0.1775	0.1800	-0.5696
	(-0.0953)	(0.0227)	(0.0177)	(-0.5900)
Caffeine	35.8437***	-1.0916	-0.9440	-0.6940
	(5.6605)	(-0.0449)	(-0.0308)	(-0.1508)

Note: t-statistics in the parentheses; *significant at 10% level; **significant at 5% level; ***significant at 1% level.

Demand parameter estimates represented in Table 3.1 can also be written as follows:

Price: $\alpha_i = -33.91 - 0.85\ D_{inc} - 0.55\ D_{children} + 0.33\ v_i$

Calorie: $\beta_{1i} = -0.16 + 0.17\ D_{inc} + 0.18\ D_{children} - 0.56\ v_i$

Caffeine: $\beta_{2i} = 35.84 - 1.09\ D_{inc} - 0.94\ D_{children} - 0.69\ v_i$

These equations do not refer to single-point estimates. They provide a distribution of the parameter of interest. Since there are 39,000 simulated households (78 markets and 500 households in each market), there are 39,000 price, calorie, and caffeine parameter estimates for each variable.

The distribution of the price parameter estimate is shown in Figure 3.1. The price parameter estimates are negative for all the households in data, consistent with the law of demand. The price parameters' distribution approximates a normal distribution with a mean of -35.32 and a standard deviation of 1.09. Figure 3.2 shows how price sensitivity is distributed from low to high-income households, while Figure

3.3 shows price parameters distribution by the number of children in the household. From these figures, it can be seen that families with no children are less price-sensitive than families with one or more children, and low-income households are less sensitive to CSDs prices than middle-income and high-income households.

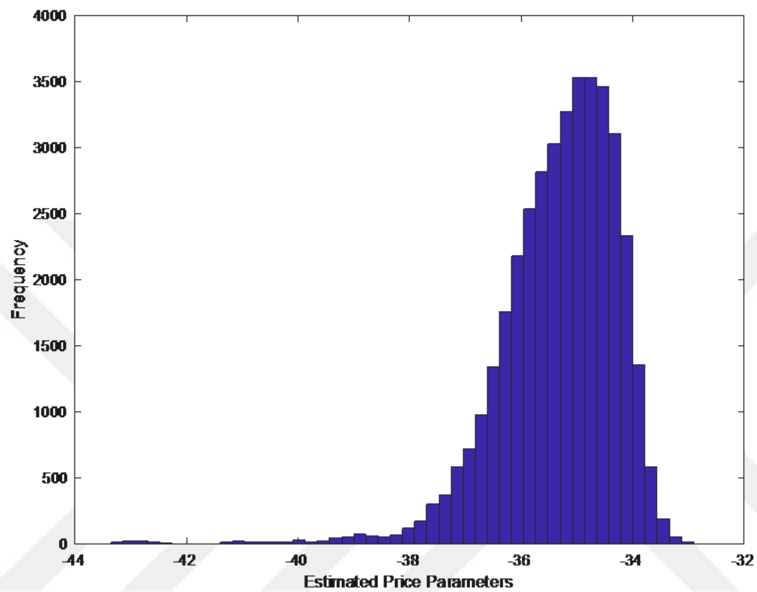

Figure 3. 1: Frequency Distribution of Price Parameter Estimates at the Brand Level

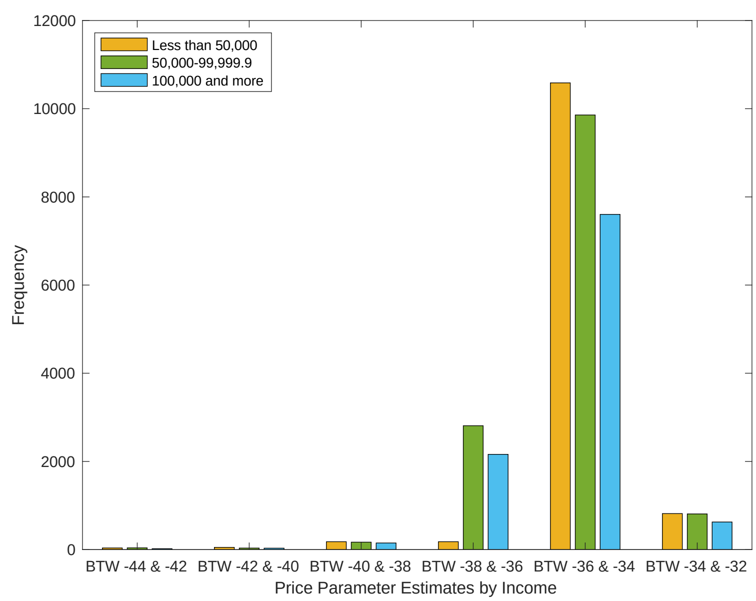

Figure 3. 2: Distribution Price Parameter Estimates by Income Categories at the Brand Level

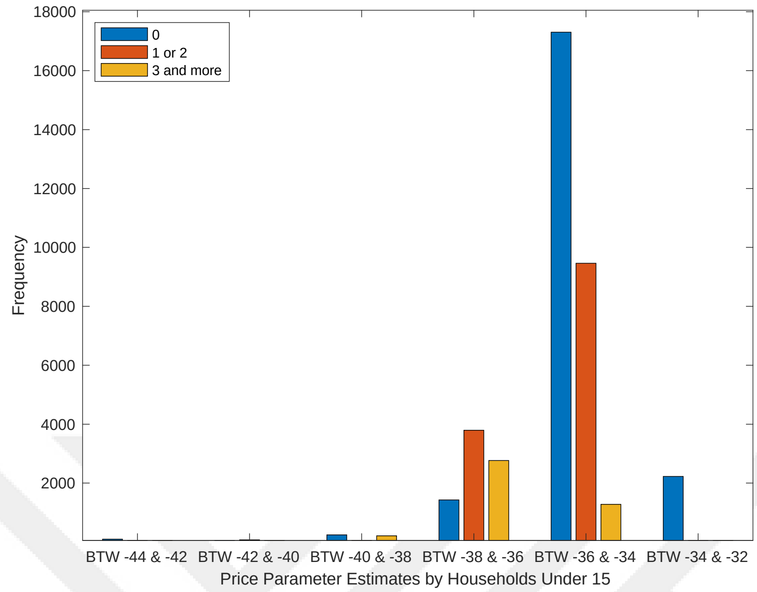

Figure 3. 3: Distribution of Price Parameter Estimates by the Number of Children at the Brand Level

Figure 3.4 shows the frequency distribution of calorie parameter estimates with a mean of -1.14 and a standard deviation of 1.08. The histogram indicates the distribution does not mimic a normal distribution. Some consumers have a positive valuation for the calories, while others value the soft drink calorie content negatively. Figure 3.5 displays the distribution of calorie parameter estimates by income categories at the brand level estimation. The results show no consistent pattern across different income categories of households. Some households see calories as positive regardless of their income. Moreover, Figure 3.6 illustrates households with three and more children are more calorie sensitive. In contrast, households with no children are less sensitive to the drinks' calories, and even some households with no children perceive calories positively.

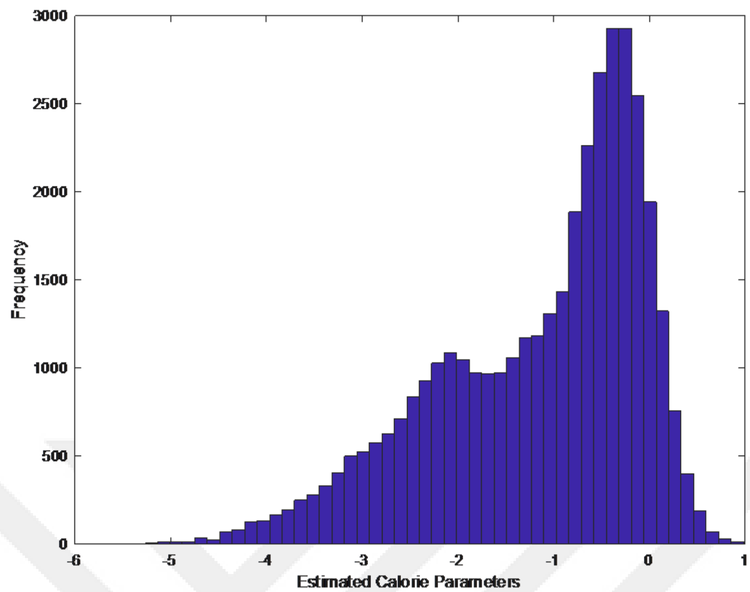

Figure 3. 4: Frequency Distribution of Calorie Content Parameter Estimates at the Brand Level

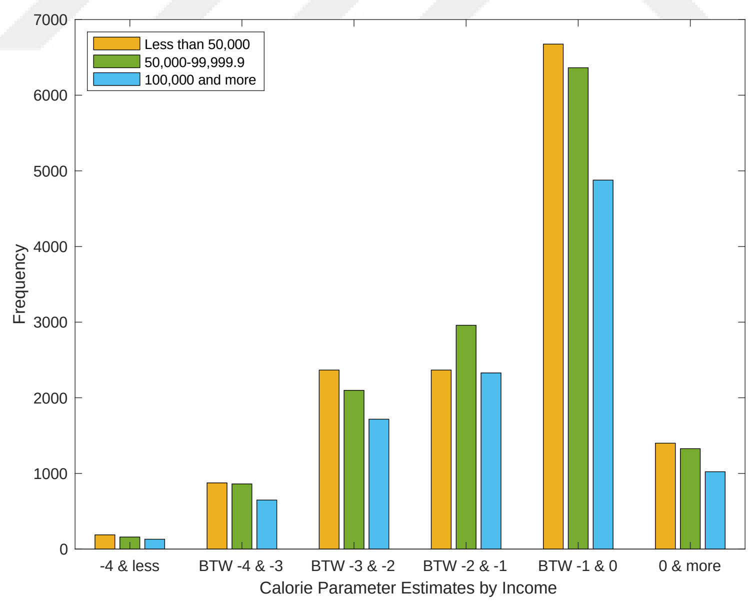

Figure 3. 5: Distribution of the Calorie Content Parameter Estimates by Income Categories at the Brand Level

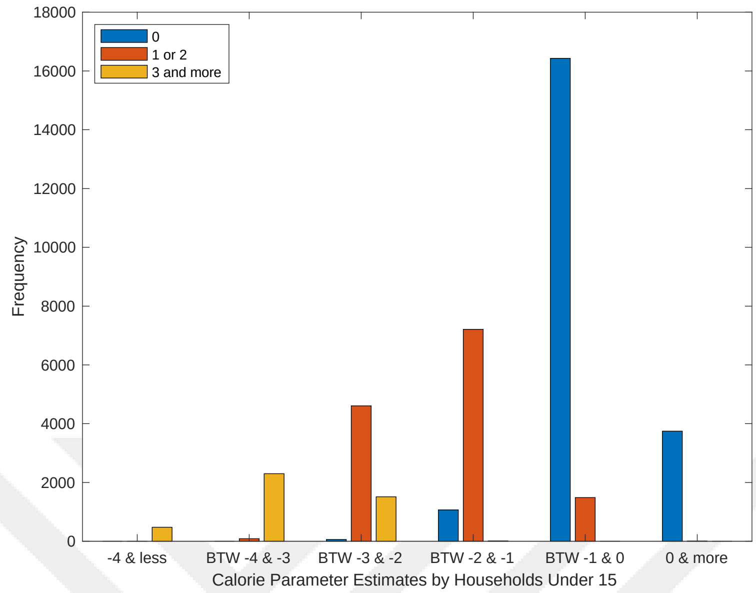

Figure 3. 6: Range of Calorie Content Parameter Estimates by the Number of Children at the Brand Level

Estimated caffeine parameters are positive for all households, and it ranges from 22 to 38 (See Figure 3.7). They approximate a normal distribution with a mean of 33.41 and a standard deviation of 1.97. Figure 3.8 displays the distribution of caffeine content parameter estimates by income categories in the brand level estimation. Households with middle-income are clustered more in the range of 32 to 35 caffeine parameter estimates than low- and high-income households. Families with no children care more about caffeine content in CSDs, as shown in Figure 3.9. Additionally, households with one or more children prefer less caffeine content.

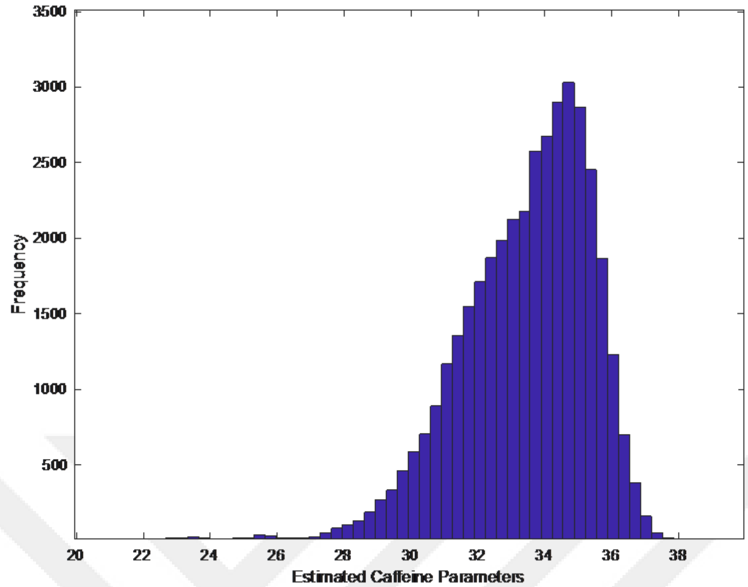

Figure 3. 7: Frequency Distribution of Caffeine Content Parameter Estimates at the Brand Level

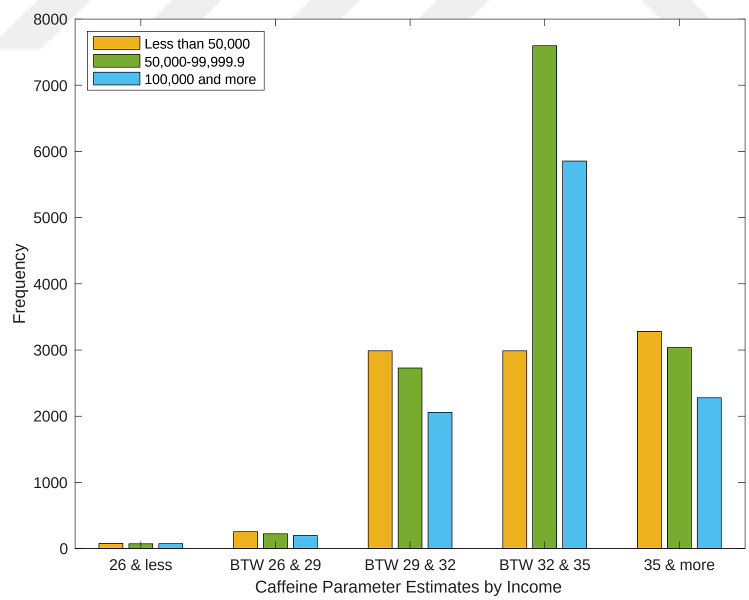

Figure 3. 8: Distribution of Caffeine Content Parameter Estimates by Income Categories at the Brand Level

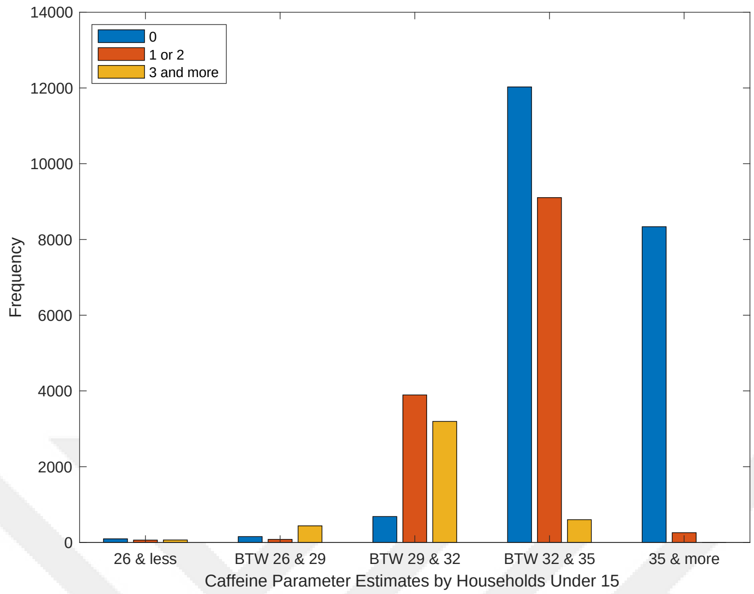

Figure 3. 9: Distribution of Caffeine Content Parameter Estimates by the Number of Children at the Brand Level

To summarize, the estimation of the random coefficient multinomial logit demand model at the brand level indicates that for all the households in the study data, the price variable negatively affects the consumer's total utility. The distribution of this effect across demographic variables does not show any consistent pattern; it is somewhat random.

3.5.2 Bottle-size Level Analysis

In this part, we present the results of estimating the demand for soft drinks in the Dallas market at the bottle-size level. Table 3.2 shows BLP's random coefficient logit demand parameter estimates at the bottle-size level. Compared to brand level results, the price parameter's magnitude in the mean utility is bigger in bottle-size level. While the mean utility of price parameter estimates is -84.4 for the bottle-size level demand, it is -33.9 for the brand size level. The mean utility of the calorie parameter is positive in the bottle-size level while it is negative at the brand level. Liu and Lopez (2014) and Lopez and Fantuzzi (2012) find negative sugar[3] and calorie

[3] Some papers exclude calorie and use sugar content instead. In this research, calorie is taken into account and sugar content is excluded since they provide similar information for CSDs.

parameters in the mean utility, respectively. On the other hand, Lopez et al. (2015) find a positive mean utility of the sugar parameter.

Each caffeine parameter estimates in the two demand estimations are positive, but the caffeine parameter estimate's mean utility for the bottle-size level has a slightly lower magnitude. Liu and Lopez (2014), Lopez et al. (2015), and Lopez and Fantuzzi (2012) find a positive mean utility of caffeine parameters; thus, our results are consistent with these papers. At the bottle-size level, the mean utility of price is significant at 1% level while calorie and caffeine parameters are not statistically significant. At the bottle-size level estimation, signs of mean utility parameter estimates indicate that CSD brands with lower prices, higher caffeine, and higher calorie content are more favorable for the consumers on average.

Table 3. 2: Demand Parameter Estimates at the Bottle-Size Level

	Mean Utility	Interactions		
Variables		Income	Children	Unobserved
Constant	-5.3807***	0.0043	0.0771	-0.0112
	(-3.6213)	(0.0138)	(0.0509)	(-0.0209)
Price	-84.4738***	0.2584	0.5076	0.7969
	(-7.4635)	(0.0191)	(0.0362)	(0.0392)
Calorie	3.1771	0.1386	-0.1189	0.0040
	(0.4148)	(0.0361)	(-0.0284)	(0.0036)
Caffeine	12.0187	1.4317	-0.1557	-1.2948
	(0.3812)	(0.1806)	(-0.0046)	(-0.0967)

Note: t-statistics in the parentheses; *significant at 10% level; **significant at 5% level; ***significant at 1% level.

As before, we can express the demand parameter estimates represented in Table 3.2 as follows:

Price: $\alpha_i = -84.47 + 0.25\ D_{inc} + 0.50\ D_{children} + 0.79\ v_i$

Calorie: $\beta_{1i} = 3.17 + 0.13\ D_{inc} - 0.11\ D_{children} + 0.004\ v_i$

Caffeine: $\beta_{2i} = 12.01 + 1.43\ D_{inc} - 0.15\ D_{children} - 1.29\ v_i$

The random coefficient logit has the advantage of yielding parameter distributions instead of point estimates. For example, Figure 3.10 shows the frequency distribution of price parameters at the bottle-size level. All price parameter estimates are negative and range between -88 to -79. The distribution approximates a normal distribution with a mean of -83.77 and a standard deviation of 1.07. According to Figure 3.11, high-income households are less sensitive to CSD prices than other income categories. Furthermore, families with no children are more price-sensitive than families with children (Figure 3.12). As shown by comparing the indications of price parameters by income and the number of children, they are opposite at the bottle-size level and brand level estimation.

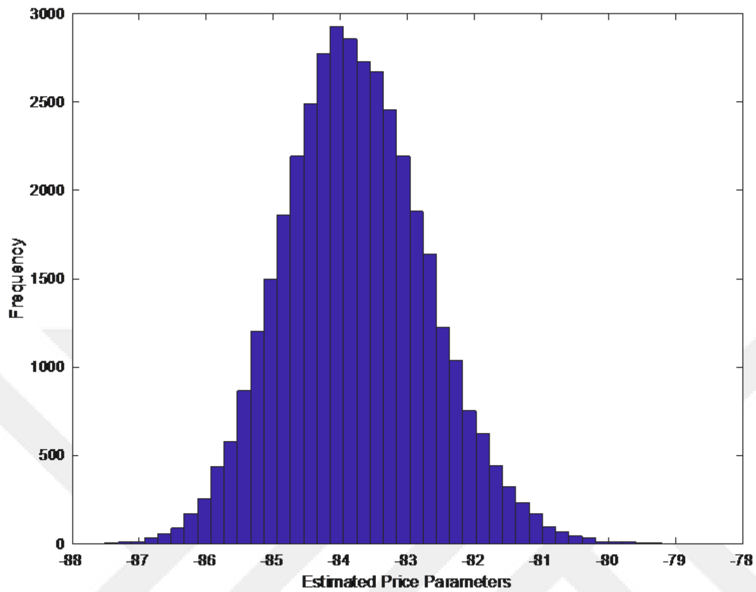

Figure 3. 10: Frequency Distribution of Price Parameter Estimates at the Bottle-Size Level

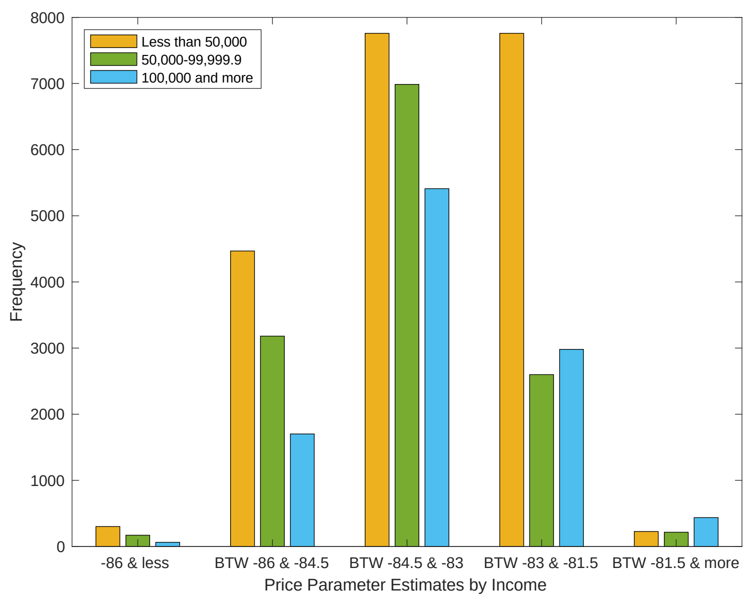

Figure 3. 11: Distribution of the Price Parameter Estimates by Income Categories at Bottle-Size Level

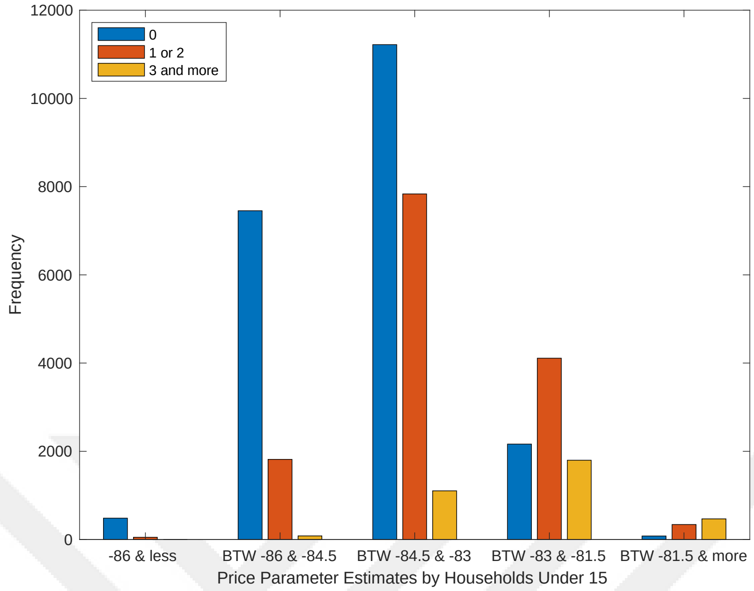

Figure 3. 12: Distribution of the Price Parameter Estimates by the Number of Children at Bottle-Size Level

Figure 3.13 shows the frequency distribution of calorie parameter estimates at the bottle-size level. The parameters' distribution approximates a normal distribution with a mean of 3.23 and a standard deviation of 0.81. All calorie parameters are positive in the bottle-size level, but calories are more valuable for high-income households than middle- and low-income ones (See Figure 3.14). Regardless of having children, all households value the calorie content of CSDs positively (Figure 3.15). The implications of bottle-size demand results regarding the calorie content parameter by income and the number of children are not parallel compared to the brand level.

Likewise, caffeine parameter estimates are positive for all households, and the distribution of the parameters approximate a normal distribution with a mean of 13.50 and a standard deviation of 2.15 (See Figure 3.16). However, high-income households prefer high caffeine drinks more than other income categories (Figure 3.17). Like calorie parameters, households value caffeine content positively regardless of the number of children in the household (Figure 3.18). At both levels of demand, caffeine parameters are positive, as mentioned above. However, the distribution of caffeine parameter estimates by income and the number of children does not yield similar implications.

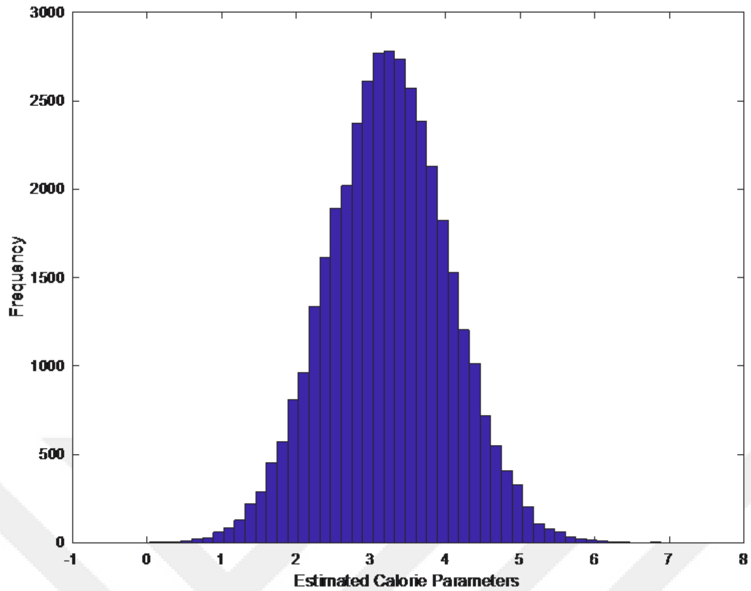

Figure 3. 13: Frequency Distribution of Calorie Parameter Estimates at the Bottle-Size Level

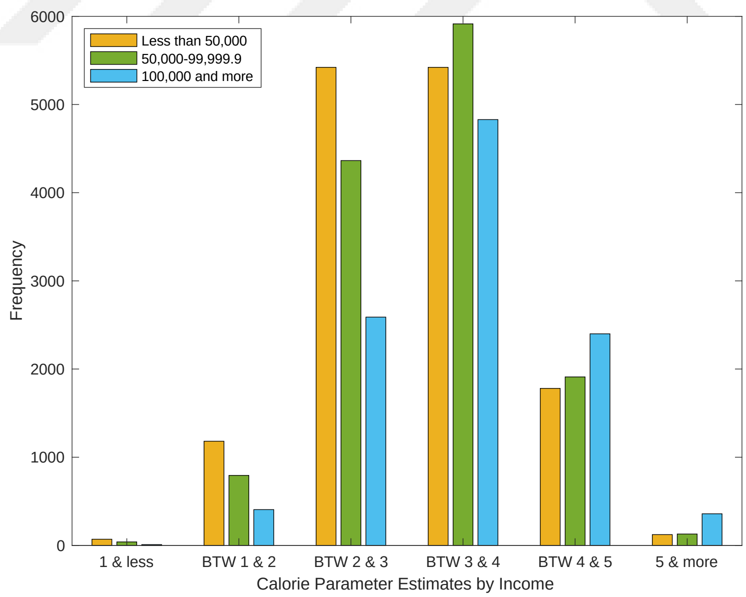

Figure 3. 14: Distribution of the Calorie Content Parameter Estimates by Income Categories at Bottle-Size Level

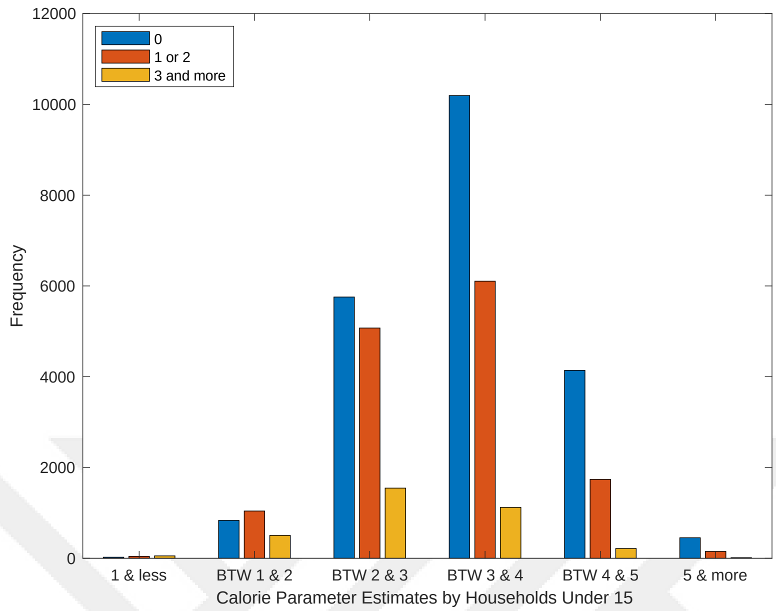

Figure 3. 15: The Distribution of the Calorie Content Parameter Estimates by the Number of Children at the Bottle-Size Level

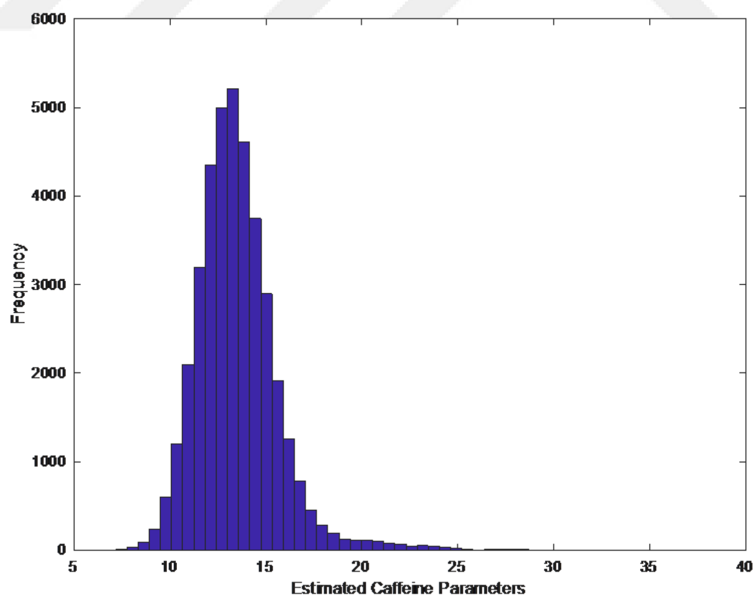

Figure 3. 16: Frequency Distribution of the Caffeine Content Parameter Estimates at the Bottle-Size Level

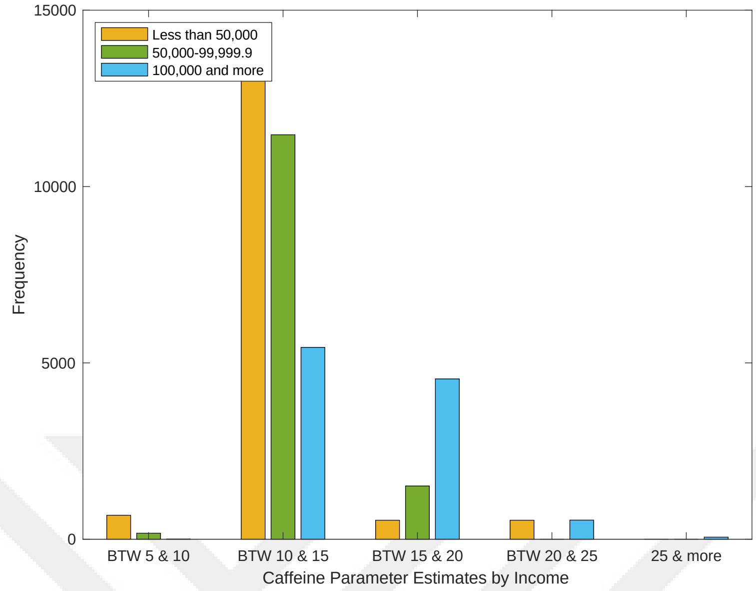

Figure 3. 17: Distribution of the Caffeine Content Parameter Estimates by Income Categories at the Bottle-Size Level

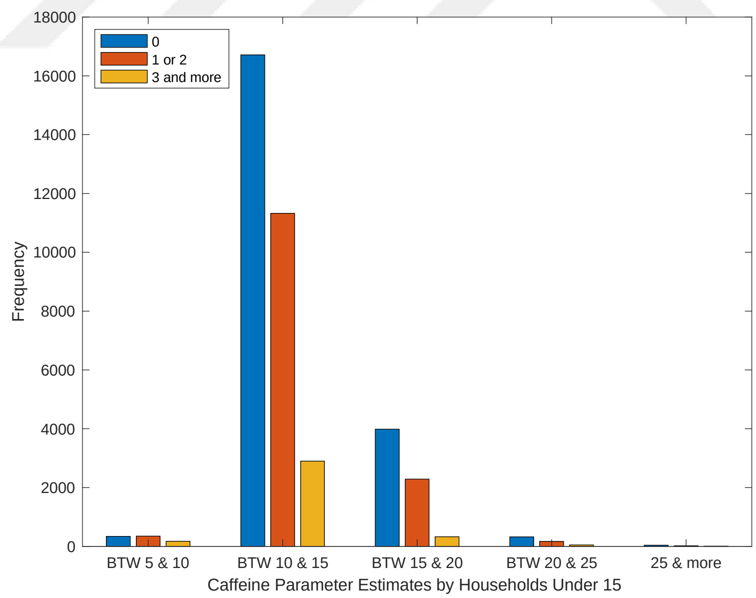

Figure 3. 18: Distribution of the Caffeine Parameter Estimates by the Number of Children at the Bottle-Size Level

3.5.3 Brand Level and Bottle-Size Level Elasticities

Having estimated the demand at the brand and bottle-size levels, we can use a simulated version of equation 3.22 to compute the corresponding elasticities. The results yield 400 (the square of 20) own- and cross-price elasticities at the brand level. For the bottle-size level, there are 1764 (the square of 42) own- and cross-price. The dimensionality is not a problem for the BLP's random coefficient model, unlike traditional demand models (i.e., AIDS, Rotterdam model).

In BLP's random coefficient logit model, every household has its elasticities. We report the elasticities on average (averaged across periods and consumers). Figure 3.19 shows the box-and-whiskers plot of own-price elasticities at the brand level and the bottle-size level, respectively. It displays the minimum and the maximum values along with the median of own-price elasticities. At the brand level, own-price elasticities range between -1.9 (RC Cola) to -3.2 (Coke Zero) with the median of -2.39 and the mean of -2.48. The bottle-size level's own-price elasticities are bigger in magnitude; they range between -3.06 (7 Up 2-liter single pack) to -5.48 (Coke Zero 6 packs of 16.9 oz.) with a median of -4.06 and a mean of -4.08.

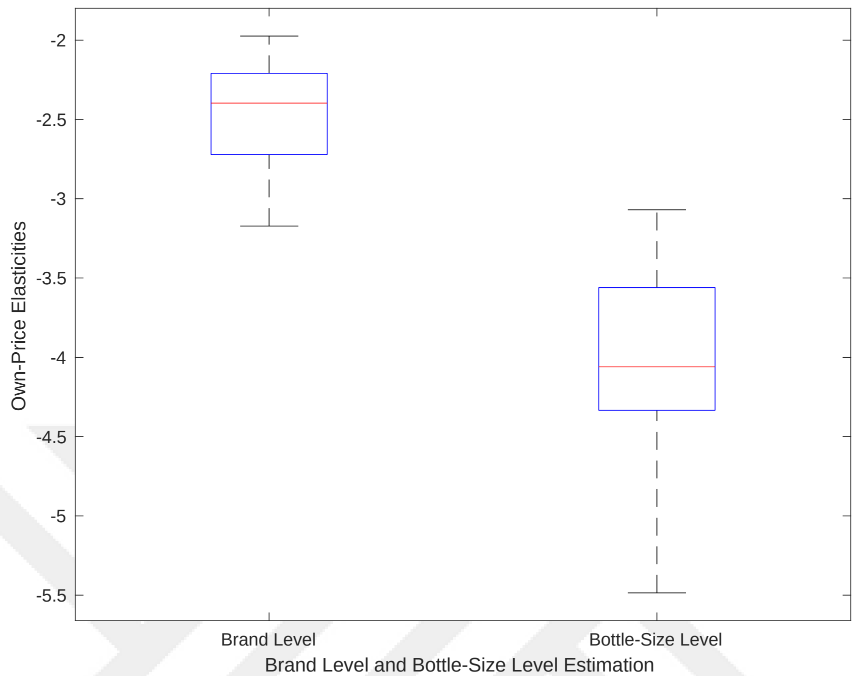

Figure 3. 19: Box-and-Whiskers Plot for Own-price Elasticities at the Brand Level and the Bottle-Size Level

Table 3.3 and 3.4 show own-price and cross-price elasticities for the brand level and the bottle-size level, respectively. All estimated own-price elasticities are negative for both levels of demand estimation. The magnitude of own-price elasticities indicates that consumers are pretty sensitive to CSD prices. All cross-price elasticities for both levels are positive, suggesting that the products are substitutes. Magnitudes of cross-price elasticities are pretty low compared to own-price elasticities. It supports that consumers have brand loyalty, and they switch to the outside good rather than another brand of carbonated soft drinks even if they are sensitive to CSD prices of their chosen brands.

At the brand level, the lowest own-price elasticity, in absolute value, is for RC Cola (-1.97) while the highest is for Coke Zero (-3.17). Lopez et al. (2015) estimate brand-level demand and find own-price elasticities to range between -2.3 and -1.8. On the other hand, Lopez and Fantuzzi (2012) find brand-level elasticities to range between -10.1 and -3.1.

As shown in Table 3.3, cross-price elasticities are positive and range from 0.0030 to 0.3115. In the column of Coke Classic and Dr Pepper, cross-price elasticities of a particular brand with respect to Coke Classic (e.g., cross-price elasticity of RC Cola with respect to Coke Classic), and with respect to Dr Pepper (e.g., cross-price elasticity of Canada Dry with regard to Dr Pepper) have bigger magnitudes than other cross-price elasticities. These two brands have the highest market shares in the data, so they are leading brands. It indicates that an increase in Coke Classic (or Dr Pepper) brand's price leads to a higher percentage change in the quantity demanded of the other brand than the other way around.

For example, the cross-price elasticity of RC Cola with respect to Coke Classic is 0.2283, and it indicates that when Coke Classic's price increase by 1%, the quantity demanded of RC Cola will increase by 0.2283 %. On the other hand, Coke Classic's cross-price elasticity with respect to RC Cola is 0.0075, meaning that when RC Cola's price increases by 1 %, the quantity demanded of Coke Classic increases by 0.0075 %. Comparing to 0.2283 % and 0.0075 %, 0.2283 %. is about 30 times bigger than 0.0075 %. These results indicate that consumers are brand loyal, and they are more responsive to changes in the leading brands' prices(i.e., Coke Classic, Dr Pepper). These findings regarding cross-price elasticities are similar to the findings in Lopez et al. (2015).

For the bottle-size level, own-price elasticities have a higher magnitude than those found at the brand level (see Tables 3.3 and 3.4). They range between -5.48 and -3.06. Dube (2004) estimates the bottle-size level CSD elasticities and own-price elasticities to vary between -3.61 and -2.11.

The lowest (in absolute value) own-price elasticity is for 7 Up 2-liter single pack, and the highest own-price elasticity (in absolute value) is for Coke Zero 6 packs of 16.9 oz. Relatively, brands with 6 packs of 16.9 oz. drinks are more price-elastic than brands with 2-liter single-pack drinks. Moreover, the brands' own-price elasticities with 12 oz. 12 cans are between 2-liter single bottle and 6 packs of 16.9 drinks. For example, Dr Pepper's 2-liter single bottle's own-price elasticity is -3.28, Dr Pepper 12 packs 12 oz. is -3.88, and Dr Pepper 6 packs of 16.9 oz. is -4.93. Similarly, the own-price elasticity of Coke Classic 2 liter is -3.56, Coke Classic 12 packs 12 oz. is -4.21, and Coke Classic 6 packs 16.9 oz. is -4.73.

Bottle-size level cross-price elasticities are between 0.0041 to 0.3316, as shown in Table 3.4. They indicate similar findings as brand level in that consumers have brand loyalty and are more sensitive to price changes of the leading brands. Coke Classic 12 packs of 12 oz and Dr Pepper 12 packs of 12 oz are the top brands at the bottle-size level. As shown in Table 3.4, columns of the leading brands include higher cross-price elasticities than the other brands. For example, the cross-price elasticity of Diet Pepsi 2-liter single package with respect to Dr Pepper 12 packs of 12 oz. is 0.2523. It shows that if the price of Dr Pepper 12 packs of 12 oz. increases by 1%, the quantity demanded of Diet Pepsi 2-liter single package increases by 0.2523%. On the other hand, the cross-price elasticity of Dr Pepper 12 packs of 12 oz. with respect to Diet Pepsi 2-liter single package is 0.0091. If Diet Pepsi's 2-liter single package's price increase by 1 %, the quantity demanded of Dr Pepper 12 packs of 12 oz. will increase by 0.0091 %.

Table 3. 3: Own-price and Cross-price Elasticities of the Random Coefficient Logit Model in the Brand Level

	7 UP	A&W RT-BR	A&W CRM-SD	CFFR DI COKE	CFFR DI DR PEP	CND DRY	COKE CLSC	COKE ZR	DI 7 UP	DI COKE
7 UP	-2.2616	0.0215	0.0034	0.0296	0.0131	0.0089	0.2502	0.0366	0.0138	0.1418
A&W RT-BR	0.0369	-2.2735	0.0033	0.0284	0.0125	0.0085	0.2407	0.0351	0.0132	0.1360
A&W CRM-SD	0.0368	0.0206	-2.1025	0.0282	0.0125	0.0085	0.2398	0.035	0.0132	0.1354
CFFR DI COKE	0.0479	0.0268	0.0043	-3.0375	0.0167	0.0111	0.3103	0.0463	0.0175	0.1787
CFFR DI DR PEP	0.0481	0.0269	0.0043	0.0378	-2.6577	0.0111	0.3115	0.0465	0.0176	0.1794
CND DRY	0.0386	0.0216	0.0035	0.0298	0.0132	-2.4033	0.2515	0.0368	0.0139	0.1425
COKE CLSC	0.0360	0.0202	0.0032	0.0276	0.0122	0.0083	-2.2056	0.0342	0.0128	0.1330
COKE ZR	0.0445	0.0249	0.0040	0.0348	0.0154	0.0103	0.2902	-3.1719	0.0162	0.1664
DI 7 UP	0.0481	0.0269	0.0043	0.0378	0.0167	0.0111	0.3114	0.0465	-2.6921	0.1794
DI COKE	0.0436	0.0244	0.0039	0.0340	0.0150	0.0101	0.2844	0.0420	0.0158	-2.8852
DI DR PEP	0.0441	0.0247	0.0039	0.0344	0.0152	0.0102	0.2876	0.0425	0.0160	0.1648
DI PEPSI	0.0447	0.0250	0.0040	0.0349	0.0154	0.0103	0.2909	0.0431	0.0162	0.1668
DR PEP	0.0356	0.0200	0.0032	0.0273	0.0121	0.0082	0.2336	0.0339	0.0127	0.1317
FANTA	0.0373	0.0209	0.0033	0.0287	0.0127	0.0086	0.2433	0.0355	0.0134	0.1376
M DEW	0.0333	0.0187	0.0030	0.0253	0.0112	0.0077	0.2190	0.0315	0.0118	0.1229
PEPSI	0.0355	0.0199	0.0032	0.0272	0.0120	0.0082	0.2331	0.0338	0.0127	0.1314
RC COLA	0.0348	0.0195	0.0031	0.0266	0.0118	0.0080	0.2283	0.0330	0.0124	0.1285
SPRITE	0.0386	0.0216	0.0035	0.0298	0.0132	0.0089	0.2517	0.0368	0.0139	0.1427
SPRITE ZR	0.0479	0.0268	0.0043	0.0376	0.0167	0.0111	0.3103	0.0463	0.0175	0.1787
SUNKIST	0.0361	0.0203	0.0032	0.0277	0.0123	0.0083	0.2362	0.0343	0.0129	0.1333

Notes: RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLSC= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3.3. Continued

	DI DR PEP	DI PEPSI	DR PEP	FANTA	M DEW	PEPSI	RC COLA	SPRITE	SPRITE ZR	SUNKIST
7 UP	0.0776	0.0336	0.1930	0.0125	0.0217	0.0732	0.0080	0.0734	0.0186	0.0325
A&W RT-BR	0.0745	0.0322	0.1857	0.0120	0.0209	0.0704	0.0077	0.0705	0.0178	0.0313
A&W CRM-SD	0.0741	0.0321	0.1850	0.0120	0.0209	0.0702	0.0077	0.0702	0.0178	0.0312
CFFR DI COKE	0.0980	0.0424	0.2390	0.0156	0.0268	0.0906	0.0099	0.0916	0.0237	0.0403
CFFR DI DR PEP	0.0984	0.0426	0.2399	0.0156	0.0269	0.0910	0.0099	0.0920	0.0238	0.0405
CND DRY	0.0781	0.0338	0.1939	0.0126	0.0218	0.0735	0.0080	0.0737	0.0187	0.0327
COKE CLSC	0.0728	0.0315	0.1820	0.0117	0.0206	0.0690	0.0075	0.0687	0.0173	0.0306
COKE ZR	0.0911	0.0394	0.2237	0.0145	0.0251	0.0848	0.0092	0.0851	0.0219	0.0377
DI 7 UP	0.0984	0.0426	0.2398	0.0156	0.0268	0.0909	0.0099	0.0920	0.0238	0.0405
DI COKE	0.0892	0.0386	0.2194	0.0142	0.0247	0.0832	0.0091	0.0833	0.0213	0.0369
DI DR PEP	-2.7113	0.0391	0.2218	0.0143	0.0249	0.0841	0.0092	0.0843	0.0216	0.0373
DI PEPSI	0.0914	-2.7309	0.2243	0.0145	0.0252	0.0850	0.0093	0.0853	0.0219	0.0378
DR PEP	0.0720	0.0311	-2.1024	0.0116	0.0204	0.0684	0.0075	0.0680	0.0171	0.0303
FANTA	0.0753	0.0326	0.1877	-2.3902	0.0212	0.0712	0.0078	0.0713	0.0180	0.0316
M DEW	0.0671	0.0290	0.1692	0.0108	-2.2769	0.0642	0.0070	0.0635	0.0159	0.0284
PEPSI	0.0718	0.0311	0.1799	0.0116	0.0203	-2.0878	0.0075	0.0679	0.0171	0.0302
RC COLA	0.0702	0.0304	0.1763	0.0113	0.0200	0.0668	-1.9739	0.0664	0.0167	0.0296
SPRITE	0.0781	0.0338	0.1941	0.0126	0.0219	0.0736	0.0080	-2.5373	0.0187	0.0327
SPRITE ZR	0.0980	0.0424	0.2390	0.0156	0.0268	0.0906	0.0099	0.0916	-3.0349	0.0403
SUNKIST	0.0729	0.0315	0.1823	0.0118	0.0206	0.0691	0.0075	0.0690	0.0174	-2.2118

Notes: RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLSC= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3. 4: Own-price and Cross-price Elasticities of the Random Coefficient Logit Model in the Bottle-Size Level

	7UP 2LT	7UP 12P	A&W RT-BR 12P	A&W CRM-SD 12P	CFFR DI COKE 12P	CFFR DI DR PEP 12P	CND DRY 2LT	CND DRY 12P	COKE CLS 2LT	COKE CLS 6P	COKE CLS 12P	COKE CLS 24P	COKE ZR 2LT	COKE ZR 6P
7UP 2LT	-3.0696	0.0410	0.0258	0.0058	0.0224	0.0143	0.0064	0.0090	0.0795	0.0527	0.2682	0.0579	0.0072	0.0082
7UP 12P	0.0130	-3.8184	0.0258	0.0058	0.0224	0.0143	0.0064	0.0090	0.0796	0.0528	0.2685	0.0579	0.0072	0.0083
A&W RT-BR 12P	0.0132	0.0416	-3.9227	0.0059	0.0226	0.0144	0.0065	0.0091	0.0807	0.0535	0.2721	0.0586	0.0073	0.0084
A&W CRM-SD 12P	0.0132	0.0416	0.0262	-4.1177	0.0226	0.0144	0.0065	0.0091	0.0807	0.0535	0.2722	0.0586	0.0073	0.0084
CFFR DI COKE 12P	0.0123	0.0389	0.0244	0.0055	-4.2280	0.0136	0.0060	0.0085	0.0751	0.0498	0.2535	0.0549	0.0068	0.0078
CFFR DI DR PEP 12P	0.0123	0.0389	0.0244	0.0055	0.0214	-3.9065	0.0060	0.0085	0.0751	0.0498	0.2535	0.0549	0.0068	0.0078
CND DRY 2LT	0.0130	0.0410	0.0258	0.0058	0.0224	0.0143	-3.3104	0.0090	0.0795	0.0528	0.2683	0.0579	0.0072	0.0082
CND DRY 12P	0.0130	0.0411	0.0258	0.0058	0.0224	0.0143	0.0064	-4.2735	0.0796	0.0528	0.2686	0.0579	0.0072	0.0083
COKE CLS 2LT	0.0141	0.0443	0.0279	0.0063	0.0241	0.0154	0.0069	0.0097	-3.5609	0.0577	0.2930	0.0626	0.0079	0.0091
COKE CLS 6P	0.0141	0.0444	0.0279	0.0063	0.0241	0.0154	0.0069	0.0097	0.0870	-4.7339	0.2934	0.0627	0.0079	0.0091
COKE CLS 12P	0.0141	0.0443	0.0279	0.0063	0.0241	0.0154	0.0069	0.0097	0.0870	0.0578	-4.2186	0.0627	0.0079	0.0091
COKE CLS 24P	0.0137	0.0441	0.0273	0.0060	0.0235	0.0154	0.0064	0.0089	0.0849	0.0548	0.2769	-4.3338	0.0073	0.0081
COKE ZR 2LT	0.0133	0.0419	0.0263	0.0059	0.0230	0.0147	0.0065	0.0092	0.0818	0.0543	0.2759	0.0593	-3.5459	0.0086
COKE ZR 6P	0.0150	0.0417	0.0278	0.0065	0.0240	0.0152	0.0080	0.0113	0.0929	0.0652	0.2946	0.0388	0.0097	-5.4852
COKE ZR 12P	0.0133	0.0419	0.0263	0.0059	0.0230	0.0147	0.0065	0.0092	0.0819	0.0544	0.2762	0.0593	0.0075	0.0086
COKE ZR 24P	0.0130	0.0424	0.0262	0.0058	0.0223	0.0148	0.0061	0.0084	0.0797	0.0521	0.2613	0.0589	0.0069	0.0075
DI 7UP 12P	0.0123	0.0389	0.0244	0.0055	0.0214	0.0136	0.0060	0.0085	0.0751	0.0498	0.2535	0.0549	0.0068	0.0078
DI COKE 2LT	0.0137	0.0431	0.0271	0.0061	0.0236	0.0151	0.0067	0.0094	0.0844	0.0561	0.2848	0.0610	0.0077	0.0089
DI COKE 6P	0.0137	0.0431	0.0271	0.0061	0.0237	0.0151	0.0067	0.0095	0.0846	0.0562	0.2853	0.0610	0.0077	0.0089
DI COKE 12P	0.0137	0.0431	0.0271	0.0061	0.0237	0.0151	0.0067	0.0095	0.0845	0.0561	0.2851	0.0610	0.0077	0.0089
DI COKE 24P	0.0136	0.0433	0.0270	0.0060	0.0235	0.0151	0.0066	0.0091	0.0840	0.0553	0.2810	0.0628	0.0075	0.0086

Notes: 2LT= 2-liter (single bottle (67.9 oz.)); 6P= 6 Packs (16.9 oz. each) 1; 12P=12 Packs (12 oz. each); 24P= 24 Packs (12 oz. each); RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLS= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3.4. Continued

	7UP 2LT	7UP 12P	A&W RT-BR 12P	A&W CRM-SD 12P	CFFR DI COKE 12P	CFFR DI DR PEP 12P	CND DRY 2LT	CND DRY 12P	COKE CLS 2LT	COKE CLS 6P	COKE CLS 12P	COKE CLS 24P	COKE ZR 2LT	COKE ZR 6P
DI DR PEP 2LT	0.0135	0.0426	0.0268	0.0060	0.0234	0.0149	0.0066	0.0093	0.0833	0.0553	0.2809	0.0602	0.0076	0.0087
DI DR PEP 6P	0.0136	0.0426	0.0268	0.0060	0.0234	0.0149	0.0066	0.0093	0.0834	0.0554	0.2815	0.0604	0.0076	0.0088
DI DR PEP 12P	0.0135	0.0426	0.0268	0.0060	0.0234	0.0149	0.0066	0.0093	0.0833	0.0554	0.2812	0.0603	0.0076	0.0087
DI PEPSI 2LT	0.0133	0.0420	0.0264	0.0059	0.0231	0.0147	0.0065	0.0092	0.0820	0.0544	0.2765	0.0594	0.0075	0.0086
DI PEPSI 6P	0.0169	0.0410	0.0275	0.0067	0.0246	0.0144	0.0094	0.0132	0.0998	0.0696	0.3090	0.0203	0.0112	0.0107
DI PEPSI 12P	0.0133	0.0420	0.0264	0.0059	0.0231	0.0147	0.0065	0.0092	0.0820	0.0545	0.2768	0.0594	0.0075	0.0086
DR PEP 2LT	0.0144	0.0452	0.0285	0.0064	0.0246	0.0157	0.0071	0.0099	0.0889	0.0591	0.2998	0.0640	0.0080	0.0093
DR PEP 6P	0.0144	0.0453	0.0285	0.0064	0.0246	0.0157	0.0071	0.0100	0.0891	0.0592	0.3004	0.0641	0.0081	0.0093
DR PEP 12P	0.0144	0.0453	0.0285	0.0064	0.0246	0.0157	0.0071	0.0099	0.0890	0.0591	0.3002	0.0640	0.0080	0.0093
FANTA 12P	0.0131	0.0414	0.0261	0.0058	0.0225	0.0144	0.0064	0.0090	0.0803	0.0533	0.2710	0.0584	0.0073	0.0083
M DEW 2LT	0.0150	0.0471	0.0297	0.0067	0.0256	0.0163	0.0074	0.0104	0.0931	0.0619	0.3138	0.0666	0.0084	0.0097
M DEW 12P	0.0150	0.0471	0.0297	0.0067	0.0256	0.0163	0.0074	0.0104	0.0932	0.0620	0.3142	0.0667	0.0084	0.0097
PEPSI 2LT	0.0143	0.0449	0.0283	0.0063	0.0244	0.0156	0.0070	0.0099	0.0882	0.0586	0.2974	0.0635	0.0080	0.0092
PEPSI 6P	0.0178	0.0438	0.0293	0.0071	0.0261	0.0150	0.0100	0.0140	0.1064	0.0735	0.3316	0.0176	0.0119	0.0117
PEPSI 12P	0.0143	0.0449	0.0283	0.0064	0.0244	0.0156	0.0070	0.0099	0.0883	0.0587	0.2977	0.0635	0.0080	0.0092
PEPSI 24P	0.0139	0.0449	0.0283	0.0063	0.0244	0.0156	0.0069	0.0097	0.0874	0.0579	0.2965	0.0657	0.0078	0.0091
RC COLA 12P	0.0145	0.0457	0.0288	0.0065	0.0248	0.0158	0.0071	0.0100	0.0900	0.0598	0.3032	0.0646	0.0081	0.0094
SPRITE 2LT	0.0130	0.0410	0.0258	0.0058	0.0224	0.0143	0.0064	0.0090	0.0795	0.0528	0.2684	0.0579	0.0072	0.0082
SPRITE 12P	0.0130	0.0411	0.0258	0.0058	0.0224	0.0143	0.0064	0.0090	0.0796	0.0528	0.2685	0.0579	0.0072	0.0083
SPRITE ZR 12P	0.0123	0.0389	0.0244	0.0055	0.0214	0.0136	0.0060	0.0085	0.0751	0.0498	0.2535	0.0549	0.0068	0.0078
SUNKIST 12P	0.0137	0.0432	0.0272	0.0061	0.0235	0.0150	0.0067	0.0095	0.0843	0.0560	0.2843	0.0610	0.0076	0.0088

Notes: 2LT= 2-liter (single bottle (67.9 oz.)); 6P= 6 Packs (16.9 oz. each) 1; 12P=12 Packs (12 oz. each); 24P= 24 Packs (12 oz. each); RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLS= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3.4. Continued

	COKE ZR 12P	COKE ZR 24P	DI 7UP 12P	DI COKE 2LT	DI COKE 6P	DI COKE 12P	DI COKE 24P	DI DR PEP 2LT	DI DR PEP 6P	DI DR PEP 12P	DI PEPSI 2LT	DI PEPSI 6P	DI PEPSI 12P	DR PEP 2LT
7UP 2LT	0.0296	0.0054	0.0122	0.0294	0.0285	0.1216	0.0275	0.0143	0.0145	0.0706	0.0082	0.0124	0.0271	0.0565
7UP 12P	0.0297	0.0054	0.0122	0.0294	0.0285	0.1217	0.0275	0.0143	0.0145	0.0707	0.0082	0.0124	0.0271	0.0566
A&W RT-BR 12P	0.0300	0.0055	0.0124	0.0298	0.0288	0.1231	0.0278	0.0144	0.0147	0.0715	0.0083	0.0125	0.0274	0.0574
A&W CRM-SD 12P	0.0300	0.0055	0.0124	0.0298	0.0289	0.1232	0.0278	0.0144	0.0147	0.0715	0.0083	0.0126	0.0274	0.0574
CFFR DI COKE 12P	0.0282	0.0052	0.0117	0.0280	0.0271	0.1159	0.0263	0.0136	0.0138	0.0673	0.0078	0.0117	0.0258	0.0533
CFFR DI DR PEP 12P	0.0282	0.0052	0.0117	0.0280	0.0271	0.1158	0.0262	0.0136	0.0138	0.0673	0.0078	0.0117	0.0258	0.0533
CND DRY 2LT	0.0297	0.0054	0.0122	0.0294	0.0285	0.1216	0.0275	0.0143	0.0145	0.0706	0.0082	0.0124	0.0271	0.0565
CND DRY 12P	0.0297	0.0054	0.0122	0.0294	0.0285	0.1217	0.0275	0.0143	0.0145	0.0707	0.0082	0.0124	0.0271	0.0566
COKE CLS 2LT	0.0324	0.0059	0.0132	0.0321	0.0312	0.1328	0.0298	0.0156	0.0159	0.0769	0.0089	0.0137	0.0294	0.0620
COKE CLS 6P	0.0324	0.0059	0.0132	0.0322	0.0312	0.1330	0.0298	0.0156	0.0159	0.0770	0.0089	0.0137	0.0295	0.0620
COKE CLS 12P	0.0324	0.0059	0.0132	0.0321	0.0312	0.1329	0.0298	0.0156	0.0159	0.0770	0.0089	0.0137	0.0294	0.0620
COKE CLS 24P	0.0292	0.0059	0.0131	0.0315	0.0296	0.1276	0.0324	0.0149	0.0142	0.0762	0.0087	0.0129	0.0296	0.0590
COKE ZR 2LT	0.0307	0.0056	0.0126	0.0305	0.0296	0.1261	0.0284	0.0148	0.0151	0.0731	0.0085	0.0129	0.0280	0.0582
COKE ZR 6P	0.0378	0.0057	0.0135	0.0345	0.0347	0.1353	0.0213	0.0173	0.0204	0.0770	0.0090	0.0129	0.0286	0.0686
COKE ZR 12P	-4.4102	0.0056	0.0126	0.0305	0.0296	0.1262	0.0284	0.0148	0.0151	0.0732	0.0085	0.0129	0.0280	0.0583
COKE ZR 24P	0.0277	-4.2163	0.0127	0.0297	0.0281	0.1215	0.0309	0.0142	0.0133	0.0730	0.0083	0.0122	0.0282	0.0557
DI 7UP 12P	0.0282	0.0052	-3.9058	0.0280	0.0271	0.1158	0.0262	0.0136	0.0138	0.0673	0.0078	0.0117	0.0258	0.0533
DI COKE 2LT	0.0317	0.0058	0.0129	-3.5500	0.0305	0.1301	0.0292	0.0152	0.0156	0.0754	0.0087	0.0134	0.0288	0.0602
DI COKE 6P	0.0318	0.0058	0.0129	0.0315	-5.0457	0.1303	0.0292	0.0153	0.0156	0.0755	0.0087	0.0134	0.0289	0.0603
DI COKE 12P	0.0317	0.0058	0.0129	0.0315	0.0306	-4.3452	0.0292	0.0153	0.0156	0.0754	0.0087	0.0134	0.0289	0.0602
DI COKE 24P	0.0307	0.0059	0.0130	0.0313	0.0301	0.1288	-4.4501	0.0151	0.0148	0.0753	0.0086	0.0132	0.0290	0.0595

Notes: 2LT= 2-liter (single bottle (67.9 oz.)); 6P= 6 Packs (16.9 oz. each) 1; 12P=12 Packs (12 oz. each); 24P= 24 Packs (12 oz. each); RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLS= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3.4. Continued

	COKE ZR 12P	COKE ZR 24P	DI 7UP 12P	DI COKE 2LT	DI COKE 6P	DI COKE 12P	DI COKE 24P	DI DR PEP 2LT	DI DR PEP 6P	DI DR PEP 12P	DI PEPSI 2LT	DI PEPSI 6P	DI PEPSI 12P	DR PEP 2LT
DI DR PEP 2LT	0.0313	0.0057	0.0128	0.0310	0.0301	0.1283	0.0288	-3.1637	0.0153	0.0744	0.0086	0.0132	0.0285	0.0593
DI DR PEP 6P	0.0313	0.0057	0.0128	0.0311	0.0302	0.1286	0.0289	0.0151	-4.8519	0.0745	0.0086	0.0132	0.0285	0.0595
DI DR PEP 12P	0.0313	0.0057	0.0128	0.0311	0.0301	0.1285	0.0289	0.0151	0.0154	-3.9263	0.0086	0.0132	0.0285	0.0594
DI PEPSI 2LT	0.0308	0.0056	0.0126	0.0305	0.0296	0.1264	0.0284	0.0148	0.0151	0.0733	-3.1928	0.0129	0.0280	0.0584
DI PEPSI 6P	0.0427	0.0044	0.0134	0.0368	0.0381	0.1411	0.0134	0.0194	0.0245	0.0761	0.0098	-5.1328	0.0268	0.0778
DI PEPSI 12P	0.0308	0.0056	0.0126	0.0306	0.0297	0.1265	0.0284	0.0148	0.0151	0.0733	0.0085	0.0130	-4.0038	0.0584
DR PEP 2LT	0.0331	0.0060	0.0134	0.0328	0.0319	0.1358	0.0304	0.0159	0.0163	0.0786	0.0091	0.0140	0.0300	-3.2810
DR PEP 6P	0.0332	0.0060	0.0135	0.0329	0.0319	0.1361	0.0304	0.0159	0.0163	0.0788	0.0091	0.0140	0.0301	0.0636
DR PEP 12P	0.0331	0.0060	0.0135	0.0329	0.0319	0.1359	0.0304	0.0159	0.0163	0.0787	0.0091	0.0140	0.0301	0.0635
FANTA 12P	0.0299	0.0055	0.0123	0.0296	0.0287	0.1227	0.0277	0.0144	0.0146	0.0712	0.0083	0.0125	0.0273	0.0571
M DEW 2LT	0.0346	0.0063	0.0140	0.0343	0.0334	0.1419	0.0316	0.0166	0.0170	0.0821	0.0095	0.0147	0.0313	0.0665
M DEW 12P	0.0347	0.0063	0.0140	0.0344	0.0334	0.1421	0.0317	0.0167	0.0171	0.0822	0.0095	0.0147	0.0314	0.0666
PEPSI 2LT	0.0328	0.0060	0.0134	0.0326	0.0316	0.1347	0.0302	0.0158	0.0161	0.0780	0.0090	0.0139	0.0298	0.0629
PEPSI 6P	0.0451	0.0041	0.0139	0.0389	0.0401	0.1499	0.0124	0.0203	0.0258	0.0799	0.0103	0.0144	0.0282	0.0825
PEPSI 12P	0.0329	0.0060	0.0134	0.0326	0.0317	0.1348	0.0302	0.0158	0.0162	0.0781	0.0090	0.0139	0.0298	0.0630
PEPSI 24P	0.0325	0.0061	0.0133	0.0323	0.0313	0.1342	0.0309	0.0155	0.0158	0.0781	0.0090	0.0138	0.0300	0.0618
RC COLA 12P	0.0335	0.0061	0.0136	0.0332	0.0322	0.1373	0.0307	0.0161	0.0165	0.0794	0.0092	0.0142	0.0304	0.0642
SPRITE 2LT	0.0297	0.0054	0.0122	0.0294	0.0285	0.1216	0.0275	0.0143	0.0145	0.0706	0.0082	0.0124	0.0271	0.0565
SPRITE 12P	0.0297	0.0054	0.0122	0.0294	0.0285	0.1217	0.0275	0.0143	0.0145	0.0707	0.0082	0.0124	0.0271	0.0566
SPRITE ZR 12P	0.0282	0.0052	0.0117	0.0280	0.0271	0.1159	0.0263	0.0136	0.0138	0.0673	0.0078	0.0117	0.0258	0.0533
SUNKIST 12P	0.0314	0.0057	0.0128	0.0311	0.0302	0.1287	0.0289	0.0151	0.0154	0.0746	0.0087	0.0132	0.0286	0.0600

Notes: 2LT= 2-liter (single bottle (67.9 oz.)); 6P= 6 Packs (16.9 oz. each) 1; 12P=12 Packs (12 oz. each); 24P= 24 Packs (12 oz. each); RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLS= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

Table 3.4. Continued

	DR PEP 6P	DR PEP 12P	FANTA 12P	M DEW 2LT	M DEW 12P	PEPSI 2LT	PEPSI 6P	PEPSI 12P	PEPSI 24P	RC COLA 12P	SPRITE 2LT	SPRITE 12P	SPRITE ZR 12P	SUNKIST 12P
DI DR PEP 2LT	0.0319	0.2563	0.0164	0.0076	0.0279	0.0292	0.0252	0.1006	0.0141	0.0129	0.0258	0.0681	0.0177	0.0444
DI DR PEP 6P	0.0320	0.2569	0.0164	0.0076	0.0280	0.0293	0.0253	0.1008	0.0141	0.0130	0.0258	0.0682	0.0177	0.0445
DI DR PEP 12P	0.0319	0.2566	0.0164	0.0076	0.0280	0.0292	0.0253	0.1007	0.0141	0.0130	0.0258	0.0681	0.0177	0.0444
DI PEPSI 2LT	0.0314	0.2523	0.0162	0.0074	0.0275	0.0287	0.0248	0.0990	0.0139	0.0127	0.0254	0.0671	0.0175	0.0437
DI PEPSI 6P	0.0540	0.2592	0.0188	0.0093	0.0288	0.0331	0.0257	0.0954	0.0095	0.0119	0.0308	0.0781	0.0198	0.0393
DI PEPSI 12P	0.0314	0.2526	0.0162	0.0075	0.0275	0.0288	0.0248	0.0991	0.0139	0.0128	0.0255	0.0672	0.0175	0.0438
DR PEP 2LT	0.0342	0.2739	0.0175	0.0081	0.0300	0.0312	0.0272	0.1074	0.0150	0.0138	0.0275	0.0724	0.0187	0.0473
DR PEP 6P	-4.9365	0.2744	0.0175	0.0081	0.0300	0.0313	0.0272	0.1076	0.0150	0.0139	0.0275	0.0725	0.0187	0.0474
DR PEP 12P	0.0343	-3.8860	0.0175	0.0081	0.0300	0.0312	0.0272	0.1075	0.0150	0.0139	0.0275	0.0725	0.0187	0.0473
FANTA 12P	0.0306	0.2473	-4.1863	0.0073	0.0269	0.0282	0.0241	0.0971	0.0136	0.0125	0.0251	0.0661	0.0171	0.0431
M DEW 2LT	0.0360	0.2868	0.0182	-3.5514	0.0314	0.0327	0.0287	0.1123	0.0157	0.0145	0.0286	0.0755	0.0194	0.0493
M DEW 12P	0.0360	0.2872	0.0182	0.0085	-4.3067	0.0327	0.0287	0.1125	0.0157	0.0145	0.0287	0.0755	0.0194	0.0494
PEPSI 2LT	0.0339	0.2717	0.0174	0.0081	0.0297	-3.4126	0.0269	0.1065	0.0149	0.0137	0.0273	0.0719	0.0185	0.0469
PEPSI 6P	0.0576	0.2757	0.0200	0.0100	0.0308	0.0351	-5.2218	0.1010	0.0093	0.0125	0.0328	0.0837	0.0209	0.0417
PEPSI 12P	0.0340	0.2719	0.0174	0.0081	0.0297	0.0310	0.0270	-4.0027	0.0149	0.0137	0.0273	0.0719	0.0185	0.0470
PEPSI 24P	0.0332	0.2722	0.0173	0.0080	0.0298	0.0309	0.0265	0.1072	-3.9047	0.0138	0.0270	0.0716	0.0185	0.0472
RC COLA 12P	0.0347	0.2770	0.0177	0.0082	0.0303	0.0316	0.0276	0.1086	0.0152	-4.1628	0.0277	0.0731	0.0188	0.0478
SPRITE 2LT	0.0303	0.2448	0.0158	0.0072	0.0266	0.0279	0.0239	0.0962	0.0135	0.0124	-3.4250	0.0655	0.0170	0.0427
SPRITE 12P	0.0304	0.2450	0.0158	0.0072	0.0266	0.0279	0.0239	0.0963	0.0135	0.0124	0.0248	-4.1705	0.0170	0.0427
SPRITE ZR 12P	0.0285	0.2311	0.0149	0.0068	0.0251	0.0263	0.0224	0.0909	0.0128	0.0117	0.0235	0.0620	-4.2992	0.0403
SUNKIST 12P	0.0323	0.2596	0.0167	0.0077	0.0283	0.0296	0.0255	0.1019	0.0143	0.0131	0.0262	0.0690	0.0178	-3.9059

Notes: 2LT= 2-liter (single bottle (67.9 oz.)); 6P= 6 Packs (16.9 oz. each) 1; 12P=12 Packs (12 oz. each); 24P= 24 Packs (12 oz. each); RT-BR= Root Beer, CRM-SD=Cream Soda, CFFR= Caffeine Free; DI= Diet, DR PEP= Dr Pepper; CND DRY= Canada Dry; CLS= Classic; ZR= Zero; M Dew= Mountain Dew; RC= Royal Crown; Shaded values are own-price elasticities.

3.6 Conclusion

This chapter estimates an analysis of differentiated demand for carbonated soft drinks (CSDs) at the brand and bottle-size levels in Dallas, Texas. There are 20 CSD brands at the brand level and 42 CSD brands at the bottle-size level. The random coefficient logit model by BLP (1995) is used for the demand analysis because it solves dimensionality problems arising from many brands in the differentiated goods demand analysis, taking into account consumer heterogeneity and deals with endogenous prices. Moreover, it provides unrestrictive substitution patterns.

Brand level demand estimation results indicate that consumers prefer CSD brands with low price, high caffeine, and low calorie, on average. On the other hand, bottle-size level estimation shows that CSD brands with lower prices, higher caffeine, and higher calorie content are more favorable for consumers.

Furthermore, brand level demand estimation results indicate that households with no children are less price-sensitive than households with one or more children, and low-income households are less sensitive to CSDs prices than middle-income and high-income households. Contrarily, in the bottle-size level estimation, high-income households are less sensitive to CSD prices than other income categories. Furthermore, households with no children are more price-sensitive than households with children. Comparing the indications of price parameters by income and the number of children, they are opposite in bottle-size level and the brand level estimation.

Moreover, brand level estimation results show that some consumers view calorie of CSDs as less favorable while others think higher calories are better. Some households see calories as positive regardless of their income. Moreover, households with three and more children are more calorie sensitive. In contrast, households with no children are less sensitive to the drinks' calories, and even some households with no children perceive calories positively. At the bottle-size level, all calorie parameters are positive, but calories are more favorable for high-income households than middle- and low-income households. Regardless of having children or not, all households value the calorie content of CSDs positively. The implications of bottle-size demand results regarding calorie parameter by income and the number of children are not parallel compared to the brand level.

Further, brand level demand results show that estimated caffeine parameters are positive for all households. Households with no children care more about caffeine content in CSDs and with one or more children prefer less caffeine content. Besides, there is no particular pattern in the distribution of caffeine parameters by income in the brand level estimation. At the bottle-size level, high-income households prefer high caffeine drinks more than other income categories. Like calorie parameters, households value caffeine content positively without a matter of the number of children in the household.

At the brand level, own-price elasticities range between -1.9 (RC Cola) to -3.2 (Coke Zero) with the median of -2.39 and the mean of -2.48. The bottle-size level's own-price elasticities are bigger in magnitude; they range between -3.06 (7 Up 2-liter single pack) to -5.48 (Coke Zero 6 packs of 16.9 oz.) with a median of -4.06 and a mean of -4.08. For both demand estimation levels, the magnitude of own-price elasticities indicates that consumers are sensitive to CSD prices.

All cross-price elasticities for both levels are positive, and it implies that the products are substitutes. Brand level cross-price elasticities are positive and range from 0.0030 to 0.3115, while bottle-size level cross-price elasticities are between 0.0041 to 0.3316. Magnitudes of cross-price elasticities are low comparing to own-price elasticities in both levels of demand. It supports that consumers have brand loyalty, and they switch to the outside good rather than another brand of carbonated soft drinks even if they are sensitive to CSDs prices of their chosen brands.

Furthermore, in both level demands, cross-price elasticities show that consumers are brand loyal, and they are more responsive to changes of the leading brands (i.e., Coke Classic and Dr Pepper in the brand level and Coke Classic 12 packs of 12 oz. and Dr Pepper 12 packs of 12 oz. in the bottle-size level). For example, an increase in the price of Coke Classic brand leads to a higher percentage change in the quantity demanded of a nonleading brand (i.e., RC Cola) than comparing to the case of increase in the nonleading brand price, quantity demanded of Coke Classic change in a lower percentage.

CHAPTER 4

MARKET POWER OF THE CARBONATED SOFT DRINKS INDUSTRY

4.1 Introduction

In this chapter, I report the estimates of the market power for soft drinks at the Dallas metropolitan area's brand and bottle-size levels. There are three major CSDs companies: the Coca-Cola Co., PepsiCo, and Dr Pepper Snapple Group. Market power for two different aggregation levels for brands, namely brand level and bottle-size level brands, are analyzed and compared. There are 20 brands in the brand level (i.e., Coke Classic, Diet Pepsi, and 7 Up). In the second level of aggregation, brands with different package sizes are considered as separate products, and there are 42 bottle-size level brands (i.e., Diet Pepsi 12 packs 12 oz. cans, Diet Pepsi 67.6 oz. single plastic bottle, and Coke Classic 6 packs 16.9 oz. plastic bottles). Two different pricing conducts, Bertrand-Nash and joint-profit maximization, are evaluated under both demand analyses.

The next section includes a literature review of market power. Sections 4.3 and 4.4 present the theoretical frameworks and methods. Section 4.5 presents the empirical results of market power and its implications for the carbonated soft drinks industry. Section 4.6 discusses and concludes the chapter.

4.2 Literature Review of the Market Power

Two common approaches empirically focus on estimating and examining market power in Industrial Organizations (IO) literature. The first one is the Structure Conduct Performance Paradigm (SCPP), and the second one is the New Empirical Industrial Organizations (NEIO).

The SCPP is known as the traditional approach to estimate market power and pricing conducts. It is the early work of the empirical IO, and it dates back to the 1950s Bain's seminal work (1951). The SCCP emphasizes the relationship between structure, conduct, and performance, as its name implies. The structure of a market includes characteristics such as the concentration of the market, growth, scale economies, barriers to entry, and the degree of product differentiation (Kadiyali et al., 2001; Martin, 2002). Further, a firm's conduct is related to marketing mix variables (i.e., price, product, promotion, place) decisions, entering a market, and research and development investments. Finally, industry performance is defined by profitability and innovation rate (Kadiyali et al., 2001; Martin, 2002).

The SCCP framework states that a market structure's characteristics define a firm's conduct, which determines the market performance. However, this may not be true because of relationships between structure, conduct, and performance that do not necessarily have a causal link. For example, the structure of a market and its profitability may affect firms' conduct and influence the market structure and profitability. Therefore, the relationships among structure, conduct, and performance are correlational instead of causal (Kadiyali et al., 2001). The definition of the SCPP models implies this one-way relationship, and it causes an endogeneity problem.

The second issue with the SCCP is that there is a data problem because of its unavailability and measurement. Cost data is needed to do this analysis, and mostly it is hard to find data that provides marginal cost. Many studies used accounting costs, which give average cost (AC) instead of marginal cost (MC), and using these types of data makes the analysis suspicious (Kadiyali et al., 2001). The suspicion arises because the average cost and marginal cost are different measures of cost.

Another issue is that the SCPP examines relationships between structure, firm behavior, and profitability across industries instead of exploring them within a specific industry. It gives broad points across industries. This approach of the SCCP is highly criticized since the marketing mix and profitability relationships differ across industries because of demand and cost structure differences. Game theory by the breakthrough in the late 1970s shows that marketing mix choices and profitability are not the only functions of broad structural characteristics. That is why SCPP cannot capture heterogeneity across industries and firms. The heterogeneity can be captured effectively by modeling the relationship in a specific industry (Kadiyali et al., 2001).

On the other hand, NEIO primarily focuses on a specific industry or closely related markets, unlike the SCCP's across industry studies. Hence, it provides a more insightful view of firms' conduct in a particular sector. NEIO, proposed by Bresnahan (1989), does not require cost data to analyze market power and firms' conduct. It allows using market data, and it is possible to get marginal costs reversely by using the Lerner index.

NEIO is a structural model of firms' strategic and competitive behavior, and Kadiyali et al. (2001) emphasize that this kind of approach has some advantages. The first advantage is "theory testing." The structural approach compares and tests strategic behavior alternatives by choosing a theoretical model that fits the best market data. The second advantage is "ease of interpretation." The basis of structural models is to optimize the behavior of firms, such as profit maximization. Therefore, there are economical and behavioral responses on the estimated parameters which provide relevant interpretations.

The third advantage, highlighted by Kadiyali et al. (2001), is "what-if analysis." Decision-makers can use the estimated parameters of structural models to evaluate different scenarios and actions on the market. The last advantage is "decomposing the determinants of market power and profitability." The Lerner index is used in NEIO studies to measure market power, and market power is the indicator of the firms' profitability.

Structural NEIO models include three components, which are demand structure, cost structure, and competitive reactions, to measure market power and to examine the source of profitability differences among firms. When the industry's structure or closely related markets are examined, firms can make their marketing mix variables decisions (Kadiyali et al., 2001).

Demand models have a wide range of specifications in NEIO literature such as linear demand (Kadiyali et al., 1996), log-linear (Kadiyali et al., 2000), double-log (Bresnahan, 1987), LA-AIDS (Rojas, 2008), and discrete choice models (BLP, 1995; Nevo, 2001; Sudhir, 2001; Chidmi and Murova 2011). In contrast, cost specification can be a constant marginal cost (MC) (most of the studies, i.e., Kadiyali et al., 1996) or linear (Besanko et al., 1998) or log-linear (Sudhir, 2001) function of factor cost.

Competitive reaction specifications are approached in two ways: the conjectural variation approach (i.e., Vilcassim et al.,1999; Appelbaum, 1982; Gollop and Roberts, 1979) and the menu approach (i.e., Roy et al., 1994; Kadiyali et al., 1996; Villas-Boas and Zhao, 2005; Bonnet and Dubois, 2010; Chidmi and Murova, 2011; Besanko et al., 1998; Chintagunta and Jain, 1995; Dhar et al., 2005).

The conjectural variation (CV) approach, proposed by Iwata (1974), estimates a conduct parameter that measures the degree of competition among firms in an industry or a market. Concisely, the CV approach focuses on capturing the firms' conduct by a single parameter. However, it has been criticized for some issues. It is asserted that CV cannot measure market power accurately because of mismeasuring the degree of competition (Corts, 1999). Additionally, Nevo (1998) discusses the identification problem of the conduct parameter because an increase in the number of firms and marketing variables in the analysis makes the identification of CV models most likely impossible (Kadiyali et al., 2001).

In the menu approach, the first-order conditions (FOCs) are derived for each equilibrium scenario, such as Bertrand-Nash, Stackelberg leader-follower, and perfect collusion, and the equilibrium is chosen according to the best fit for the data. The menu approach offers two practical alternatives for price-setting behavior: the simultaneous approach (Gasmi et al., 1992; Chintagunta and Jain, 1995; Kadiyali et al., 1996; Sudhir, 2001; Berry et al., 1995; Besanko et al., 1998; Chintagunta et al., 2006), and the two-step approach (Nevo, 2001; Chidmi and Lopez, 2007; Chidmi and Murova, 2011; Villas-Boas, 2007; Bonnet and Dubois, 2010).

In the simultaneous approach, demand and supply equations are estimated simultaneously; the simultaneity of the market share, price, and other marketing mix variables is considered. Additionally, this method deals with the endogeneity of prices and other marketing mix variables. In the two-step approach, the demand model is estimated, and these estimates are used to calculate price cost margins (PCMs). In this approach, the simultaneity of market shares and price and non-price decision variables is ignored, but the endogeneity of prices and other non-price variables is solved by the instrumental variables (IV) method (Nevo, 2001; Chidmi and Lopez, 2007; Villas-Boas, 2007).

Measuring market power by using NEIO is a prevalent empirical analysis in differentiated goods markets. The literature abounds of studies measuring market power. For instance, Nevo (2001) and Chidmi and Lopez (2007) estimate the market power in the ready to eat breakfast cereal market at the manufacturer and retailer's levels; Chidmi and Murova (2011) evaluate the market power of Seattle-Tacoma fluid milk retailers; Gasmi et al. (1992) and Dhar et al. (2005) examine market power in the case of carbonated soft drink industry. Other industry studies include Rojas (2008) for the beer market, Kadiyali et al. (1996) for the laundry detergent market, and Berry et al. (1995), and Sudhir (2001) for the automobile industry.

In a market, firms can exhibit different types of pricing conduct. For example, in Bertrand Nash equilibrium, each firm simultaneously makes its pricing decision and assumes that firms do not react to any change in rival's price change. Another possible pricing conduct scenario is perfect collusion, where firms are assumed to maximize the industry's profits jointly. Another scenario can be Stackelberg leader-follower conduct, where the followers choose their prices, and the leader foresees the followers' reaction and uses this information when deciding its pricing behavior.

Most of the studies assume Bertrand-Nash for pricing conduct due to its simplicity and the ease of empirical estimation. The Stackelberg leader-follower conduct becomes challenging to estimate when the number of players/brands increases. Most often, studies ignore the Stackelberg conduct even when they use the menu approach (see, for example, Berry (1994); Berry et al., (1995), Nevo (2001), Chidmi and Lopez (2007), and Villas-Boas (2007)). Only a few studies have considered Stackelberg leader-follower pricing conduct (i.e., Chidmi and Murova (2011); Rojas (2008); Kadiyali et al., (1996)) because of the limited number of players.

There is no single equilibrium of oligopolistic markets. Firms may have different pricing behaviors for different categories, such as different industries or different industry segments, different time frames, and different geographical markets. For example, Gasmi et al. (1992) find that until 1976, Coca-Cola behaved like a price leader, and Pepsi was the follower. After 1976, they find collusive behavior in advertising for Coca-Cola and PepsiCo in the CSD industry; besides, no evidence is found for collusive behavior in pricing.

Nevo (2001) finds that for the ready-to-eat cereal (RTEC) industry, Bertrand-Nash is a better fit as a price behavior. Sudhir (2001) finds different pricing behaviors in different segments of the automobile industry. For the full-sized cars segment, Bertrand-Nash behavior explains more the firms' behavior, while in the mid-size segment, firms have cooperative behavior, and for mini-compact and subcompact segments, aggressive pricing behavior is found.

Chidmi and Murova (2011) find that the Seattle-Tacoma milk market is more consistent with the Stackelberg equilibrium. Moreover, Rojas (2008) finds that Stackelberg is a better fit for the beer market. Additionally, Roy et al. (1994) find that Stackelberg's conduct is more consistent than the Bertrand-Nash pricing rule for the mid-size sedan segment for the U.S. automobile market. Kadiyali et al. (1996) examine price competition in the laundry detergent market and find that two companies, P&G and Lever, by selling two brands each have the position of Stackelberg leader for their strong brands while other small rivals are followers.

The menu approach requires evaluating and choosing between alternative models that present different pricing scenarios. Vuong's test (1989) is used to test alternative supply models that can be either nested or non-nested models. Rivers and Vuong (2002) is a generalized version of Voung (1989). It can be used in a wide range of estimation methods such as maximum likelihood estimation, GMM, nonlinear least squares, and some semiparametric estimators. Both Vuong (1989) and Rivers and Vuong (2002) do not require that the evaluated model is to be correctly specified under the tested null hypothesis while some approaches such as Cox's test expect to meet the requirement (Bonnet and Dubois, 2010). The Vuong test allows the analyzer to choose between models by selecting the asymptotically closer to the data.

The carbonated soft drink (CSD) industry is an interesting case for market power study. The industry represents oligopolistic competition with highly differentiated products with a few national companies. For the CSD industry, there are various approaches to the study of market power. Gasmi et al. (1992) use a menu approach to evaluate Coca-Cola Co and PepsiCo's market power using both price and advertising specifically to investigate a collusive behavior. They estimate demand and cost functions simultaneously and use Vuong's test (1989) for non-nested models to select the best fit for the data.

They test variation of six scenarios for Nash-Bertrand, Stackelberg, collusion in both price and advertising, and collusion in one dimension (advertising) and competition in the other (price). Additionally, due to the regime's potential change probably coming from the mid 70s sugar crisis, they examine market conduct before and after 1976 and test for additional four scenarios. In the first six scenarios, the best fit is on two models: total collusion of both prices and advertising and collusion on advertising and Nash-Bertrand competition on prices. After distinguishing the time frame before and after 1976, the best fit is that Coca-Cola is a price and advertising leader until 1976. After 1976, they collude in advertising and compete in prices.

Langan and Cotterill (1994) analyze regular soft drinks by using the AIDS model. They found a high correlation between Coke's and Pepsi's prices, but they do not confirm collusive pricing. Cotterill et al. (1996) measure the market power effect in differentiated product industries with the soft drink industry's application, and they find that product differentiation produces market power.

Golan et al. (2000) estimate two different oligopoly strategies, precisely Coke's and Pepsi's price and advertising strategies. In the first method, namely generalized maximum entropy (GME), firms' strategies are based on variables that affect cost and demand. The second one is called the GME-Nash that includes game-theoretical restrictions. They use the same data as Gasmi et al. (1992) and include only a single product for each firm. The authors find that the profit-maximizing behavior is consistent with the data. They reject that GME and the GME-Nash are identical, which implies that Nash restrictions are compatible with the data.

By comparing the firms' strategies using the GME-Nash model, Golan et al. (2000) find that they have different strategies. For example, while Coke has a moderate price and a moderately intense advertising strategy, Pepsi has a high price and intensive advertising strategy. They calculate the Lerner Indices for Coke and Pepsi and compare them with Gasmi et al.'s (1992) results. GME-Nash estimates smaller market power than maximum likelihood (ML) Bertrand-Nash equilibrium. They indicate that this difference comes from cost estimates, where GME-Nash estimates considerably higher cost than ML Bertrand-Nash.

Dhar et al. (2005) estimate brand-level pure strategy models by using the conjectural variation model. The study only includes four brands of regular CSDs: Coke, Pepsi, Sprite, and Mountain Dew, unlike Gasmi et al. (1992) and Golan et al. (2002), which examine one brand for each company. Sprite is the only drink with no caffeine, and Sprite and Coke are produced by the Coca-Cola Co. while PepsiCo produces others. The study estimates a flexible nonlinear AIDS model and tests twelve representative games based on pure strategy. Some examples of the twelve games are 1) Coke leads Pepsi in a Stackelberg game, and the rest of the brands follow a Bertrand pricing conduct, 2) both firms follow Bertrand game, and 3) Pepsi leads Coke, and Sprite leads Mountain Dew in a Stackelberg game, and the rest of the brands follow a Bertrand pricing conduct. The study rejects all games, and there is no evidence of collusion, Bertrand, and Stackelberg pricing conduct.

Besides, the results are more complicated. According to the finding of an asymmetric price conjecture between Coke and Pepsi, Coke is the market leader, plays a cooperative game, and expects Pepsi to follow its price. Still, Pepsi perceives Coke plays an aggressive game and expects it to decrease its price when Pepsi increases its price. Another possible result, according to the significance of the price conjectures, is that Coke expects Pepsi to play a Bertrand-Nash game or a cooperative game, but

Pepsi's expectation of Coke is aggressive on Coke's price but cooperative for Sprite's price.

Some studies in the literature approach the interest of the market vertically. They assume the market is vertically related and evaluate market power among retailers and wholesalers under this assumption. Allender and Richards (2012) assess wholesale and retail margins and assume Bertrand-Nash price competition. The wholesaler offers a price for the retailer by considering its response, and the retailer sets prices in a two-stage non-cooperative game framework for the US CSDs market. They find that wholesalers set their prices in a cooperative behavior rather than the Bertrand-Nash pricing rule. The authors suggest that because of competitiveness in retail stores, wholesalers may take advantage of the retailers' dependence on CSDs promotions; hence, wholesalers may extend their margins and profit. They emphasize that there is a possibility of wholesale competition for extending market share by introducing new products rather than using their prices. Bonnet and Requillart (2013) investigate the French soft drink market by examining possible vertical relationships. They find that manufacturers have the bargaining power, and retailers do not choose national brands' prices; besides, private labels do not affect the relationship between manufacturers and retailers. Therefore, they conclude manufacturers have the market power by having strong brands.

This study assumes a horizontal CSDs price competition at the manufacturers' level, unlike Allender and Richards (2012) and Bonnet and Requillart (2013), who assume vertical competition among CSDs manufacturers and retailers. Unlike market power studies of the CSDs market, such as Golan et al. (2000), Dhar et al. (2005), and Gasmi et al. (1992), who include a limited number of brands and analyzed the market power between only Coca-Cola Co and PepsiCo, this study also contains Dr Pepper/Snapple Group products and the vast majority of brands in CSDs market as well as their package sizes. There are two levels of aggregation for brands, and their implications for market power are investigated. The first one is at the brand level, such as Diet Dr Pepper, Fanta, and Pepsi, and the second one is at the bottle-size level. Each brand's package size is treated as a separate brand. For example, Diet Dr Pepper

16.9 oz. 6 packs plastic bottles, Sprite 67.9 oz, single plastic bottle, and Coke Classic 12 oz. 12 cans.

Mariuzzo et al. (2003) investigate firm size and market power relationships in the Irish CSD market. They detect markups vary by packaging such that 1.5- and 2-liters bottle markups are greater than cans and standard bottle sizes.

By adopting the menu approach to evaluate market power, estimating the substitution pattern between products is necessary. As discussed in the previous chapter, when the number of brands increases, it may create a dimensionality problem in demand estimation. This study adopts a flexible demand which is the random coefficient logit model that solves the dimensionality problem by projecting the products onto a characteristics space. Unlike classical demand models and the multinomial logit model, the random coefficient logit model provides unrestrictive substitution patterns and includes consumer heterogeneity by allowing taste parameters to vary across consumers.

This study examines the degree of competitiveness of Dallas, Texas, carbonated soft drinks' price competition. For the estimation, the two-step approach is used, hence firstly, the demand model is estimated, and these estimates are used to calculate price cost margins (PCMs). Using the menu approach, PCMs are evaluated under different pricing scenarios, namely Bertrand-Nash and joint-profit maximization. The menu approach allows the researcher to choose between alternative models, and Vuong's test is used for model selection by selecting a model that fits the best data.

4.3 Theoretical Framework

4.3.1 Bertrand-Nash

In the Bertrand-Nash equilibrium, each firm simultaneously makes its pricing decisions and assumes that firms do not react to any change in rival's price change.

Each firms' profit is given by

$$\pi_f = \sum_{j \in F_f} (p_j - mc_j) M s_j(p) \tag{4.1}$$

where p_j is the price of product *j* produced by firm *f*, mc_j is the marginal cost of product *j*, *M* is the market size, and s_j is the market share of product *j*.

This part is given for exposition purposes. Assume there are two firms (1 and 2) with five products: Firm 1 produces products 1,2, and 3, while firm 2 produces products 4 and 5.

Firm 1's and firm 2's profits are given by

$$\pi_1 = (p_1 - mc_1) M s_1(p) + (p_2 - mc_2) M s_2(p) + (p_3 - mc_3) M s_3(p) \tag{4.2}$$

$$\pi_2 = (p_4 - mc_4) M s_4(p) + (p_5 - mc_5) M s_5(p) \tag{4.3}$$

where p_1, p_2, p_3, p_4, and p_5 are the prices of brands 1, 2, 3, 4, and 5, mc_1, mc_2, mc_3, mc_4, and mc_5 are their corresponding marginal costs, s_1, s_2, s_3, s_4, and s_5 are their market shares, and *M* is the market size.

Firms 1's first-order conditions (FOCs) are given by

$$\frac{\partial \pi_1}{\partial p_1} = s_1(p) + (p_1 - mc_1)\frac{\partial s_1(p)}{\partial p_1} + (p_2 - mc_2)\frac{\partial s_2(p)}{\partial p_1} + (p_3 - mc_3)\frac{\partial s_3(p)}{\partial p_1} = 0 \tag{4.4}$$

$$\frac{\partial \pi_1}{\partial p_2} = s_2(p) + (p_1 - mc_1)\frac{\partial s_1(p)}{\partial p_2} + (p_2 - mc_2)\frac{\partial s_2(p)}{\partial p_2} + (p_3 - mc_3)\frac{\partial s_3(p)}{\partial p_2} = 0 \tag{4.5}$$

$$\frac{\partial \pi_1}{\partial p_3} = s_3(p) + (p_1 - mc_1)\frac{\partial s_1(p)}{\partial p_3} + (p_2 - mc_2)\frac{\partial s_2(p)}{\partial p_3} + (p_3 - mc_3)\frac{\partial s_3(p)}{\partial p_3} = 0$$

(4.6)

Firm 2's FOCs are given by

$$\frac{\partial \pi_2}{\partial p_4} = s_4(p) + (p_4 - mc_4)\frac{\partial s_4(p)}{\partial p_4} + (p_5 - mc_5)\frac{\partial s_5(p)}{\partial p_4} = 0$$

(4.7)

$$\frac{\partial \pi_2}{\partial p_5} = s_5(p) + (p_4 - mc_4)\frac{\partial s_4(p)}{\partial p_5} + (p_5 - mc_5)\frac{\partial s_5(p)}{\partial p_5} = 0$$

(4.8)

Note that firms do not react to any change in rival's price change. That is,

$$\frac{\partial p_1}{\partial p_4} = \frac{\partial p_2}{\partial p_4} = \frac{\partial p_3}{\partial p_4} = \frac{\partial p_1}{\partial p_5} = \frac{\partial p_2}{\partial p_5} = \frac{\partial p_3}{\partial p_5} = \frac{\partial p_4}{\partial p_1} = \frac{\partial p_4}{\partial p_2} = \frac{\partial p_4}{\partial p_3} = \frac{\partial p_5}{\partial p_1} = \frac{\partial p_5}{\partial p_2} = \frac{\partial p_5}{\partial p_3} = 0$$

The FOCs of all products can be written in a compact form as

$$s(p) + \Omega \frac{\partial s(p)}{\partial p}(p - mc) = 0$$

(4.9)

where Ω is the ownership matrix, with the elements Ω_{jk} equals one if the brands j and k are owned by the same firm, and it is zero otherwise.

We can then solve for the price-cost margins (PCM = p – mc) as

$$(p - mc) = -\,\Omega\left(\frac{\partial s(p)}{\partial p}\right)^{-1} s(p),$$

(4.10)

Price cost margins are functions of the demand parameters discussed in the previous chapter. From equation (3.22), we have

$$\frac{\partial s_j}{\partial p_k} = \begin{cases} \iint \alpha_i s_{ij}\left(1 - s_{ij}\right) dP_v^*(v)\, d\hat{P}_D^*(D) & if\ j = k \\ \iint \alpha_i s_{ij}\, s_{ik}\, dP_v^*(v)\, d\hat{P}_D^*(D) & if\ j \neq k \end{cases}$$

In our example, we can write equation (4.10) as

$$\begin{pmatrix} p_1 - mc_1 \\ p_2 - mc_2 \\ p_3 - mc_3 \\ p_4 - mc_4 \\ p_5 - mc_5 \end{pmatrix} = -\begin{pmatrix} 1\ 1\ 1\ 0\ 0 \\ 1\ 1\ 1\ 0\ 0 \\ 1\ 1\ 1\ 0\ 0 \\ 0\ 0\ 0\ 1\ 1 \\ 0\ 0\ 0\ 1\ 1 \end{pmatrix} \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \frac{\partial s_2}{\partial p_1} & \frac{\partial s_3}{\partial p_1} & \frac{\partial s_4}{\partial p_1} & \frac{\partial s_5}{\partial p_1} \\ \frac{\partial s_1}{\partial p_2} & \frac{\partial s_2}{\partial p_2} & \frac{\partial s_3}{\partial p_2} & \frac{\partial s_4}{\partial p_2} & \frac{\partial s_5}{\partial p_2} \\ \frac{\partial s_1}{\partial p_3} & \frac{\partial s_2}{\partial p_3} & \frac{\partial s_3}{\partial p_3} & \frac{\partial s_4}{\partial p_3} & \frac{\partial s_5}{\partial p_3} \\ \frac{\partial s_1}{\partial p_4} & \frac{\partial s_2}{\partial p_4} & \frac{\partial s_3}{\partial p_4} & \frac{\partial s_4}{\partial p_4} & \frac{\partial s_5}{\partial p_4} \\ \frac{\partial s_1}{\partial p_5} & \frac{\partial s_2}{\partial p_5} & \frac{\partial s_3}{\partial p_5} & \frac{\partial s_4}{\partial p_5} & \frac{\partial s_5}{\partial p_5} \end{pmatrix}^{-1} \begin{pmatrix} s_1(p) \\ s_2(p) \\ s_3(p) \\ s_4(p) \\ s_5(p) \end{pmatrix}$$

(4.11)

4.3.2 Joint-Profit Maximization

For the joint-profit maximization pricing conduct, firms jointly maximize the industry/market profit. Profit function is given by

$$\pi = (p_1 - mc_1)Ms_1(p) + (p_2 - mc_2)Ms_2(p) + (p_3 - mc_3)Ms_3(p) + (p_4 - mc_4)Ms_4(p) + (p_5 - mc_5)Ms_5(p)$$

(4.12)

The FOCs can be written in a compact way as

$$s(p) + \Omega \frac{\partial s(p)}{\partial p}(p - mc) = 0$$

(4.13)

Solving the FOCs for price cost margins yields

$$(p - mc) = -\,\Omega \left(\frac{\partial s(p)}{\partial p}\right)^{-1} s(p) \tag{4.14}$$

In our example, the joint-profit maximization implies the ownership matrix, Ω, is a matrix full of ones.

$$\begin{pmatrix} p_1 - mc_1 \\ p_2 - mc_2 \\ p_3 - mc_3 \\ p_4 - mc_4 \\ p_5 - mc_5 \end{pmatrix} = -\begin{pmatrix} 1\ 1\ 1\ 1\ 1 \\ 1\ 1\ 1\ 1\ 1 \\ 1\ 1\ 1\ 1\ 1 \\ 1\ 1\ 1\ 1\ 1 \\ 1\ 1\ 1\ 1\ 1 \end{pmatrix} \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \frac{\partial s_2}{\partial p_1} & \frac{\partial s_3}{\partial p_1} & \frac{\partial s_4}{\partial p_1} & \frac{\partial s_5}{\partial p_1} \\ \frac{\partial s_1}{\partial p_2} & \frac{\partial s_2}{\partial p_2} & \frac{\partial s_3}{\partial p_2} & \frac{\partial s_4}{\partial p_2} & \frac{\partial s_5}{\partial p_2} \\ \frac{\partial s_1}{\partial p_3} & \frac{\partial s_2}{\partial p_3} & \frac{\partial s_3}{\partial p_3} & \frac{\partial s_4}{\partial p_3} & \frac{\partial s_5}{\partial p_3} \\ \frac{\partial s_1}{\partial p_4} & \frac{\partial s_2}{\partial p_4} & \frac{\partial s_3}{\partial p_4} & \frac{\partial s_4}{\partial p_4} & \frac{\partial s_5}{\partial p_4} \\ \frac{\partial s_1}{\partial p_5} & \frac{\partial s_2}{\partial p_5} & \frac{\partial s_3}{\partial p_5} & \frac{\partial s_4}{\partial p_5} & \frac{\partial s_5}{\partial p_5} \end{pmatrix}^{-1} \begin{pmatrix} s_1(p) \\ s_2(p) \\ s_3(p) \\ s_4(p) \\ s_5(p) \end{pmatrix} \tag{4.15}$$

4.4 Methods

This study adopts the two-step estimation approach. In the first step, the demand is estimated using the random coefficient logit model. The demand estimates are then used to calculate the price-cost margins for each product and recover the marginal costs. The menu approach raises a need for choosing between alternative supply models. Since the supply models are non-nested, Vuong's test (Vuong, 1989 and Rivers and Vuong, 2002) is used to find the best-fitted supply model.

Rivers and Vuong (2002) is a generalized version of Voung (1989), and it can be used in a wide range of estimation methods, such as maximum likelihood estimation, generalized method of moments (GMM), nonlinear least squares, and some semiparametric estimators. Both Vuong (1989) and Rivers and Vuong (2002) do not require that the evaluated model is to be correctly specified under the tested null hypothesis while some approaches, such as Cox's test, expect to meet the requirement (Bonnet and Dubois, 2010).

For each supply model, the marginal cost is calculated and then regressed on marginal cost shifters. Vuong's test compares the asymptotic lack of criterion among the supply models.

Let H denotes the different pricing conducts considered in the previous section. We can calculate each supply model's marginal cost by using the implied price-cost margins for each brand. The marginal cost is given by

$$MC_j^H = p_j - pcm_j^H \tag{16}$$

where p_j is the price of brand j, $j = 1, \dots, J$, pcm_j^H is the price cost margins of the brand *j* under the supply model of H.

By assuming the marginal cost is affected by some exogenous cost shifters, W_j, we can estimate the marginal cost model given by

$$MC_j^H = \exp\left(\alpha^H + W_j'\beta^H\right)e^H$$

$$lnMC_j^H = \alpha^H + W_j'\beta^H + \varepsilon^H \tag{17}$$

where α^H and β^H are unknown parameters, W_j are exogenous cost shifters, $\varepsilon^H = lne^H$ and ε^H are unobservable random shocks to the marginal cost.

Using least squares, we estimate each supply model. To compare the two competing models H and H', the null hypothesis, H_0, that the two non-nested models are asymptotically equivalent is given by

$$H_0: \lim_{n\to\infty}\{\bar{Q}_n^H(\bar{\alpha}^H, \bar{\beta}^H) - \bar{Q}_n^{H'}(\bar{\alpha}^{H'}, \bar{\beta}^{H'})\} = 0, \tag{18}$$

where $\bar{Q}_n^H(\bar{\alpha}^H, \bar{\beta}^H)$ is the expectation of a lack of criterion Q_n^H evaluated for model H at the pseudo-true values of parameters $\bar{\alpha}^H$ and $\bar{\beta}^H$. Similarly, $\bar{Q}_n^{H'}(\bar{\alpha}^{H'}, \bar{\beta}^{H'})$ is the expectation of a lack of criterion $Q_n^{H'}$ evaluated for model H' at the pseudo-true values of parameters $\bar{\alpha}^{H'}$ and $\bar{\beta}^{H'}$. The lack of criterion is considered as the opposite of the goodness of fit criterion.

The first alternative hypothesis is that model H is asymptotically better than the model H' when

$$H_1: \lim_{n\to\infty}\{ \bar{Q}_n^H(\bar{\alpha}^H, \bar{\beta}^H) - \bar{Q}_n^{H'}(\bar{\alpha}^{H'}, \bar{\beta}^{H'})\} < 0 \tag{19}$$

Similarly, the second alternative hypothesis is that model H' is asymptotically better than model H when

$$H_2: \lim_{n\to\infty}\{ \bar{Q}_n^H(\bar{\alpha}^H, \bar{\beta}^H) - \bar{Q}_n^{H'}(\bar{\alpha}^{H'}, \bar{\beta}^{H'})\} > 0 \tag{20}$$

The test statistics T_n captures the statistical variation that indicates the sample values of the lack of fit criterion, and it is characterized as a suitably normalized difference of the sample lack of criteria. It is given by

$$T_n = \frac{\sqrt{n}}{\hat{\sigma}_n^{HH'}} \{Q_n^H\left(\hat{\alpha}^H, \hat{\beta}^H\right) - Q_n^{H'}(\hat{\alpha}^{H'}, \hat{\beta}^{H'})\}, \tag{21}$$

where $Q_n^H\left(\hat{\alpha}^H, \hat{\beta}^H\right)$ is the sample lack of fit variation evaluated for the model H at the model's estimated parameters $\hat{\alpha}^H$ and $\hat{\beta}^H$, $Q_n^{H'}\left(\hat{\alpha}^{H'}, \hat{\beta}^{H'}\right)$ is the sample lack of fit variation evaluated in the model H' at the model's estimated parameters $\hat{\alpha}^{H'}$ and $\hat{\beta}^{H'}$, and $\hat{\sigma}_n^{HH'}$ is the estimated variance of the difference of the lack of fit criterion between the two models. Rivers and Vuong (2002) show that the asymptotic distribution of the test statistics T_n follows a standard normal distribution.

4.5 Empirical Results

Under two pricing conducts, both brand level and bottle-size level price-cost margins are computed from their demand parameter estimates using the random coefficients logit model. Then marginal costs are recovered from price-cost margins by subtracting prices. Lerner Index is a measure of market power, and it is calculated by dividing the price-cost margin by the price. Lerner Index for brand j is given by

$$LI_j = \frac{p_j - mc_j}{p_j} \tag{4.22}$$

As seen from equation (4.22), Lerner Index is a percentage markup of price over marginal cost, and it ranges from 0 to 1, $0 < LI_j < 1$. When the Lerner index is zero, the market is perfectly competitive, and there is no market power. When it is equal to one, we have a monopoly or joint-profit maximization market. When the Lerner Index between 0 to 1, firms exert some market power.

Table 4.1 presents the results of the computed price-cost margins, Lerner index, and marginal cost at the brand level under different pricing conducts, namely Bertrand-Nash and joint-profit maximization. I also added the price to have a complete picture of the pricing behavior.

Under Bertrand-Nash, the mean of marginal costs, price-cost margins, and Lerner indices are lower than under the joint-profit maximization scenario. It is consistent with the economic theory that a higher Lerner index represents higher market power. Thus the joint-profit maximization case implies higher Lerner indices for the brands.

As seen in table 4.1, under joint-profit maximization, some of the estimated marginal costs are negative, which is unrealistic. This is because the Lerner index has to be between 0 and 1; some of the Lerner indices are greater than one because of negative marginal cost. Before moving to Vuong's test, which tells which model is asymptotically better, we can say that the brand level joint-profit maximization scenario seems unrealistic. Intuitively, we expect that this scenario needs to be rejected.

Table 4. 1: Summary Statistics of the Variables in the Brand Level Under Different Pricing Conducts

	Variables	Mean	Standard Deviation	Min	Max
	Price	0.0232	0.0026	0.0161	0.0309
Under Bertrand-Nash					
	Marginal cost	0.0117	0.0037	0.0006	0.0212
	Price-cost margins	0.0114	0.0016	0.0070	0.0162
	Lerner Index	0.5039	0.1142	0.2734	0.9614
Under Joint-Profit Maximization					
	Marginal cost	0.0058	0.0049	-0.0091	0.0168
	Price-cost margins	0.0174	0.0029	0.0116	0.0254
	Lerner Index	0.7681	0.1991	0.4179	1.5610

Table 4.2 presents summary statistics of variables at the bottle-size level brands under two pricing conduct. Similar to the brand level estimation, marginal costs, price-cost margins, and Lerner indices are higher under the joint-profit maximization scenario than Bertrand-Nash. Unlike the brand level, bottle-size level brands do not include any negative marginal costs in both pricing conducts. Therefore, the Lerner index lies between 0 and 1. Thus, it is consistent with the theory.

Table 4. 2: Summary Statistics of the Variables in the Bottle-Size Level Under Different Pricing Conducts

	Variables	Mean	Standard Deviation	Min	Max
	Price	0.0218	0.0035	0.0123	0.0347
Under Bertrand-Nash					
	Marginal cost	0.0152	0.0038	0.0058	0.0297
	Price-cost margins	0.0066	0.0010	0.0042	0.0095
	Lerner Index	0.3105	0.0764	0.1444	0.5811
Under Joint-Profit Maximization					
	Marginal cost	0.0120	0.0043	0.0002	0.0277
	Price-cost margins	0.0098	0.0015	0.0069	0.0143
	Lerner Index	0.4652	0.1239	0.2013	0.9848

Table 4.3 presents the same results as Table 4.1, but it is for each brand, while Table 4.4 contains the bottle-size level brands results. The Lerner Index is relatively higher at the brand level under both pricing conducts than the one at the bottle-size level. Lerner index under Bertrand-Nash pricing conduct ranges from 39% to 62% at the brand level, while in the case of joint-profit maximization, the Lerner index ranges from 62% to 91%. On the other hand, for the bottle-size level under Bertrand-Nash pricing conduct, the Lerner index ranges from 20% to 39%. It varies from 31% to 58% under the joint-profit maximization game. Again, both level brands' results are consistent with the theory because joint-profit maximization implies a higher Lerner index than Bertrand-Nash.

Golan et al. (2000) analyze only two CSD brands, Coke and Pepsi, using the generalized maximum entropy Nash model. They find that Coke's Lerner index is 24%, and the Lerner index of Pepsi is 27%. Additionally, Golan et al. (2000) calculate Lerner indices from Gasmi et al.'s (1992) model of Bertrand-Nash and find that Coke has 42% and Pepsi has 45%. Furthermore, Dhar et al. (2005) find that Coke's Lerner index is 32% in conjectural variation game, 26% in Bertrand-Nash game, and 72% in a collusion game. Additionally, they find that Lerner indices for Sprite are 37%, 29%, and 19%; for Pepsi, they are 32%, 26%, and 67%; and for Mountain Dew, they are

51%, 46%, and 63%, in conjectural variation game, Bertrand-Nash game, and collusive game, respectively. In our findings of brand level price competition estimation, Lerner indices under Bertrand-Nash and joint-profit maximization scenarios are higher than the studies of Golan et al. (2000), Gasmi et al. (1992), and Dhar et al. (2005).

Table 4. 3: Brand Level Brands Marginal Costs, Price Cost Margins, and Lerner Indices Under Different Pricing Conducts

		Bertrand-Nash			Joint-Profit Maximization		
Brands	Average Price	MC	PCM	Lerner Index	MC	PCM	Lerner Index
By the Coca-Cola Co.							
Caffeine Free Diet Coke	0.0210	0.0135	0.0108	0.4495	0.0081	0.0162	0.6793
		(0.0031)	(0.0013)	(0.0889)	(0.0043)	(0.0027)	(0.1629)
Coke Classic	0.0216	0.0117	0.0128	0.5304	0.0064	0.0180	0.7495
		(0.0033)	(0.0014)	(0.1026)	(0.0045)	(0.0028)	(0.1749)
Coke Zero	0.0220	0.0155	0.0110	0.4225	0.0101	0.0164	0.6279
		(0.0033)	(0.0013)	(0.0835)	(0.0045)	(0.0027)	(0.1511)
Diet Coke	0.0266	0.0143	0.0111	0.4435	0.0090	0.0164	0.6561
		(0.0032)	(0.0013)	(0.0877)	(0.0045)	(0.0027)	(0.1581)
Fanta	0.0237	0.0110	0.0127	0.5466	0.0057	0.0181	0.7787
		(0.0037)	(0.0015)	(0.1140)	(0.0050)	(0.0028)	(0.1929)
Sprite	0.0200	0.0126	0.0124	0.5057	0.0072	0.0178	0.7259
		(0.0037)	(0.0014)	(0.1047)	(0.0049)	(0.0028)	(0.1788)
Sprite Zero	0.0230	0.0134	0.0108	0.4521	0.0079	0.0162	0.6833
		(0.0030)	(0.0013)	(0.0892)	(0.0043)	(0.0027)	(0.1635)
By PepsiCo							
Diet Pepsi	0.0238	0.0138	0.0089	0.3987	0.0064	0.0164	0.7318
		(0.0028)	(0.0009)	(0.0727)	(0.0044)	(0.0027)	(0.1754)
Mountain Dew	0.0230	0.0129	0.0113	0.4753	0.0058	0.0184	0.7784
		(0.0035)	(0.0011)	(0.0926)	(0.0051)	(0.0028)	(0.1931)
Pepsi	0.0211	0.0109	0.0108	0.5104	0.0036	0.0181	0.8565
		(0.0034)	(0.0011)	(0.1065)	(0.0051)	(0.0028)	(0.2249)
By Dr Pepper Snapple Group							
7 Up	0.0240	0.0103	0.0119	0.5457	0.0043	0.0178	0.8212
		(0.0032)	(0.0013)	(0.1103)	(0.0046)	(0.0028)	(0.2004)
A&W Root Beer	0.0226	0.0107	0.0122	0.5449	0.0047	0.0182	0.8116
		(0.0035)	(0.0014)	(0.1155)	(0.0049)	(0.0028)	(0.2068)
A&W Cream Soda	0.0250	0.0089	0.0123	0.5884	0.0030	0.0182	0.8745
		(0.0029)	(0.0014)	(0.1091)	(0.0042)	(0.0028)	(0.1992)
Caffeine Free Diet Dr Pepper	0.0245	0.0109	0.0101	0.4883	0.0048	0.0162	0.7834
		(0.0028)	(0.0012)	(0.0953)	(0.0041)	(0.0027)	(0.1886)
Canada Dry	0.0229	0.0114	0.0118	0.5161	0.0054	0.0178	0.7770
		(0.0027)	(0.0013)	(0.0893)	(0.0041)	(0.0028)	(0.1674)
Diet 7 Up	0.0223	0.0112	0.0101	0.4836	0.0051	0.0162	0.7761
		(0.0030)	(0.0012)	(0.1003)	(0.0043)	(0.0027)	(0.1957)
Diet Dr Pepper	0.0238	0.0127	0.0105	0.4583	0.0068	0.0164	0.7184
		(0.0030)	(0.0012)	(0.0892)	(0.0043)	(0.0027)	(0.1735)
Dr Pepper	0.0223	0.0107	0.0122	0.5420	0.0049	0.0180	0.8006
		(0.0032)	(0.0013)	(0.1062)	(0.0046)	(0.0028)	(0.1922)
RC Cola	0.0207	0.0079	0.0124	0.6217	0.0022	0.0182	0.9120
		(0.0030)	(0.0013)	(0.1217)	(0.0043)	(0.0028)	(0.2173)
Sunkist	0.0221	0.0103	0.0123	0.5541	0.0044	0.0181	0.8208
		(0.0033)	(0.0013)	(0.1129)	(0.0047)	(0.0028)	(0.2021)

Note: The values in parentheses are standard deviations. MC=marginal cost, PCM=price-cost margin.

Table 4. 4: Bottle-Size Level Brands Marginal Costs, Price Cost Margins, and Lerner Indices Under Different Pricing Conducts

		Bertrand-Nash			Joint-Profit Maximization		
Brands	Average Price	MC	PCM	Lerner Index	MC	PCM	Lerner Index
By the Coca-Cola Co.							
Cf-Fr Diet Coke 12 oz 12 Cans	0.0234	0.0169	0.0072	0.3043	0.0141	0.0099	0.4203
		(0.0030)	(0.0010)	(0.0673)	(0.0034)	(0.0015)	(0.1008)
Coke Classic 67.6 oz Single Plastic	0.0187	0.0122	0.0069	0.3673	0.0093	0.0098	0.5234
		(0.0026)	(0.0010)	(0.0828)	(0.0032)	(0.0016)	(0.1268)
Coke Classic 16.9 oz 6 Packs Plastic	0.0247	0.0182	0.0069	0.2779	0.0153	0.0098	0.3962
		(0.0029)	(0.0010)	(0.0560)	(0.0034)	(0.0016)	(0.0872)
Coke Classic 12 oz 12 Cans	0.0229	0.0168	0.0069	0.2959	0.0139	0.0098	0.4214
		(0.0030)	(0.0010)	(0.0674)	(0.0035)	(0.0016)	(0.1018)
Coke Classic 12 oz 24 Cans	0.0213	0.0165	0.0070	0.3085	0.0135	0.0100	0.4411
		(0.0042)	(0.0009)	(0.0750)	(0.0047)	(0.0015)	(0.1143)
Coke Zero 67.6 oz Single Plastic	0.0193	0.0122	0.0070	0.3707	0.0094	0.0099	0.5214
		(0.0025)	(0.0010)	(0.0793)	(0.0030)	(0.0016)	(0.1210)
Coke Zero 16.9 oz 6 Packs Plastic	0.0279	0.0216	0.0065	0.2339	0.0191	0.0090	0.3241
		(0.0025)	(0.0008)	(0.0401)	(0.0028)	(0.0012)	(0.0594)
Coke Zero 12 oz 12 Cans	0.0238	0.0171	0.0070	0.2960	0.0143	0.0099	0.4162
		(0.0029)	(0.0010)	(0.0649)	(0.0033)	(0.0016)	(0.0981)
Coke Zero 12 oz 24 Cans	0.0224	0.0163	0.0072	0.3134	0.0133	0.0101	0.4429
		(0.0035)	(0.0009)	(0.0688)	(0.0040)	(0.0015)	(0.1045)
Diet Coke 67.6 oz Single Plastic	0.0188	0.0121	0.0070	0.3700	0.0093	0.0098	0.5239
		(0.0024)	(0.0010)	(0.0787)	(0.0029)	(0.0016)	(0.1203)
Diet Coke 16.9 oz 6 Packs Plastic	0.0269	0.0202	0.0070	0.2586	0.0173	0.0099	0.3662
		(0.0024)	(0.0010)	(0.0465)	(0.0029)	(0.0016)	(0.0724)
Diet Coke 12 oz 12 Cans	0.0233	0.0170	0.0070	0.2962	0.0141	0.0098	0.4193
		(0.0030)	(0.0010)	(0.0668)	(0.0034)	(0.0016)	(0.1009)
Diet Coke 12 oz 24 Cans	0.0219	0.0169	0.0070	0.3034	0.0140	0.0100	0.4309
		(0.0044)	(0.0010)	(0.0753)	(0.0049)	(0.0015)	(0.1138)
Fanta 12 oz 12 Cans	0.0222	0.0159	0.0070	0.3117	0.0131	0.0098	0.4365
		(0.0028)	(0.0010)	(0.0671)	(0.0033)	(0.0015)	(0.1013)
Sprite 67.6 oz Single Plastic	0.0183	0.0118	0.0070	0.3838	0.0090	0.0098	0.5371
		(0.0028)	(0.0010)	(0.0864)	(0.0033)	(0.0015)	(0.1324)
Sprite 12 oz 12 Cans	0.0225	0.0162	0.0070	0.3092	0.0134	0.0098	0.4321
		(0.0029)	(0.0010)	(0.0696)	(0.0034)	(0.0015)	(0.1041)
Sprite Zero 12 oz 12 Cans	0.0239	0.0172	0.0072	0.2994	0.0145	0.0099	0.4135
		(0.0029)	(0.0010)	(0.0652)	(0.0033)	(0.0015)	(0.0978)
By PepsiCo							
Diet Pepsi 67.6 oz Single Plastic	0.0170	0.0115	0.0059	0.3418	0.0075	0.0099	0.5735
		(0.0019)	(0.0007)	(0.0604)	(0.0025)	(0.0016)	(0.1181)
Diet Pepsi 16.9 oz 6 Packs Plastic	0.0248	0.0199	0.0052	0.2081	0.0167	0.0084	0.3357
		(0.0018)	(0.0005)	(0.0245)	(0.0020)	(0.0008)	(0.0438)
Diet Pepsi 12 oz 12 Cans	0.0213	0.0159	0.0059	0.2736	0.0120	0.0099	0.4599
		(0.0025)	(0.0007)	(0.0534)	(0.0032)	(0.0016)	(0.1055)
Mountain Dew 67.6 oz Single Plastic	0.0175	0.0125	0.0055	0.3132	0.0083	0.0097	0.5505
		(0.0023)	(0.0007)	(0.0662)	(0.0029)	(0.0016)	(0.1305)
Mountain Dew 12 oz 12 Cans	0.0213	0.0163	0.0055	0.2573	0.0122	0.0097	0.4527
		(0.0025)	(0.0007)	(0.0530)	(0.0033)	(0.0016)	(0.1074)
Pepsi 67.6 oz Single Plastic	0.0174	0.0123	0.0057	0.3209	0.0082	0.0098	0.5529
		(0.0021)	(0.0007)	(0.0622)	(0.0027)	(0.0016)	(0.1230)
Pepsi 16.9 oz 6 Packs Plastic	0.0241	0.0197	0.0051	0.2061	0.0164	0.0084	0.3419
		(0.0026)	(0.0006)	(0.0289)	(0.0026)	(0.0011)	(0.0515)
Pepsi 12 oz 12 Cans	0.0207	0.0156	0.0057	0.2708	0.0115	0.0098	0.4673
		(0.0025)	(0.0007)	(0.0561)	(0.0033)	(0.0016)	(0.1123)
Pepsi 12 oz 24 Cans	0.0184	0.0148	0.0057	0.2846	0.0107	0.0098	0.4906
		(0.0033)	(0.0007)	(0.0577)	(0.0038)	(0.0016)	(0.1108)

Note: Cf-Fr = Caffeine Free. The values in parentheses are standard deviations. MC=marginal cost, PCM=price-cost margin.

Table 4.4. Continued

Brands	Average Price	Bertrand-Nash MC	Bertrand-Nash PCM	Bertrand-Nash Lerner Index	Joint-Profit Maximization MC	Joint-Profit Maximization PCM	Joint-Profit Maximization Lerner Index
By Dr Pepper Snapple Group							
7 Up 67.6 oz Single Plastic	0.0167	0.0103	0.0066	0.3952	0.0071	0.0098	0.5846
		(0.0017)	(0.0008)	(0.0653)	(0.0022)	(0.0015)	(0.1115)
7 Up 12 oz 12 Cans	0.0203	0.0144	0.0066	0.3215	0.0113	0.0098	0.4767
		(0.0028)	(0.0008)	(0.0706)	(0.0034)	(0.0015)	(0.1188)
A&W Cream Soda 12 oz 12 Cans	0.0219	0.0148	0.0066	0.3144	0.0116	0.0098	0.4677
		(0.0028)	(0.0008)	(0.0679)	(0.0034)	(0.0015)	(0.1149)
A&W Root Beer 12 oz 12 Cans	0.0208	0.0157	0.0066	0.3013	0.0125	0.0098	0.4483
		(0.0029)	(0.0008)	(0.0658)	(0.0035)	(0.0015)	(0.1110)
Cf-Fr Diet Dr Pepper 12 oz 12 Cans	0.0217	0.0153	0.0068	0.3130	0.0122	0.0099	0.4575
		(0.0028)	(0.0008)	(0.0671)	(0.0034)	(0.0015)	(0.1117)
Canada Dry 67.6 oz Single Plastic	0.0180	0.0116	0.0066	0.3683	0.0084	0.0098	0.5451
		(0.0018)	(0.0008)	(0.0631)	(0.0024)	(0.0015)	(0.1085)
Canada Dry 12 oz 12 Cans	0.0232	0.0167	0.0066	0.2908	0.0136	0.0098	0.4313
		(0.0032)	(0.0008)	(0.0673)	(0.0038)	(0.0015)	(0.1124)
Diet 7 Up 12 oz 12 Cans	0.0217	0.0153	0.0068	0.3137	0.0122	0.0099	0.4585
		(0.0029)	(0.0008)	(0.0684)	(0.0035)	(0.0015)	(0.1136)
Diet Dr Pepper 67.6 oz Single Plastic	0.0169	0.0106	0.0066	0.3859	0.0073	0.0098	0.5779
		(0.0016)	(0.0008)	(0.0630)	(0.0022)	(0.0016)	(0.1092)
Diet Dr Pepper 16.9 oz 6 Packs Plastic	0.0255	0.0199	0.0066	0.2488	0.0167	0.0099	0.3721
		(0.0024)	(0.0008)	(0.0269)	(0.0022)	(0.0016)	(0.0484)
Diet Dr Pepper 12 oz 12 Cans	0.0210	0.0149	0.0066	0.3117	0.0116	0.0099	0.4677
		(0.0027)	(0.0008)	(0.0668)	(0.0033)	(0.0016)	(0.1132)
Dr Pepper 67.6 oz Single Plastic	0.0172	0.0110	0.0064	0.3707	0.0076	0.0098	0.5645
		(0.0016)	(0.0008)	(0.0602)	(0.0021)	(0.0016)	(0.1058)
Dr Pepper 16.9 oz 6 Packs Plastic	0.0250	0.0197	0.0064	0.2463	0.0163	0.0098	0.3744
		(0.0022)	(0.0008)	(0.0269)	(0.0021)	(0.0016)	(0.0485)
Dr Pepper 12 oz 12 Cans	0.0209	0.0151	0.0064	0.3038	0.0117	0.0098	0.4636
		(0.0028)	(0.0008)	(0.0671)	(0.0034)	(0.0016)	(0.1149)
RC Cola 12 oz 12 Cans	0.0207	0.0151	0.0064	0.3052	0.0117	0.0097	0.4689
		(0.0031)	(0.0009)	(0.0741)	(0.0037)	(0.0016)	(0.1240)
Sunkist 12 oz 12 Cans	0.0202	0.0145	0.0065	0.3168	0.0112	0.0098	0.4767
		(0.0027)	(0.0008)	(0.0694)	(0.0034)	(0.0016)	(0.1179)

Note: Cf-Fr = Caffeine Free. The values in parentheses are standard deviations. MC=marginal cost, PCM=price-cost margin.

For a closer look, under each scenario, I graph the results from Tables 4.3 and 4.4 and show marginal costs, price-cost margins, Lerner index, and prices for each brand for both brand level and bottle-size level. Since all brands have percentage markups higher than zero, we can conclude that all brands exert some market power.

RC Cola has the highest percentage markups at the brand level, with 62% Lerner index under the Bertrand-Nash scenario and 91% under the joint-profit maximization scenario (see Figures 4.1 and 4.2). One explanation of this result is that RC Cola has the lowest marginal cost (Figures 4.3, 4.4, and 4.5) and the second-highest price cost margins compared to other brands (see Figures 4.6 and 4.7). Even if Coke Classic has the highest price cost margins than other brands, the Lerner index for Coke Classic is not the highest due to its marginal cost and price. The percentage markup for Coke Classic is 53% and 75% under Bertrand-Nash and joint-profit maximization, respectively.

If prices were lower (or higher), the Lerner index might be higher (or lower), ceteris paribus. The bottle-size information is aggregated at the brand level, and prices might be less representative because different sizes have different unit prices, and some are more expensive. When averaging prices over bottle-sizes, valuable information is lost. Therefore, the estimation of market power might be more accurate at the bottle-size level.

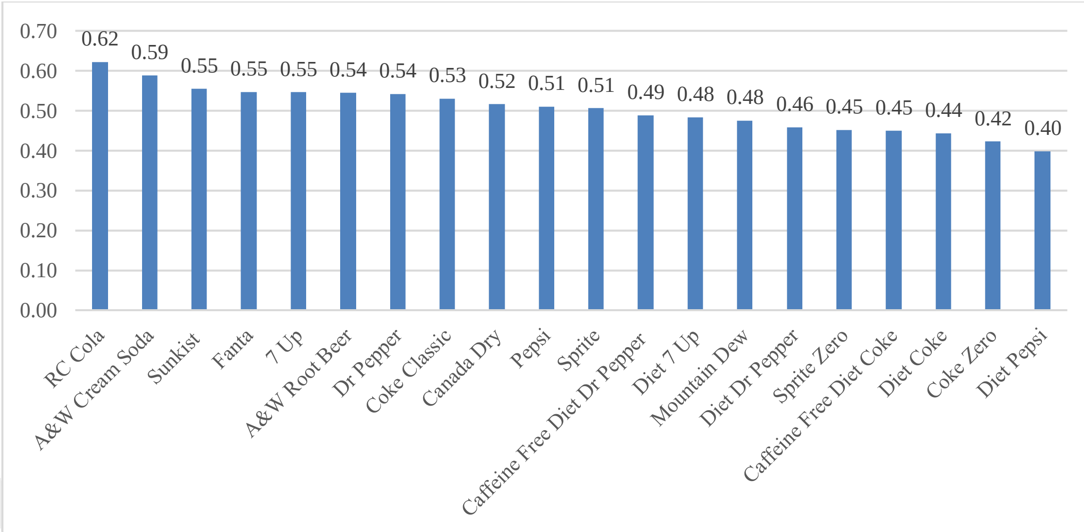

Figure 4. 1: Lerner Index in Bertrand-Nash for Brand Level

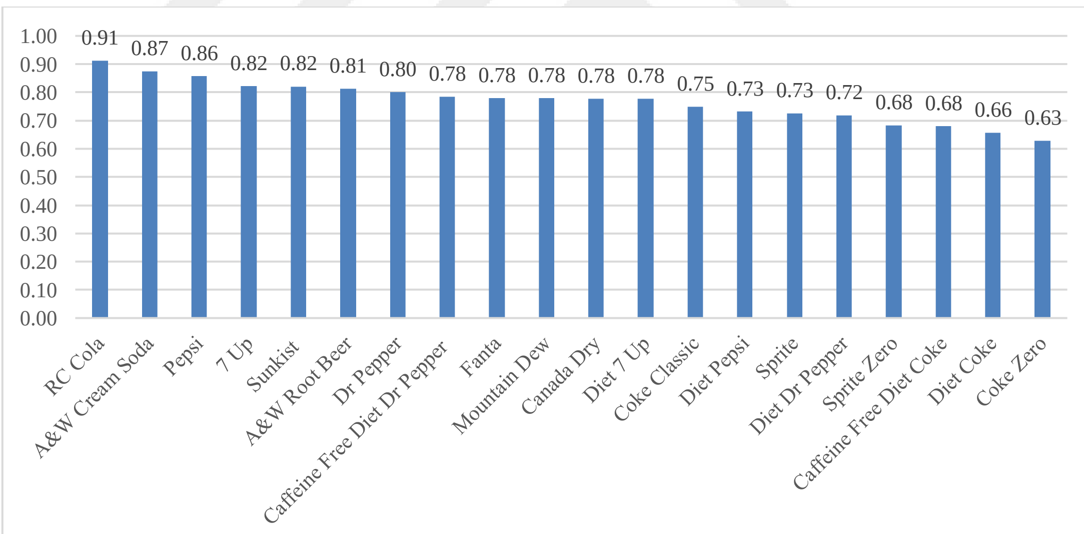

Figure 4. 2: Lerner Index in Joint-Profit Maximization for Brand Level

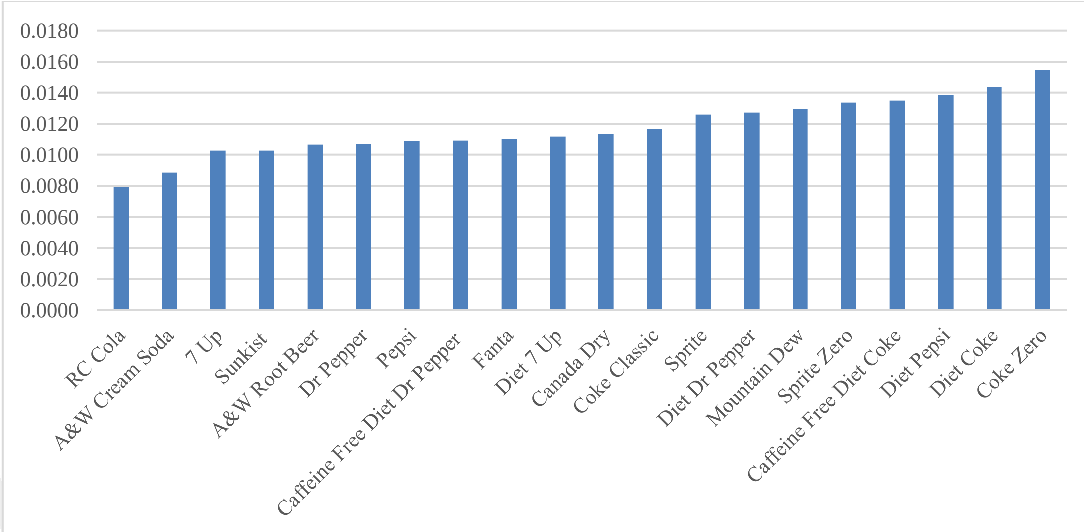

Figure 4. 3: Marginal Costs in Bertrand-Nash for Brand Level

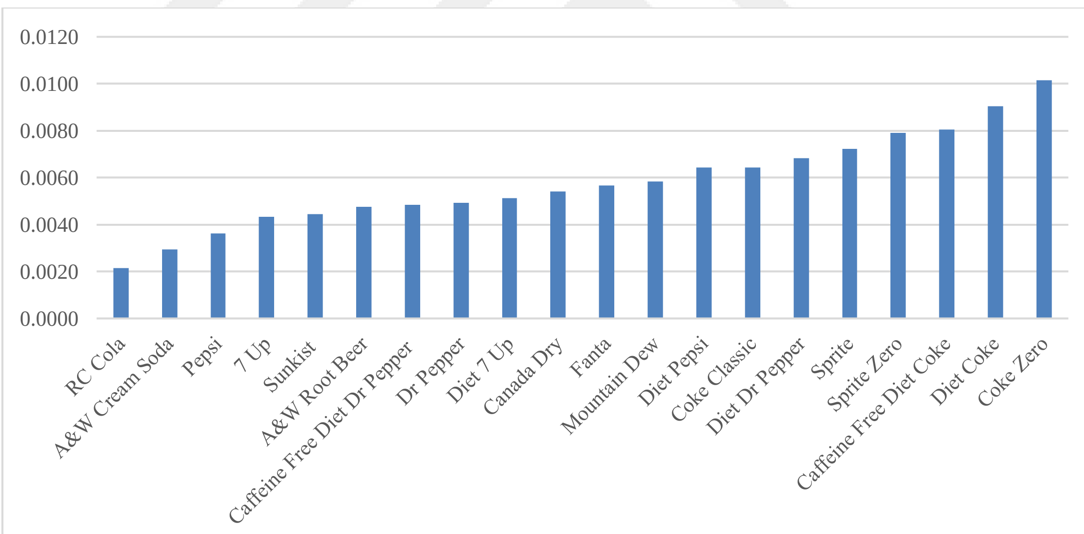

Figure 4. 4: Marginal Costs in Joint-Profit Maximization for Brand Level

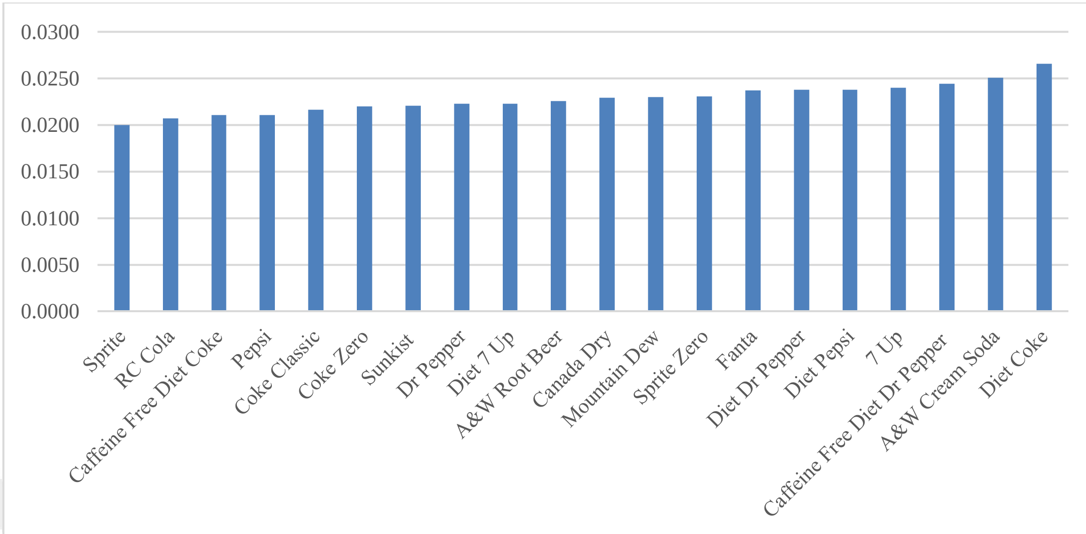

Figure 4. 5: Average Prices for Brand Level

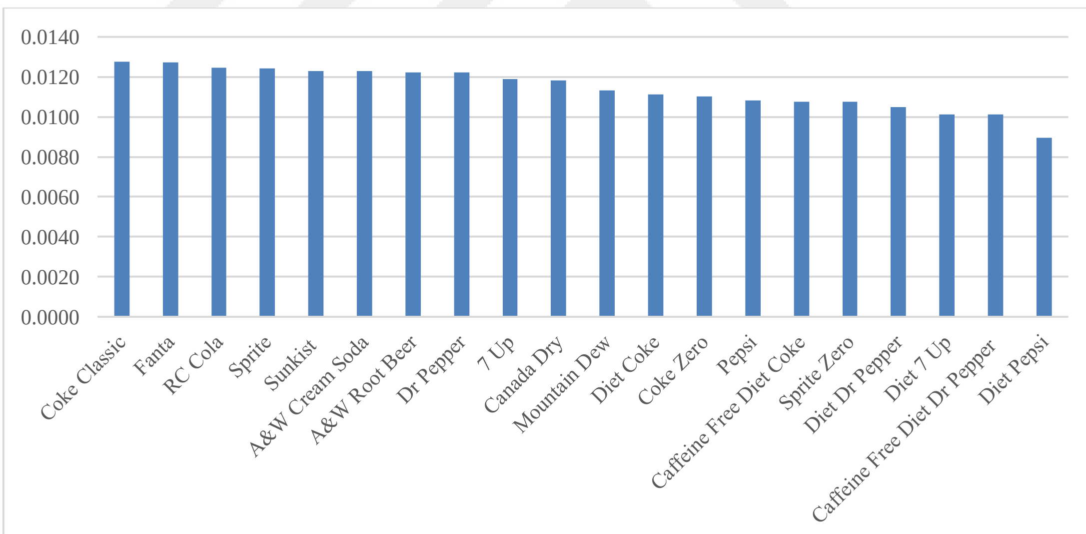

Figure 4. 6: Price Cost Margins in Bertrand-Nash for Brand Level

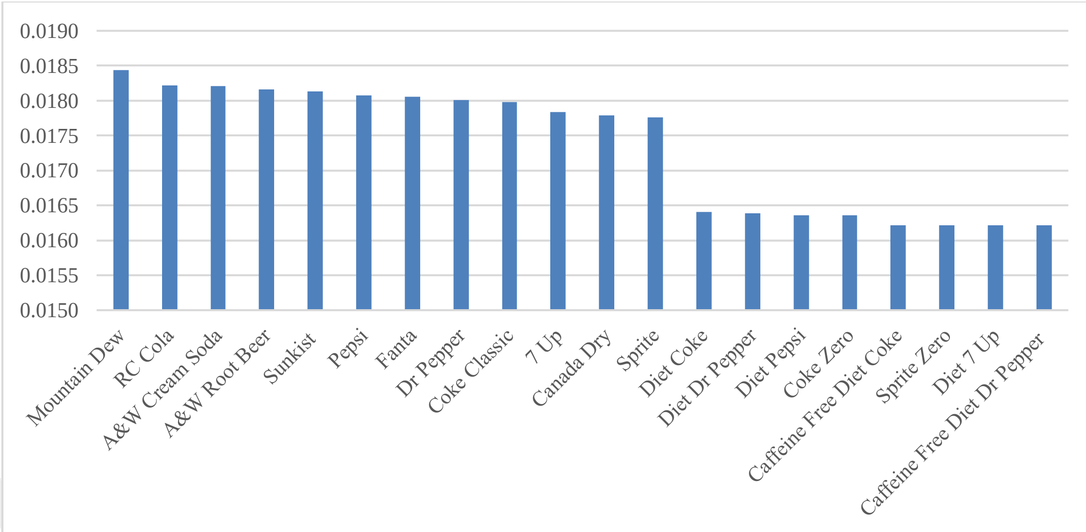

Figure 4. 7: Price Cost Margins in Joint-Profit Maximization for Brand Level

Figures 4.8 and 4.9 show the Lerner index at the bottle-size level under both pricing conducts. In both pricing conducts, brands with the size of 67.6 oz. (2 liters) single plastic bottles have higher percentage markup. It is consistent with the finding of Mariuzzo et al. (2003). They find that markups vary with packaging, and 1.5- 2-liter drinks have higher percentage markup than the other sizes. In this study, 67.6 oz. single plastic bottles have relatively lower prices and lower marginal costs compared to other size-specific brands (see Figures 4.10, 4.11, and 4.12).

7 Up 67.6 oz. single plastic bottle has the highest percentage markup in both scenarios. It is 39% in Bertrand-Nash and 58% in joint-profit maximization. 7 Up is in the top brands in both scenarios at the brand level, with 55% percentage markup under Bertrand-Nash and 82% under joint-profit maximization. As can be seen again, markups at the brand level brands are higher than markups at the bottle-size level under both pricing conducts.

Moreover, at the bottle-size level brands, sizes with 12 oz. 12 cans and 12 oz. 24 cans brands have moderate percentage markup while the lowest percentage markups are for brands with 16.9 oz 6 packs plastic bottles. Moreover, Coke Zero 12 oz. 24 cans brand has the highest price-cost margins in joint-profit maximization case, and it is in the top three price-cost margins in Bertrand-Nash pricing conduct (see

Figures 4.13 and 4.14). Even if Coke Zero 12 oz 24 cans has a high price-cost margin, because of its relatively high price, it is not one of the high percentage markup brands in both pricing conduct.

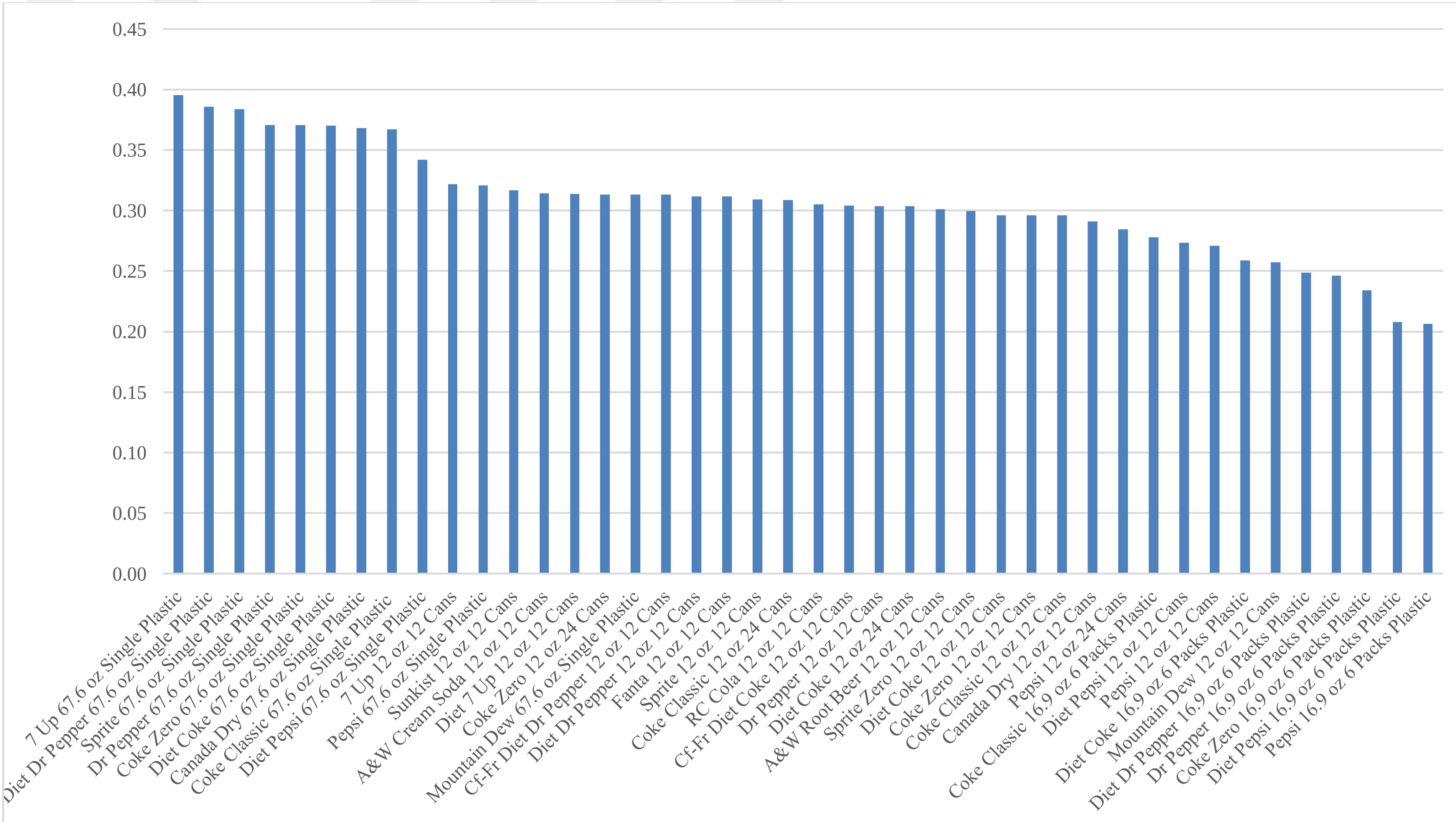

Figure 4. 8: Lerner Index in Bertrand-Nash for Bottle-Size Level

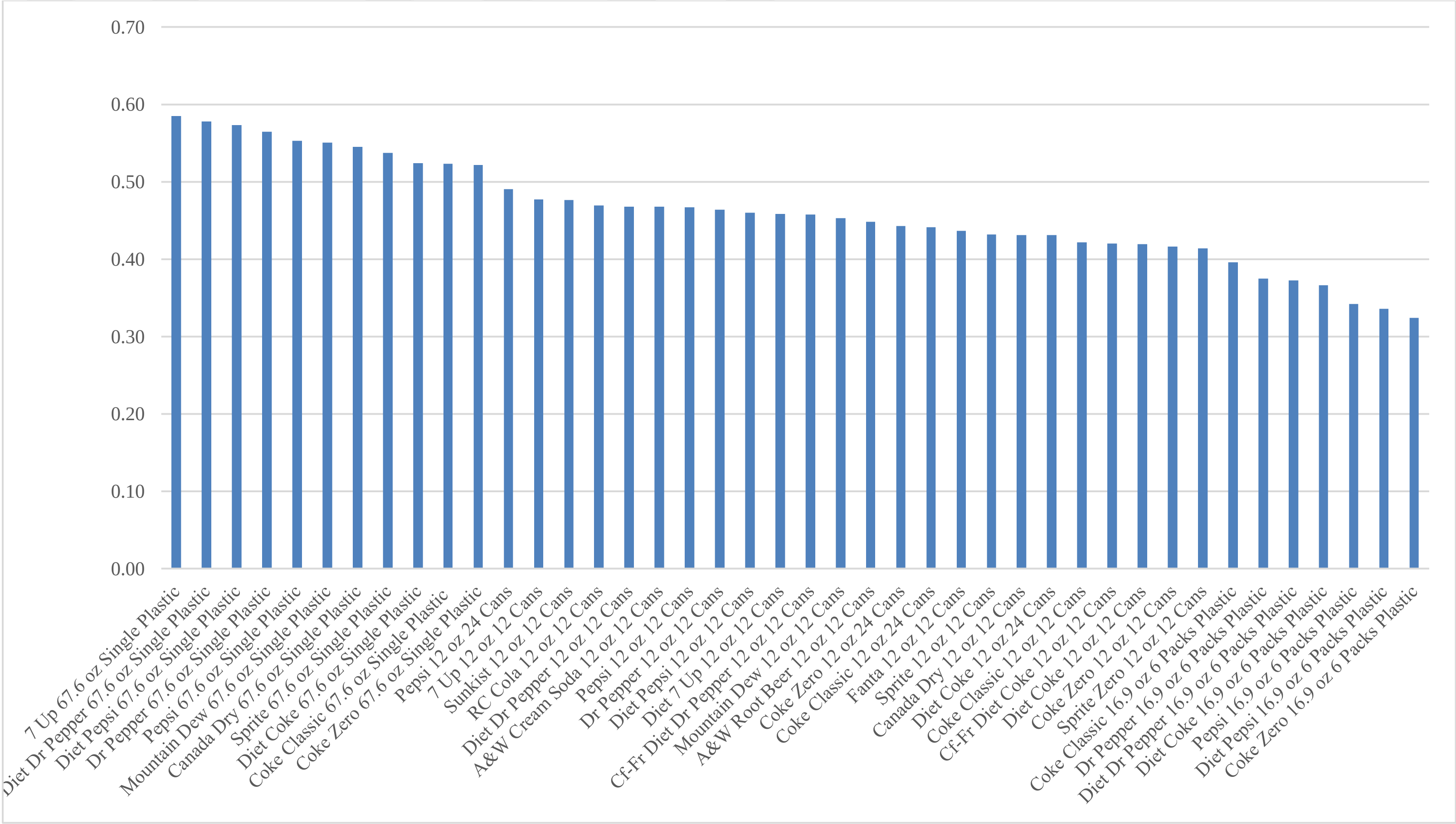

Figure 4. 9: Lerner Index in Joint-Profit Maximization for Bottle-Size Level

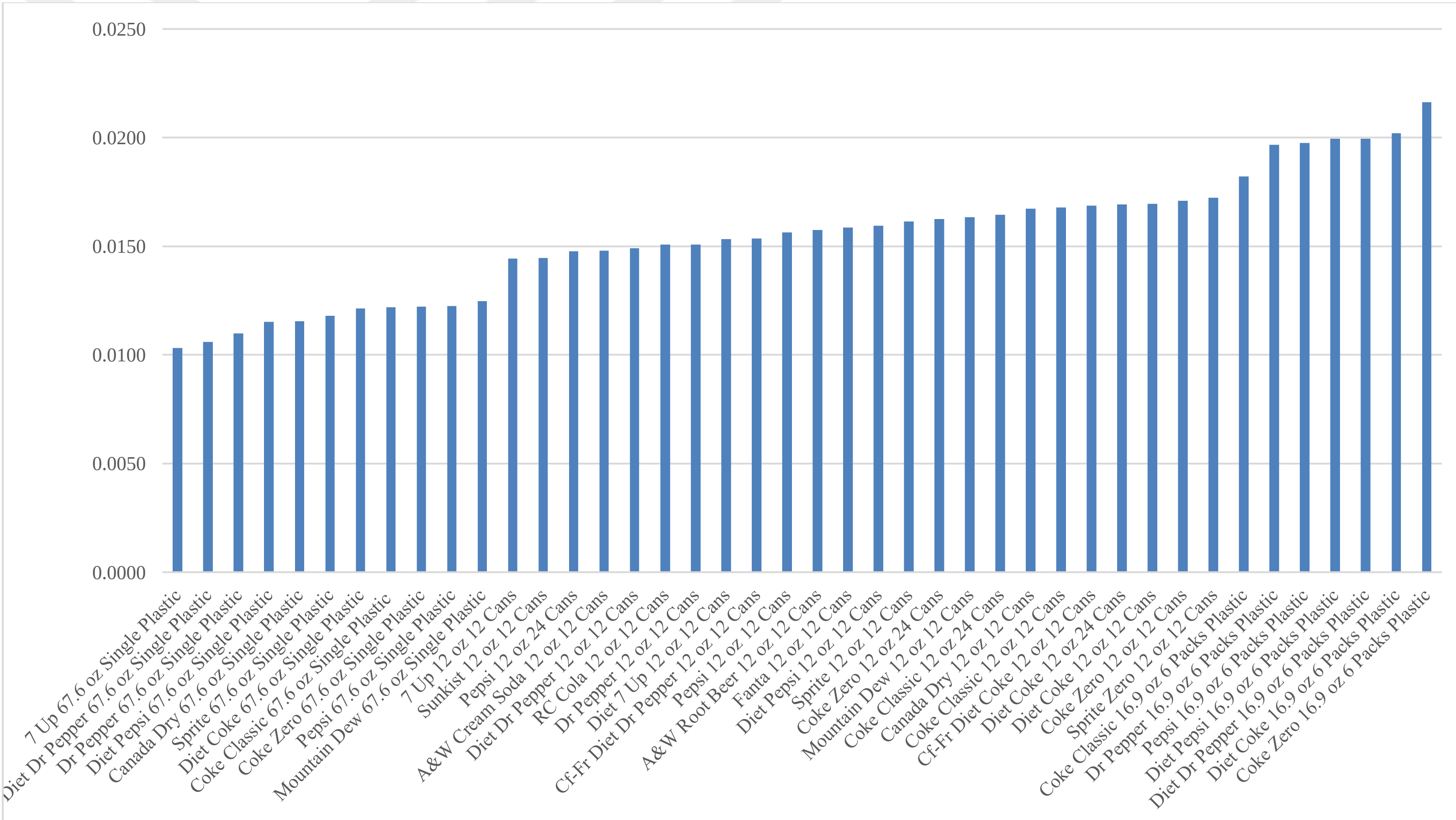

Figure 4. 10: Marginal Costs in Bertrand-Nash for Bottle-Size Level

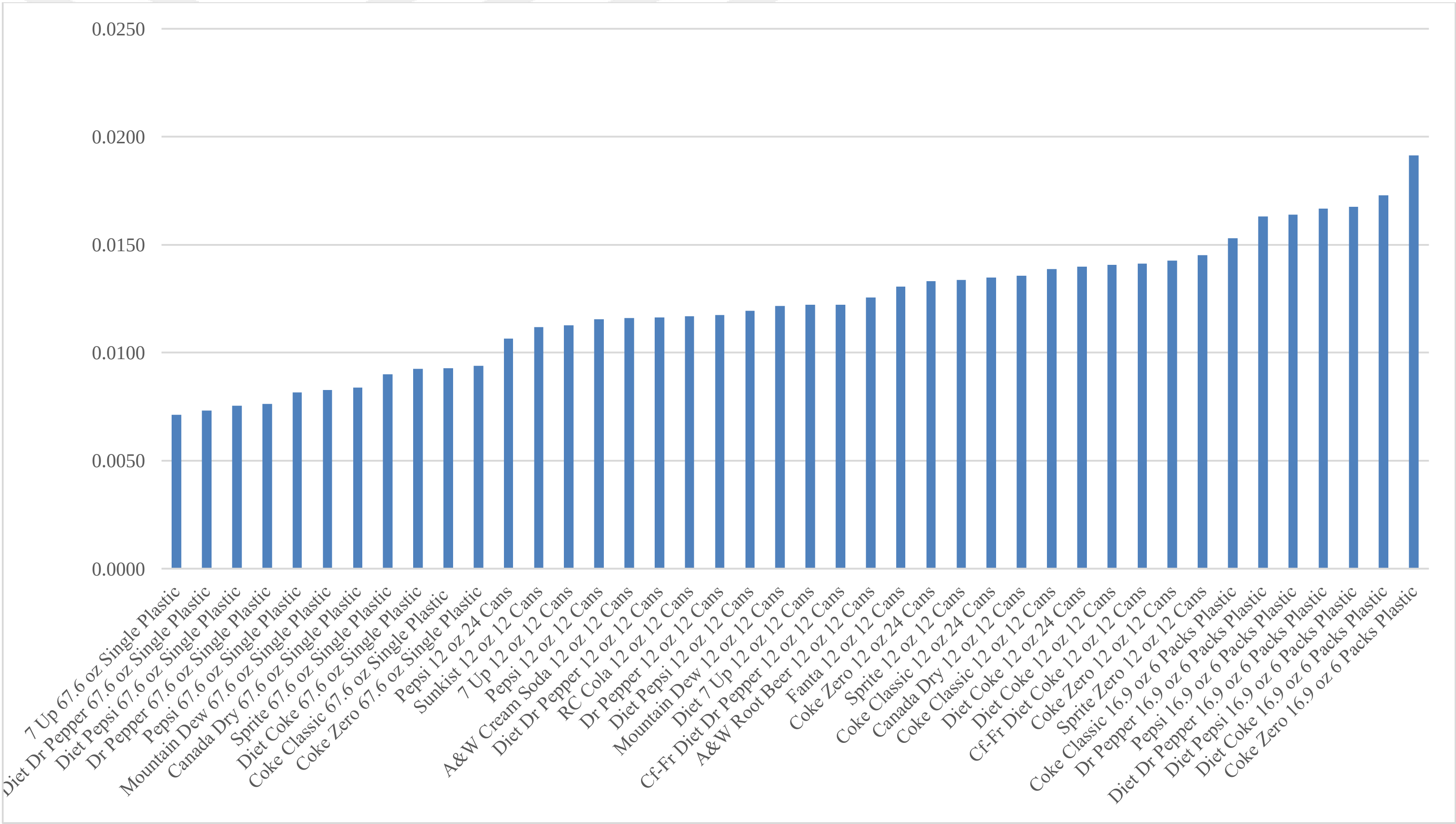

Figure 4. 11: Marginal Costs in Joint-Profit Maximization for Bottle-Size Level

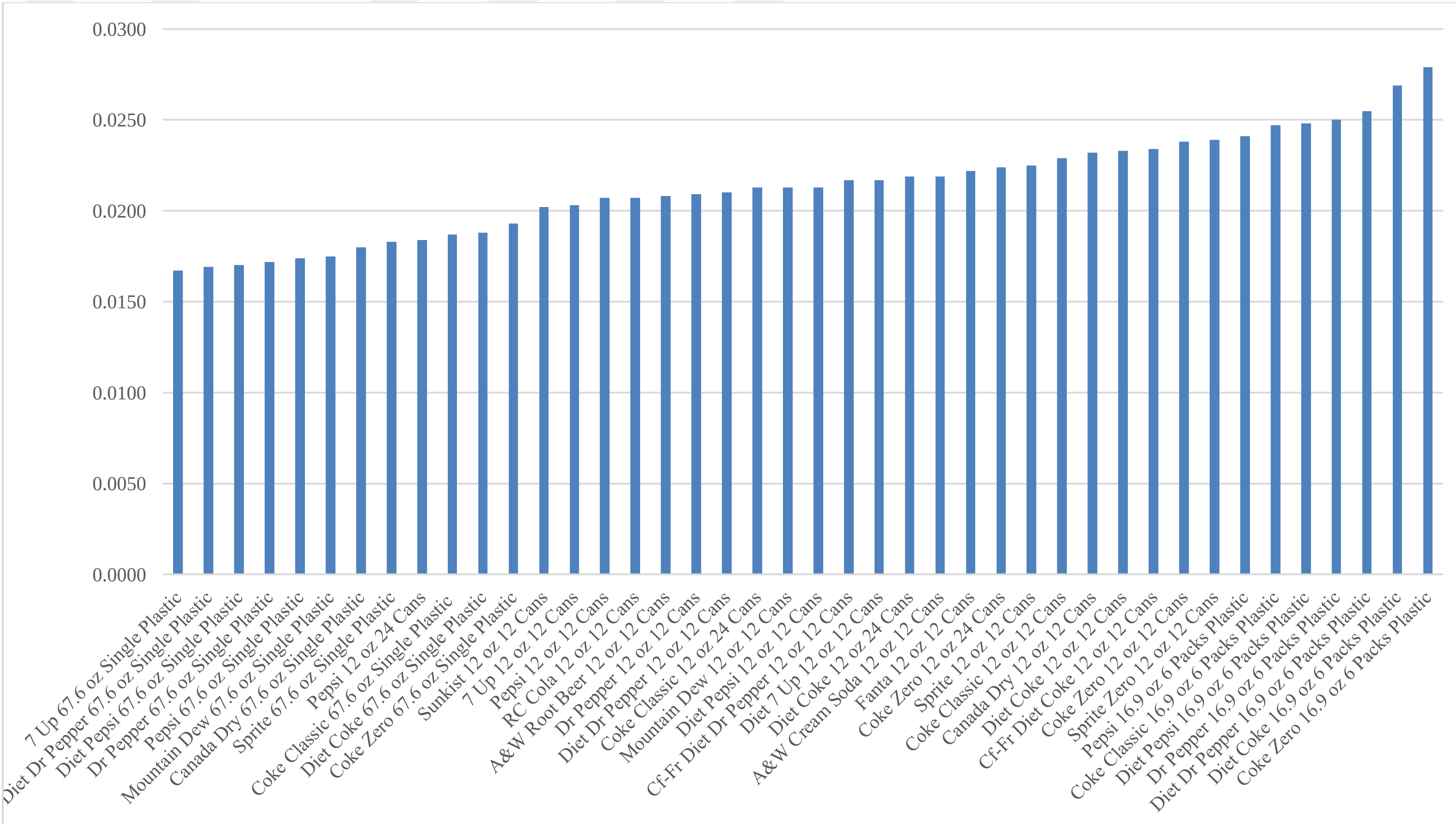

Figure 4. 12: Average Prices for Bottle-Size Level

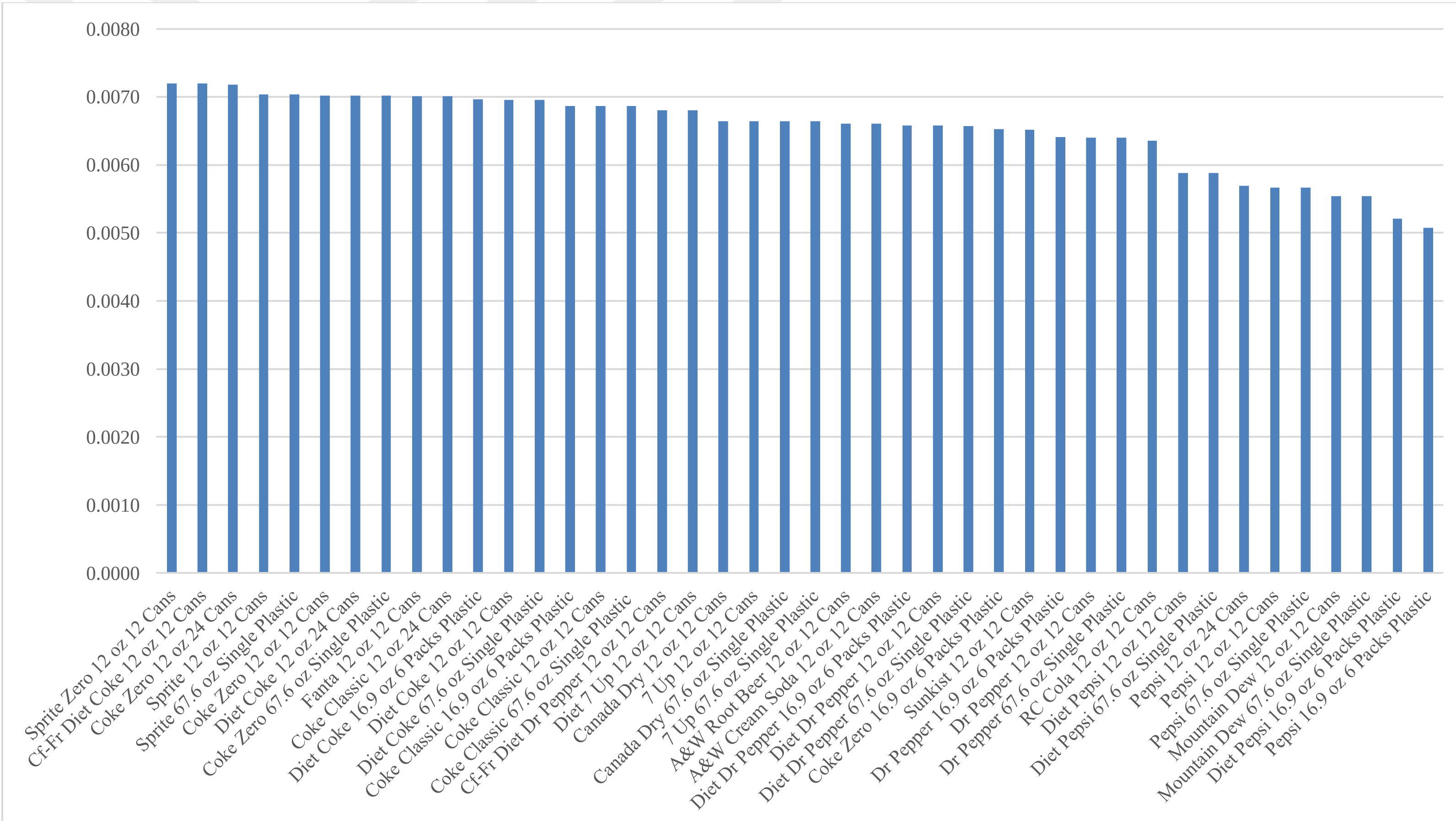

Figure 4. 13: Price Cost Margins in Bertrand-Nash for Bottle-Size Level

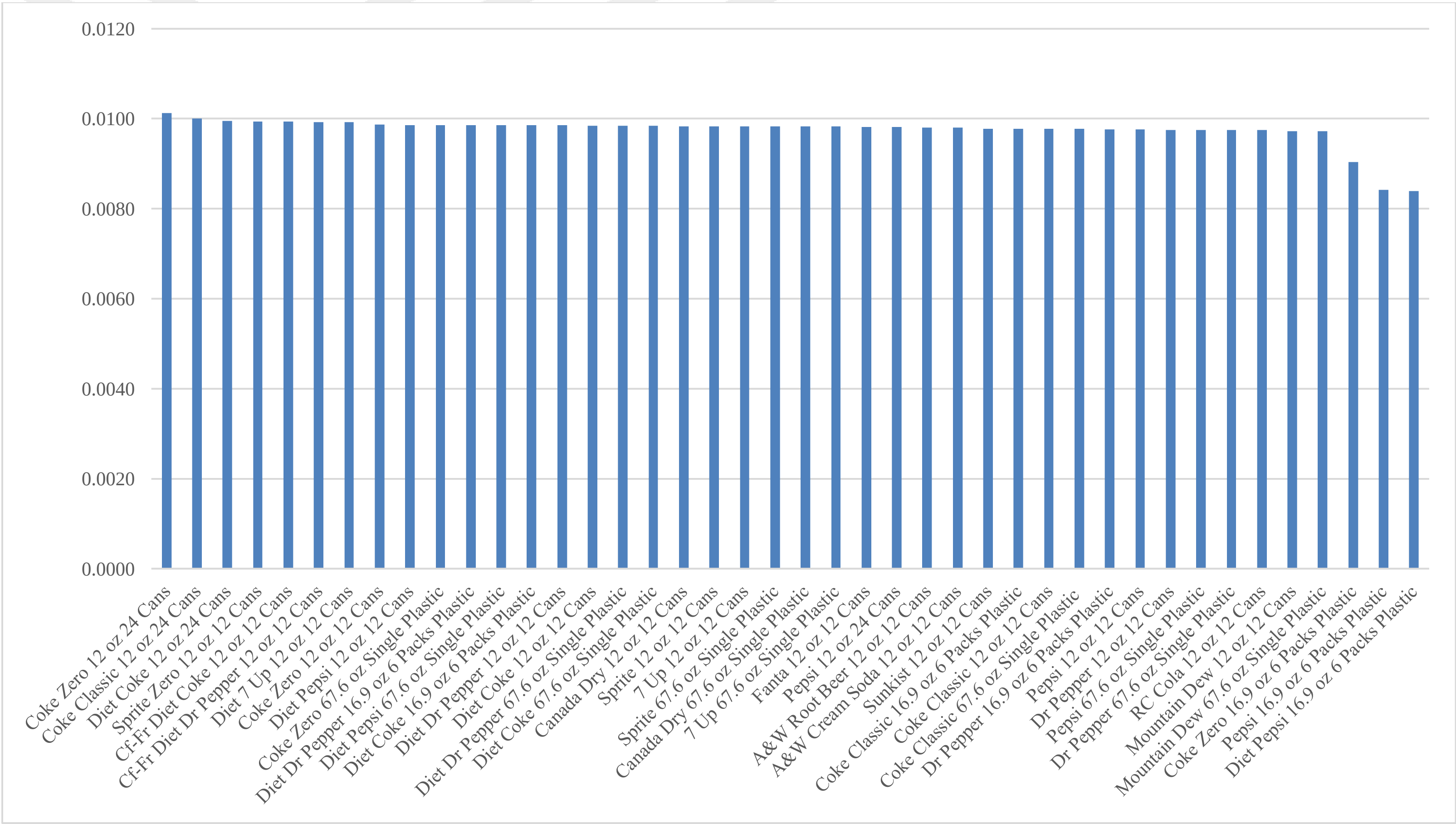

Figure 4. 14: Price Cost Margins in Joint-Profit Maximization for Bottle-Size Level

According to River and Vuong's (2002) test results (see Table 4.5), in both level analyses, joint-profit maximization pricing conduct is rejected. Bertrand-Nash's pricing conduct is a better fit for the data at the brand level and bottle-size level.

Table 4. 5: Model Comparison Between Bertrand Nash and Joint-Profit Maximization

Aggregation level	Pricing Conduct	H_0	H_1	H_2	Tn	Result
Brand Level Estimation	Bertrand Nash vs. Monopoly	Equivalent	Bertrand Nash is better	Joint-profit maximization is better	-2502253.8	Bertrand-Nash is better
Bottle-Size Level Estimation	Bertrand Nash vs. Monopoly	Equivalent	Bertrand Nash is better	Joint-profit maximization is better	-3684431.7	Bertrand-Nash is better

Note: At a 5% significance level, if T_n < -1.96, H_0 is rejected, and it is in favor of H_1; if T_n > 1.96, H_0 is rejected, and it is in favor of H_2; otherwise, fail to reject H_0.

Lerner indices are high, varying between 40% and 62% at the brand level and 20% and 39% at the bottle-size level under Bertrand-Nash pricing conduct. Our results support that even if high Lerner indices mean that brands have market power, it is not due to prices' collusion. Market power arises from product differentiation. Nevo (2001) points out that differentiated products industry brands may have high price-cost margins, but it is not due to lack of price competition. He emphasizes that it is due to the consumers' willingness to pay for their favorite brands and firms' pricing decisions according to their brands' substitutability. Our finding that product differentiation creates its market power is consistent with the conclusion of Langan and Cotterill (1994) and Cotterill et al. (1996) for the carbonated soft drink industry.

As discussed in the previous chapter, in the multinomial logit model, which does not include consumer heterogeneity, lower price brands always have higher markups, which is not valid for all cases. On the other hand, the random coefficients logit model does not necessarily have this pattern. Lower price brands do not always provide higher markups when taking into account consumer heterogeneity. In our results, even if brands with lower price and lower own price elasticities (in absolute value) tend to have higher markups, there is no exact relationship between prices and markups like in multinomial logit because of our model of random coefficient logit model's inclusion of consumer heterogeneity.

Furthermore, it is not found that one company's brands, such as the Coca-Cola Co. brands, have higher percentage markup than the other companies. It can be due to no pattern in marginal cost and price cost margins such that there is no finding one company has a lower marginal cost.

According to our results at the brand level estimation, the Coca-Cola Co. earns more from its Fanta brand, PepsiCo earns more from its Pepsi Cola brand, and Dr Pepper Snapple Group earns more from its RC Cola brand than from their other brands. The bottle-size level estimation results show that the Coca-Cola Co. earns more from its Sprite 67.6 oz. single plastic bottle brand, PepsiCo earns more from its Diet Pepsi 67.6 oz. single plastic bottle brand and Dr Pepper Snapple Group earns more from its 7 Up 67.6 oz. single plastic bottle brand compared to their other brands.

4.6 Conclusion

This chapter analyzes price competition in carbonated soft drinks (CSDs) at the manufacturer's level (The Coca-Cola Co., PepsiCo., and Dr Pepper Snapple Group) in Dallas, Texas. There are two levels of estimations for price competition. One is at the brand level and consists of 20 CSD brands, and one at the bottle-size level and includes 42 CSD brands.

We opt for a menu approach for the market power analysis. It consists of a two-step estimation. First, demand for each level is estimated. Secondly, demand estimates are used to evaluate market power for CSDs brands. Two pricing conduct, namely Bertrand-Nash and joint-profit maximization, are assessed under two aggregation levels: brand level and bottle-size level. For the demand analysis, we opt for the random coefficient logit model following BLP (1995) because it incorporates consumer heterogeneity, allows solving the endogeneity, and yields unrestrictive substitution patterns.

At both aggregation levels, the Bertrand-Nash game results in lower marginal costs, price-cost margins, and Lerner indices than the joint-profit maximization scenario. It is consistent with the economic theory that a higher Lerner index represents higher market power; thus, the joint-profit maximization case includes higher Lerner indices for the brands.

RC Cola has the highest percentage markups at the brand level, with 62% Lerner index under the Bertrand-Nash scenario and 91% under the joint-profit maximization scenario. One explanation of this result is that RC Cola has the lowest marginal cost and the second-highest price cost margins compared to other brands. Even if Coke Classic has the highest price-cost margins, the Lerner index for Coke Classic is not the highest due to its marginal cost and price.

Lerner index is quite sensitive to prices, and more disaggregated levels of brands give more realistic prices; thus, we believe more realistic percentage markups. When an aggregation level is different, the results might be different. Prices might be less accurate at the brand level because of averaging over different sizes with varying unit prices. Therefore, indications of market power might be more accurate when the analysis is at the bottle-size level.

Lerner Index at the bottle-size level shows an interesting pattern. Under Bertrand-Nash and joint-profit maximization scenarios, brands with the 67.6 oz. (2 liters) size, single plastic bottles, have higher percentage markups. Moreover, brands with 12 oz. 12 cans and 12 oz. 24 cans have moderate percentage markup, while the lowest percentage markup is observed for brands with 16.9 oz 6 packs plastic bottles.

At the bottle-size level, 7 Up 67.6 oz. single plastic bottle has the highest percentage markup under both pricing conducts. It is 39% in Bertrand-Nash and 58% in joint-profit maximization. At the brand level, 7 Up also has a high markup under the two pricing conducts, respectively 55% and 82%. We conclude brand level percentage markups are higher than bottle-size level ones under both pricing conducts.

Moreover, Coke Zero, sold as 12 oz. 24 cans, has the highest price-cost margins under the joint-profit maximization case and one of the top three price-cost margins under the Bertrand-Nash pricing conduct; however, its markup is not one of the highest due to its high price.

According to River and Vuong's (2002) test results, in both level analyses, joint-profit maximization pricing conduct is rejected. Bertrand-Nash's pricing conduct is a better fit for the data at the brand level and bottle-size level. Lerner indices vary between 40% to 62% at the brand level and 20% to 39% at the bottle-size level under Bertrand-Nash's pricing conduct. Since all brands have percentage markups higher than zero, we can conclude that all manufacturers exert some market power when selling their brands. However, our results support that this market power is not due to a collusive pricing behavior. Market power arises from product differentiation and other non-price competition behavior, such as advertising.

CHAPTER 5

CONCLUSION

This dissertation estimates manufacturer level demand for 20 carbonated soft drinks (CSDs) at the brand level and 42 CSDs at the bottle-size level brands in Dallas, Texas. The random coefficient logit model by BLP (1995) is used for the demand analysis because it provides unrestrictive substitution patterns by considering the consumer heterogeneity, deals with dimensionality, and endogenous prices. Demand estimates are used to evaluate market power for CSDs brands. Two pricing conducts, namely Bertrand Nash and joint-profit maximization, are assessed under two aggregation levels: brand level and bottle-size level.

At the brand-level demand estimation, the signs of mean utility parameter estimates indicate that consumers prefer CSD brands with low price, high caffeine, and low calorie, on average. On the other hand, at the bottle-size level estimation, signs of mean utility parameter estimates show that CSD brands with lower prices, higher caffeine, and higher calorie content are more favorable for the consumers, on average.

Besides, at the brand level demand estimation, households with no children are less price-sensitive than households with one or more children, and low-income households are less sensitive to CSDs prices than middle-income and high-income households. Contrarily, at the bottle-size level, the results indicate that high-income households are less sensitive to CSD prices than other income categories. Furthermore, households with no children are more price-sensitive than households with children. Comparing the distribution of the price parameters by income and the number of children, we reach opposite conclusions for the two levels.

The mean utility of the calorie parameter is positive at the bottle-size level, while it is negative at the brand level. Brand level estimation results show that some consumers view calorie of CSDs as less favorable while others think higher calories are better. Some households see calories as positive regardless of their income. Moreover, households with three and more children are more calorie sensitive. In contrast, households with no children are less sensitive to the drinks' calories, and even some households with no children perceive calories positively.

At the bottle-size level, all calorie parameters are positive, but calories are more favorable for high-income households than middle- and low-income households. No matter having children or not; all households value the calorie content of CSDs positively. The implications of bottle-size demand results regarding calorie parameter by income and the number of children are not parallel compared to the brand level.

At both levels of demand, caffeine parameters are positive, but the distribution of caffeine parameter estimates by income and the number of children does not yield similar implications. Brand level demand results show that estimated caffeine parameters are positive for all households. Households with no children care more about caffeine content in CSDs, and households with one or more children prefer less caffeine content. Besides, there is no particular pattern in the distribution of caffeine parameters by income in the brand level estimation.

At the bottle-size level, high-income households prefer high caffeine drinks more than other income categories. Like calorie parameters, households value caffeine content positively regardless of the number of children in the household.

At the brand level, own-price elasticities range between -1.9 (RC Cola) to -3.2 (Coke Zero) with the median of -2.39 and the mean of -2.48. The bottle-size level's own-price elasticities are bigger in magnitude; they range between -3.06 (7 Up 2-liter single pack) to -5.48 (Coke Zero 6 packs of 16.9 oz.) with a median of -4.06 and a mean of -4.08.

For both levels of demand estimation, the magnitude of own-price elasticities indicates that consumers are sensitive to CSD prices, implying elastic demand. All cross-price elasticities for both levels are positive, and it implies that the products are substitutes (by construction). Brand level cross-price elasticities are positive and range from 0.0030 to 0.3115, while bottle-size level cross-price elasticities are between 0.0041 and 0.3316. The magnitudes of cross-price elasticities are low compared to own-price elasticities in both levels of demand. It supports that consumers have brand loyalty, and they switch to the outside good rather than another brand of carbonated soft drinks even if they are sensitive to CSDs prices of their chosen brands.

Furthermore, in both levels of demand, cross-price elasticities show that consumers are brand loyal. They are more responsive to changes of the leading brands (i.e., Coke Classic and Dr Pepper in the brand level and Coke Classic 12 packs of 12 oz. and Dr Pepper 12 packs of 12 oz. in the bottle-size level). For example, an increase in the price of Coke Classic brand leads to a higher percentage change in the quantity demanded of a nonleading brand (i.e., RC Cola) than comparing to the case of increase in the nonleading brand price, quantity demanded of Coke Classic change in a lower percentage.

This study further analyzes the market power of carbonated soft drinks. Under two pricing conducts, at the brand level and bottle-size level, the price-cost margins are computed using the demand results and the marginal costs. At the brand level, under Bertrand-Nash, the mean of marginal costs, price-cost margins, and Lerner indices are lower than those under the joint-profit maximization scenario. It is consistent with the economic theory that a higher Lerner index represents higher market power. Thus, the joint-profit maximization case implies higher Lerner indices for the brands. Similar to the brand level estimation, marginal costs, price-cost margins, and Lerner indices are higher under the joint-profit maximization scenario than those under the Bertrand-Nash at the bottle-size level.

The Lerner Index is relatively higher at the brand level under both pricing conducts than at the bottle-size level. At the brand level, the Lerner index under the Bertrand-Nash pricing conduct ranges from 39% to 62%, while in the case of joint-profit maximization, the Lerner index ranges from 62% to 91%. On the other hand, for the bottle-size level under Bertrand-Nash pricing conduct, the Lerner index ranges from 20% to 39%. It ranges from 31% to 58% under the scenario of joint-profit maximization. Also, since all brands have percentage markups higher than zero, we can conclude that all brands exert some market power.

Specifically, RC Cola has the highest percentage markups at the brand level, with 62% Lerner index under the Bertrand-Nash scenario and 91% under the joint-profit maximization scenario (see Figures 4.1 and 4.2). One explanation of this result is that RC Cola has the lowest marginal cost (Figures 4.3, 4.4, and 4.5) and the second-highest price cost margins compared to other brands (see Figures 4.6 and 4.7). Even if Coke Classic has the highest price cost margins compared to other brands, the Lerner index for Coke Classic is not the highest due to its marginal cost and price. The percentage markup for Coke Classic is 53% and 75% under Bertrand-Nash and joint-profit maximization, respectively.

Lerner index is quite sensitive to prices, and more disaggregated levels of brands give more realistic prices; thus, we believe more realistic percentage markups. Hence, the bottle-size level can be more accurate for the estimation because of having more precise prices. Therefore, the market power assessment might be more accurate when the brands' prices are at the bottle-size level.

Lerner Index for the bottle-size level brands, in Bertrand-Nash and joint-profit maximization scenarios, brands with the size of 67.6 oz. (2 liters) single plastic bottles have higher percentage markups. It is consistent with Mariuzzo et al. (2003) finding that markups vary with packaging, and 1.5- 2-liter drinks have higher percentage markup than the other sizes. In this study, 67.6 oz. single plastic bottles have relatively lower prices and lower marginal costs compared to other size brands.

At the bottle-size level, 7 Up 67.6 oz. single plastic bottle has the highest percentage markup in both scenarios. It is 39% under Bertrand-Nash and 58% under joint-profit maximization. At the brand level, 7 Up is the top brand under both scenarios with 55% percentage markup under Bertrand-Nash and 82% under the joint-profit maximization case.

Moreover, at the bottle-size level, sizes with 12 oz. 12 cans and 12 oz. 24 cans brands have moderate percentage markup while the lowest percentage markup is observed for brands with 16.9 oz 6 packs plastic bottles. Moreover, Coke Zero 12 oz.

24 cans brand has the highest price-cost margins under joint-profit maximization case, and it is in the top three price-cost margins under Bertrand-Nash pricing conduct.

According to River and Vuong's (2002) test results, joint-profit maximization pricing conduct is rejected at both analysis levels. At the brand level and the bottle-size level, Bertrand-Nash's pricing conduct outperforms the joint-profit maximization game. The Bertrand-Nash game yields Lerner indices that vary between 40% and 62% at the brand level and 20% and 39% at the bottle-size level.

Our results support that even if high Lerner indices mean that brands have market power, it is not due to prices' collusion. Market power arises from product differentiation. Nevo (2001) points out that differentiated products industry brands may have high price-cost margins, but it is not due to lack of price competition. He emphasizes that it is due to the consumers' willingness to pay for their favorite brands and firms' pricing decisions according to their brands' substitutability. Our finding is that product differentiation creates its market power, which is consistent with the conclusion of Langan and Cotterill (1994) and Cotterill et al. (1996) for the carbonated soft drink industry.

According to our results at the brand level, the Coca-Cola Co. earns more from its Fanta brand, PepsiCo earns more from its Pepsi Cola brand, and Dr Pepper Snapple Group earns more from its RC Cola brand compared to their other brands. The results of bottle-size level estimation show that the Coca-Cola Co. earns more from its Sprite 67.6 oz. single plastic bottle brand, PepsiCo earns more from its Diet Pepsi 67.6 oz. single plastic bottle brand and Dr Pepper Snapple Group earns more from its 7 Up 67.6 oz. single plastic bottle brand compared to their other brands.

Product differentiation is a prominent feature of carbonated soft drinks. Even if all carbonated soft drinks serve the same purpose, such as refreshment, they are differentiated by flavor, size, color, sugar content (regular vs. diet), caffeine content, etc. In addition to these characteristics, consumers may perceive the same manufacturer's brand but sold at different points of sale to be a different product. For further research, examining horizontal supermarket price competition for carbonated soft drinks may provide different aspects since supermarket brands (i.e., Supermarket 1 Coke Classic 12 oz. 12 packs, Supermarket 2 Coke Classic 12 oz. 12 packs) are more disaggregated than the horizontal competition in a manufacturer level.

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APPENDIX A

THE US SOFT DRINK MARKET

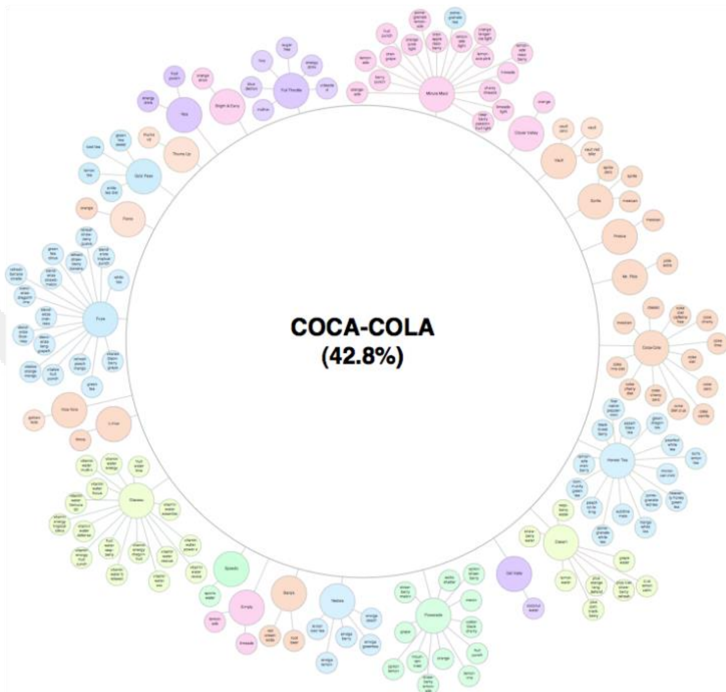

Figure A. 1: Cluster Diagram for the Coca-Cola Co. Brands and Varieties in the Soft Drink Market, 2008

Source: Adopted from Howard et al. (2010)

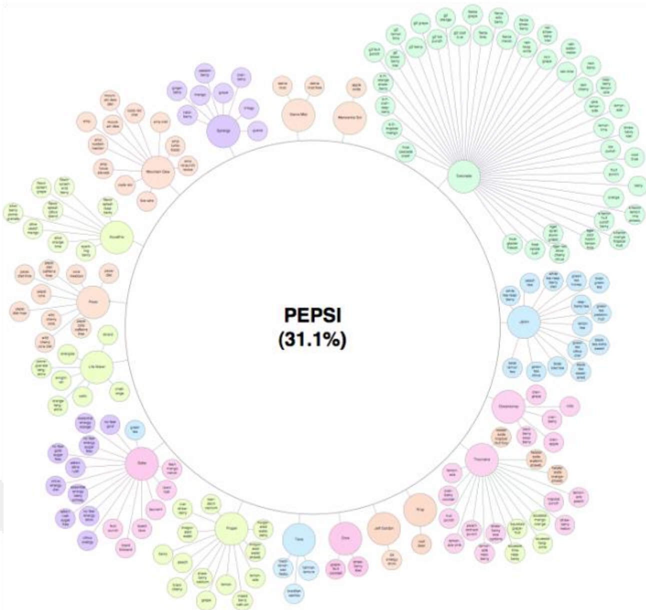

Figure A. 2: Cluster Diagram for PepsiCo Brands and Varieties in the Soft Drink Market, 2008

Source: Adopted from Howard et al. (2010)

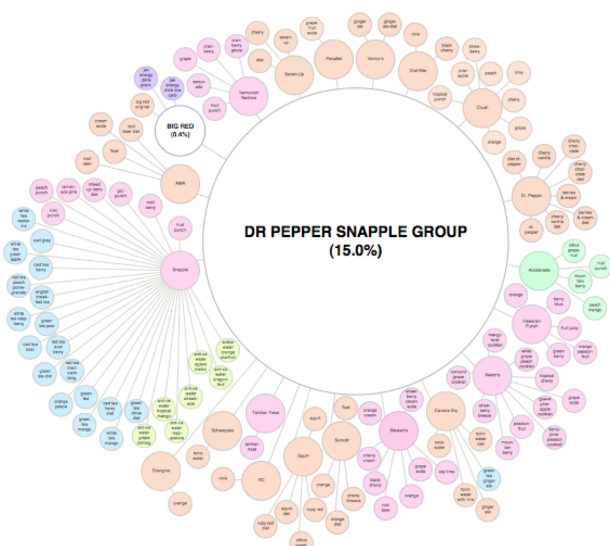

Figure A. 3: Cluster Diagram for Dr Pepper Snapple Group Brands and Varieties in the Soft Drink Market, 2008

Source: Adopted from Howard et al. (2010)

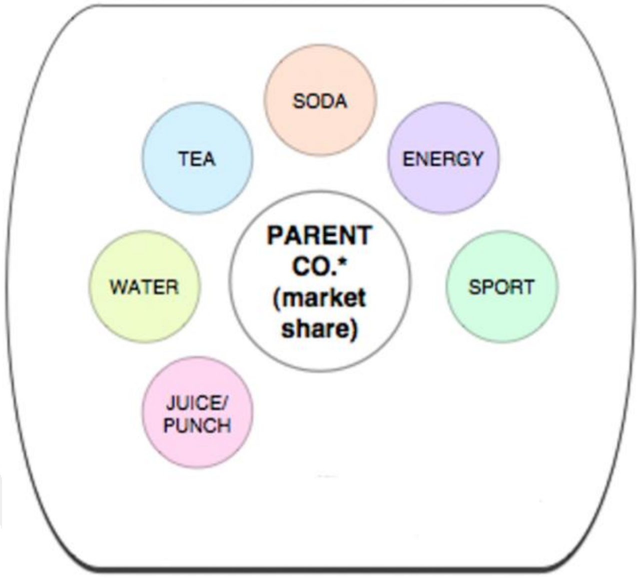

Figure A. 4: Key for the Cluster Diagrams of Visualizing Soft Drink Market, 2008

Source: Modified and Adopted from Howard et al. (2010)