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Analyzing Brand-Level Chips Demand in the United States Using the Multinomial Logit Model

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Multinomial Logit Model ile Amerika Birleşik Devletleri'nde Marka Düzeyinde Cips Talebi Analizi

Öz

Bu çalışma, IRI verilerini kullanarak 52 cips markasının talebini tahmin etmektedir. Multinomial logit modeli, talep tahmininde karşılaşılan çok sayıda parametre sorunu ve içsellik problemlerine çözüm getirmektedir. Tüm markaların fiyat esneklikleri -5.0412 ile -1.4251 aralığında değişmektedir; bu da tüketicilerin cips fiyatlarına son derece duyarlı olduklarını göstermektedir. Tortilla cips markaları, patates cipsi markalarına göre daha az esnek bulunmuştur. Ayrıca fırınlanmış cips markaları en esnek talebe sahip ürünler arasındadır. Funyuns en yüksek, Calidad Triangle ise en düşük talep esnekliğine sahip markalardır. Çapraz fiyat esneklikleri, IIA (ilişkisiz-alternatiflerin-bağımsızlığı) özelliğini sergilemektedir ve büyüklükleri (0.0010 ile 0.0263 arasında), fiyat esnekliklerinin büyüklükleriyle kıyaslandığında tüketicilerin marka sadakatine sahip olduğunu göstermektedir.

Anahtar Kelimeler: Farklılaştırılmış Ürün Talebi, Cips Talebi, Multinomial Logit Model

JEL Kodları: D12, C35

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Abstract

This study estimates demand for 52 chip brands using IRI scanner data. The multinomial logit model addresses dimensionality and endogeneity issues in demand estimation. All brands exhibit elastic demand, with own-price elasticities between -5.0412 and -1.4251, indicating high consumer responsiveness to price changes. Notably, tortilla chip brands are less elastic than potato chip brands. Baked chip brands fall under the category of highly elastic brands. Funyuns has the most elastic demand, while Calidad Triangle has the least elastic demand. Cross-price elasticities (0.0010 to 0.0263), exhibiting the IIA property, indicate that consumers have brand loyalty, as seen by comparisons with own-price elasticities' magnitudes.

Keywords: Differentiated Goods Demand, Chip Demand, Multinomial Logit Model

JEL Codes: D12, C35

Araştırma ve Yayın Etiği Beyanı	Bu çalışma bilimsel araştırma ve yayın etiği kurallarına uygun olarak hazırlanmıştır.
Yazarların Makaleye Olan Katkıları	Çalışmanın tamamı yazar tarafından hazırlanmıştır.
Çıkar Beyanı	Yazarlar açısından ya da üçüncü taraflar açısından çalışmadan kaynaklı çıkar çatışması bulunmamaktadır.

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1. Introduction

Today, companies produce similar but differentiated products in most markets, particularly within the consumer-packaged goods (CPG) industry. Such markets represent imperfectly competitive markets, where product differentiation forms the structure of these markets. Companies compete in pricing and product differentiation to increase their market shares; thus, they provide a wide variety to meet consumer demand. Due to subjective consumer demand factors, prices alone do not solely drive consumers' purchasing decisions. An individual may opt for a more expensive option for two seemingly similar products because the consumer perceives that one product is better than the other in their point of view, leading to purchasing the pricier option.

Estimating demand for differentiated goods is an interesting topic due to the diverse implications from various angles. Companies aim to increase their market power by introducing new products or adjusting existing ones, and consumer demand plays a vital role in shaping these decisions. Furthermore, the market power exerted by companies in this context can impact market competition, which is crucial for an efficient market system. Competition plays a vital role in society, as there is a risk that enterprises may engage in cooperative actions that directly affect social welfare and economic development or engage in exclusionary practices through their power. While antitrust laws prohibit collusion, tacit collusion is still possible. For example, Bresnahan's New Empirical Industrial Organization (NEIO) approach (1989) tests competition and collusion by relying on demand analysis rather than requiring observed cost data.

Health concerns are a relevant issue associated with differentiated goods. Specific categories, such as carbonated soft drinks and salty snacks, raise public health concerns that prompt adjustments in public policies, such as implementing taxes. Moreover, differentiated goods markets hold significant economic importance. Remarkably, the Consumer-Packaged Goods (CPGs) industry substantially impacts economies. For instance, according to Drug Store News (2017), CPG sales in the United States reached approximately 710 billion U.S. dollars in 2011 and steadily increased, reaching around 797 billion U.S. dollars in 2016. To sum up, demand estimation serves as a basis for analyzing various angles within the market. Evaluating market power, launching new products, product targeting, mergers, horizontal and vertical competition, welfare effects, and tax considerations are among the examples that require demand estimation as an initial step for further evaluation.

One typical example of differentiated goods is salty snacks. They are one of the most significant components of the snacking market in the U.S. For example, regarding U.S. retail snack sales in 2015, the largest category was salty snacks, representing approximately 25.1% of the market. The next category was fruits and vegetables, which accounted for around 24.9% of the market (Nielsen, 2015). The salty snacks market in the U.S. has experienced growth in recent years. In 2019, the market value reached approximately 24.808 billion U.S. dollars, and it further increased to about 26.891 billion U.S. dollars in 2020 (Orion Market Research, 2021).

The market represents a high market concentration as it comprises a relatively small number of producers. This market is a typical example of oligopolistic competition, with significant players involved. Companies such as Frito Lay (owned by PepsiCo), Calidad Foods Inc., Truco Enterprise, Gruma Company, Campbell Soup, and Kellogg's compete in this industry. Regarding popular brands, the leading salty snack brands in the U.S. in 2021 were

Lay's, Cheetos, Pringles, Ruffles, and Kettle (Statista, 2022). Its size and oligopolistic structure make the market an interesting case study.

Some categories of salty snacks may have distinct demand characteristics and might not be considered close substitutes from consumers' point of view. The chips category, which includes potato chips, tortilla chips, corn chips, extruded corn snacks, and multigrain chips, is believed to be distinct from other categories like ready-to-eat popcorn, pretzels, pork rinds, and mixed packages containing pretzels, crackers, and mini chips. Research on the demand for chips market is relatively limited compared to that available for other consumer packaged goods, such as carbonated soft drinks. Additionally, existing studies mainly concentrate on specific types like potato chips or include only potato and tortilla chips, neglecting other chip varieties such as corn chips and extruded corn snacks and options like multigrain chips. Furthermore, these studies generally lack a comprehensive representation of brands, thus failing to encompass the full array of options in the differentiated goods market.

To the best of my knowledge, there is no research currently focusing on the brand-level demand for chips covering all chip varieties. This research includes chip brands such as Lay's, Cheetos, Pringles, Mission, Ruffles, Funyuns, Doritos, Tostitos, Sunchips, On the Border, Barcel Takis Fuego, Fritos, Kettle, Calidad, and El Milagro. Including other types of chips is a relevant approach because ignored categories hold significant market shares. For example, Cheetos Cheese, an extruded corn snack, has the highest market share in the data used in this research.

The demand estimation exhibits some difficulties, such as dimensionality and endogeneity problems. The dimensionality problem arises when analyzing a differentiated goods market, as researchers encounter a large number of brands. Traditional demand estimation models, like the Linear Expenditure Model (Stone, 1954) and the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), do not solve the dimensionality issue. When n products are analyzed, there will be n^2 parameters to estimate. In contrast, discrete choice models, such as the multinomial logit model, project products onto a characteristics space, resulting in fewer parameters, mainly based on product characteristics. Given that the model relies on product attributes, this study seeks to determine which characteristics are more suitable for modeling the demand for chips. This examination assesses various specifications, including price, calorie content, sodium levels, total fat, brand name, seasonal variations, and brand-specific dummy variables.

After determining which product characteristics to use, it becomes necessary to address the endogeneity issue. As highlighted in the literature, neglecting endogeneity could result in inconsistent parameter estimates. It is due to the potential correlation between prices and unobserved product attributes, which are observable by companies and consumers but unobservable to researchers. The instrumental variables method is employed using Berry (1994) inversion in the multinomial logit model. Once the model is estimated, the own-price and cross-price elasticities of the brands can be computed and their interpretations provided. Including all types of chips in the analysis is essential, as they maintain substantial market shares. Neglecting these significant players would lead to an incomplete representation of the chips market.

This study focuses on the U.S. chips market, including potato chips, tortilla chips, corn chips, extruded corn snacks, and multigrain chips. The objectives are threefold: firstly, to examine various model specifications based on product characteristics and determine the most suitable model for explaining chip demand; secondly, to utilize instrumental variables to tackle endogeneity concerns and assess the exogeneity and relevance of these instruments; and lastly, to calculate and provide interpretations for the own-price and cross-price elasticities of 52 chip brands using Information Resources Inc. (IRI) supermarket scanner data in Dallas, Texas, in 2011.

The paper is organized as follows: The next section includes a literature review of the demand for differentiated products. The theoretical framework is discussed in Section 3, and the data is explained in Section 4. Section 5 presents the empirical results; the final section is the conclusion.

2. Literature Review on Analyzing Demand for Differentiated Products: The Case of Chips Market

Demand estimation models can be divided into two categories: representative consumer models and location or spatial models (Eaton and Lipsey, 1989; Carlton and Perloff, 2005). Traditional demand models refer to representative consumer models, such as the Linear Expenditure Model (Stone, 1954), the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), and the Rotterdam model (Theil, 1965; Barten, 1966), and they are commonly used for demand estimation. However, these models face challenges when estimating demand for differentiated products, as they assume that all products are equally substitutable and ignore product characteristics. Representative consumer models are primarily designed to evaluate demand in broad categories like food, clothing, and shelter (Nevo, 2010). On the other hand, location models consider the spatial aspect and acknowledge that certain products are better substitutes for each other, with product characteristics playing a significant role in consumers' decision-making. In location models, even if the price of a product decreases, consumers may not switch to alternative products as assumed in traditional models.

Two key concerns when estimating the demand for differentiated goods are dimensionality and endogeneity problems. Companies offer a wide range of differentiated products to gain market power. This wide range of variety requires analyzing a large number of products. Traditional demand estimation methods create a dimensionality problem due to the excessive number of parameters to be estimated. When analyzing n products, it results in n^2 parameters to estimate. For example, if there are 50 products/brands, there would be 2500 parameters to estimate. This issue is commonly called the curse of dimensionality in the literature.

Some restrictions, such as symmetry and other constraints, can be imposed to address the dimensionality problem. However, even if these restrictions are imposed, the parameters to be estimated are still proportional to the number of products. One way to address the dimensionality problem is by imposing a symmetry assumption across products. However, symmetry is generally fit for macroeconomic and trade studies rather than industrial organizations and microdata (Nevo, 2010). Aggregation is another approach to solving the dimensionality problem, but it can be helpful when the interest is on overall demand. In the context of Industrial Organization, the main focus is on understanding the substitution patterns among specific products rather than studying aggregate demand (Nevo, 2010).

An alternative strategy for addressing the dimensionality issue involves classifying products into smaller clusters and applying a flexible function within each cluster (Hausman et al., 1994; Hausman, 1996). However, defining the segmentation of products poses some difficulties. For example, ready-to-eat cereal (RTEC) is one of the typical examples of differentiated goods, and a study conducted by Cotterill and Haller (1997) classifies cereal demand into four groups: simple health nutrition, taste-enhanced wholesome, all-family basic, and kids' cereals. On the other hand, another study conducted by Hausman (1996) categorizes them into three categories: family, kids, and adults. Difficulties arising from defining segmentations are that a priori information is needed, and sometimes, it may not be enough because some products are multilayered.

On the other hand, location models project products onto a characteristics space rather than a product space. Instead of examining goods in product space, which results in parameter estimation proportional to the square of the number of products, location models analyze products based on their characteristics. Therefore, only a few parameters are estimated, representing the product characteristics. In this concept, certain products are considered better substitutes for each other compared to other products, unlike the assumption of equal substitutability in traditional demand models.

One of the applications of location models is discrete choice models (DCMs). Researchers widely used the model in differentiated goods demand studies. DCMs find extensive application across various industries in the literature. For instance, Berry et al. (1995) and Verboven (1996) examine the automobile industry, while Hiller et al. (2018) explore the smartphone industry. DCMs are also used to analyze markets such as the local telephone service market (Train et al., 1987), the frozen foods market (Mojduszka et al., 2001), the carbonated soft drink market (i.e., Dube, 2004; Lopez and Fantuzzi, 2012), the coffee market (i.e., Guadagni and Little, 1983; 1998; Villas-Boas, 2007a), and the ready-to-eat cereal market (i.e., Nevo, 2001; Chidmi and Lopez, 2007), among many others.

McFadden introduced the discrete choice model in various papers published in 1974, 1981, and 1984. The main idea behind this model is to provide a choice set consisting of a set of alternatives. The choice set needs to fulfill three requirements: it needs to be finite, and the alternatives must be exhaustive and mutually exclusive. They imply that decision-makers choose only one option from the finite choice set, which includes all potential alternatives. One of the applications of discrete choice models is the multinomial logit model. In this model, decision-makers encounter more than two choices in the choice set and select an alternative that maximizes their utility. The decision is based on the characteristics of each alternative. Therefore, the model projects products onto a characteristics space, effectively tackling the dimensionality issue. For example, a seminal paper written by Guadagni and Little (1983) analyzes the demand for regular ground coffee using scanner data and opts for the multinomial logit model. Their findings indicate that consumers exhibit brand and size loyalty in the demand for ground coffee.

The multinomial logit model maintains an available closed-form solution, simplifying the estimation process by allowing an analytical solution. However, the model has two issues when it comes to interpreting elasticities. Firstly, the price parameter linearly affects the own-price elasticities. Secondly, the cross-price elasticities hold for the independence from irrelevant alternatives (IIA) property. It implies that the cross-price elasticity of Brand 2 with respect to Brand 1 is the same as the cross-price elasticity of Brand 3 with respect to Brand 1, regardless of their level of substitutability. The model does not capture that variation because it incorporates consumer heterogeneity solely through the error term.

In order to tackle the IIA issue, it is essential to introduce variation around the mean utility that consistently differs among different options (Nevo, 2010). Another application of discrete choice models is the nested logit model (McFadden, 1978), which offers a partial solution to deal with the IIA problem by grouping brands into mutually exclusive nests, and the error term includes not only i.i.d. shock but also a group-specific component. However, segments of brands can be hard to define and distinguish because they require some prior knowledge for some industries, and even some brands are multilayered; hence, they cannot be categorized into one specific group. Like the multinomial logit model, the nested logit model also possesses a closed-form solution, but the IIA property still holds within nests or groups.

Including consumer heterogeneity in the model offers an alternative approach to resolving the IIA issue, which yields the mixed logit model proposed by Berry et al. (1995). Even if it comes with advantages, the estimation process creates some difficulty because the mixed logit model lacks a closed-form solution; simulation methods are employed for its numerical solution. Another discrete choice model that does not exhibit the IIA property is the multinomial probit model, which is also absent from a closed-form solution. Moreover, as Cameron and Trivedi (2005) emphasized, when dealing with J brands, J-1 integrals need to be solved, leading to another dimensionality problem in the model.

Each of these models has its strengths and weaknesses. Despite its limitations, the multinomial logit model offers several advantages. Therefore, the multinomial logit model is opted for estimating demand for the chips market. To sum up, the model has a closed-form solution; thus, it is estimated analytically rather than numerically. Furthermore, the model projects products onto a characteristics space, which helps address the dimensionality issue. Additionally, the model allows for addressing another significant demand estimation problem, endogeneity.

In addition to the dimensionality problem, another concern in the demand estimation process is the endogeneity problem, which arises from the potential correlation between prices and unobserved product characteristics. As Villas-Boas and Winer (1999) highlighted, ignoring the endogeneity problem causes the estimated parameters to be inconsistent. The instrumental variable (IV) method addresses the endogeneity problem. However, before Berry's (1994) research, the instrumental variable method could not be applied in discrete choice models when estimating demand for differentiated goods because the variables are not linear. Berry (1994) suggests transforming the market share function into a linear form by taking its inverse. Therefore, using discrete choice models, the IV method is applicable to solve the endogeneity problem in differentiated demand estimation.

Villas-Boas (2007b) suggests including product fixed effects (brand-specific dummy variables) and quarterly dummies as product characteristics. Product fixed effects account for time-invariant observed and unobserved product characteristics. Quarterly dummies are included in the model to capture quarterly unobserved determinants of demand. These dummies control for the factors that may influence consumer behavior in a specific quarter, such as holidays. A set of exogenous instrumental variables is needed to tackle the endogeneity problem. Villas-Boas (2007b) uses input prices because they are not correlated to unobserved non-seasonal product characteristics (since quarterly dummies are added, the unobserved includes only non-seasonal product characteristics). For example, gasoline price and change in shelf display potentially do not correlate, so input prices are good candidates for instrumental variables. They have been used widely in the demand literature. However, using only input prices is not enough because there is no variation across brands. Villas-Boas (2007b) suggests interacting input prices with brand dummies, allowing the effect of input prices on production to vary across different brands. This approach accounts for the fact that different products may use inputs in different proportions, depending on their specific characteristics. Villas-Boas (2007b) emphasizes that since the exact composition of the products is not directly observed, incorporating interactions between input prices and product dummies allows for a more accurate estimation because it enables researchers to account for the heterogeneity in input usage across different products.

The available literature on the demand for salty snacks is comparatively limited compared to other consumer packaged goods, such as carbonated soft drinks. While there is a wealth of research on carbonated soft drinks covering aspects such as demand analyses at different aggregation levels and angles, competition (both horizontal and vertical), and tax implications, there needs to be more similar research on salty snacks and chips.

The salty snack industry consists of potato chips, tortilla chips, corn snacks, cheese snacks, other extruded chips, ready-to-eat popcorn, pork rinds, pretzels, and other salty snacks, such as mixed snacks. In this study, the demand for the chips category, which includes potato chips, corn chips, extruded corn snacks, tortilla chips, and multigrain chips, is estimated under the belief that some subcategories of salty snacks are distinct and not close substitutes (i.e., excluding pretzels). The United States chip market exhibits characteristics of oligopolistic competition, with a wide variety of highly differentiated products. However, existing studies on chip demand primarily focus on the potato chips market alone or include potato and tortilla chips, disregarding other chip varieties, such as extruded corn snacks (i.e., Cheetos Cheese). Furthermore, these studies generally do not include a comprehensive representation of brands, failing to capture the full range of options in the differentiated goods market.

First of all, several studies investigate the demand for the potato chip category exclusively, including studies conducted by Kumar and Divakar (1999), Arnade et al. (2011), and Dubois et al. (2018). Kumar and Divakar (1999) opt for the Rotterdam model and examine the marketing mix elasticities of potato chips and peanut butter markets at two aggregation levels: brand size level and brand name level. They use IRI scanner data from September 1991 to April 1994. The sample includes three major potato chip brands: Pringles, Eagle, Frito Lay, and one specific store brand. At the brand size level for potato chips, there are 11 brands, including Pringles in 6-8 oz., 9-12 oz., and 13-16 oz. sizes, Frito Lay in 6-8 oz., 9-12 oz., and 13-16 oz. sizes, Eagle in 6-8 oz., 9-12 oz., and 13-16 oz. sizes, and private labels in 6-8 oz. and 13-16 oz. sizes. They claim that the brand-size model can fit more appropriately than the aggregate brand level in potato chips and peanut butter markets. The authors emphasize that Pringles is a uniquely packaged brand of potato chips with its distinct positioning and submarket. They assert that Pringles can be positioned as a rival to other salty snack foods and displayed alongside them on the snack food aisle. They compare this and draw a parallel between shelving products for teeth cleaning chewing gums in the toothpaste aisle.

Using the compensating variation approach, Arnade et al. (2011) examine how launching new potato chip brands affects consumer welfare. They estimate the city-specific AIDS model using household data from the ACNielsen Homescan database from 1998 to 2006 for ten major U.S. cities. The sample includes the top four existing brands and an aggregation of other existing brands, two or three new brands depending on the cities, and an aggregation of other new brands. The researchers compute own-price elasticities and compare consumer expenditure for a new brand's pre- and post-introduction. The own-price elasticities show that brands have highly elastic demand and high substitutability. The authors observe that some of the highest own-price elasticities are for the new brands. They point out that the potato chips market has recently experienced a shift in its nature of competition due to the introduction of baked, organic, and flavored potato chips. Furthermore, the findings indicate that consumers appreciate new brand introductions because they have a preference for greater variety. However, the impact of prices can vary depending on the competition, resulting in either a positive or negative effect. In most cities, the variety of effects is positive. On the other hand, they are negative, resulting in welfare losses in cities that exhibit the presence of high entry barriers. The authors emphasize that the outcomes of national policies regarding anti-competitive behavior can vary based on the characteristics of each region.

Another study by Dubois et al. (2018) investigates the impacts of banning ads in the junk food market, focusing on the U.K.'s potato chips market due to increased interest in restricting advertising for such products. The U.K.'s potato chips market is dominated by a relatively small number of producers who offer multiple products and allocate a significant advertising budget. The authors use Kantar Worldpanel for sales data and AC Nielsen for advertising. They establish a demand and supply model in a market where companies engage in price competition and advertising strategies. In the article, a flexible model is used that accounts for the effect of past advertising on current demand, the potential for predatory and cooperative actions of firms, and the effect of advertisements on consumers' price sensitivity and willingness to pay for specific product characteristics. The findings of Dubois et al. (2018) imply that advertising decreases consumers' price sensitivity and willingness to pay for healthier products. Additionally, advertising brings more consumers to the market and causes positive shifts in consumers' purchasing decisions towards larger packages. The study also indicates that banning ads in the market decreases potato chip demand and, eventually, reduces calorie, saturated fat, and sodium intake. However, banning advertising may cause firms to lower their prices, which, in turn, leads to an increase in the demand for potato chips. Furthermore, banning ads may encourage consumers to replace their choices with alternatives, such as other less healthy junk foods.

Secondly, several additional studies, such as those conducted by Staudigel and Anders (2016) and Staudigel and Anders (2020), focus on examining the demand for potato and tortilla chips while excluding other types of chip brands, such as extruded corn chips. Staudigel and Anders (2016) investigate the impacts of nutritional characteristics such as sodium, calories, and total fat on brand-level demand for chips in the U.S. They analyze 20 potato and tortilla chips brands using scanner data from a major North American retail chain using the mixed logit model. The dataset includes 250 outlets of this retail chain across the U.S. from the SIEPR-Giannini Data Center. The data span is from the first week of 2004 to the twenty-second week of 2007. The authors find that consumers' preferences are not solely driven by healthiness; instead, tradeoffs are involved. The perception of taste plays a significant role in consumer decision-making. Price, brand, and flavor strongly impact brand-level market shares.

Another study by Staudigel and Anders (2020) examines the potential effects of sodium reduction on sales, revenue, and total sodium intake, explicitly focusing on industry-wide versus market leader-only reformulation. The data is weekly store-level scanner data from 250 outlets of a major North American retail chain obtained from the SIEPR-Giannini Data

Center in 2005. They opt for a nested logit model, analyze 133 potato and tortilla chips in package size level, and estimate product level demand and sodium elasticities in the U.S. The key finding indicates that a 10% reduction in sodium content for products that exceed the U.S. Food and Drug Administration's (FDA's) target sales-weighted mean would result in an overall decrease in sodium intake of over 7%. The impact on sales and revenues of manufacturers engaging in reformulation is uncertain and varies across product categories. It indicates that the widely accepted belief that "unhealthy equals delicious" may not be accurate, implying that the potential negative consequences of product reformulation on consumer demand and industry benefits cannot be assured.

Finally, when examining the literature, it is worth noting that Kuchler et al. (2005) take a different approach by considering all types of chips but at a highly aggregated level. Their study analyzes the taxation of snack foods and uses price elasticities to forecast the potential implications of such taxes. A double-log model is used as the demand specification, and the data is gathered from The AC Nielsen Homescan Panel for 1999. The authors approach the brands at a highly aggregated level to deal with the dimensionality problem and focus on four categories: potato chips, other chips (tortilla and corn chips), all chips, and other salty snacks. The elasticity of the potato chips category is inelastic, at -0.45, along with the all-chips category, which is -0.22. The findings show that imposing a 20% tax on potato chips decreases annual per capita consumption by 0.28 oz., or equivalently, 830 calories.

Nevo (2010) asserts that aggregating all individual products into an aggregated commodity can be logical when there is no need to calculate substitution patterns and the only focus is on overall demand. He also emphasizes that aggregation is applied in almost all studies, but the level of aggregation depends on the research interest. Overall demand is not the answer if a study relies on product substitution (Nevo, 2010). Since Kuchler et al. (2005) approach the products at a highly aggregated level, the price elasticities are inelastic. The level of aggregation directly affects substitution patterns, which may change the study's implications. Additionally, Kuchler et al. (2005) ignore the endogeneity of prices, another factor that may change the study's implications.

This study aims to expand the understanding of the demand for chips in the U.S. market by including a wide range of brands. It considers 52 brands, including potato chips, tortilla chips, corn chips, extruded corn snacks, and multigrain chips. It is worth mentioning that the same brand name but different flavors, such as Lay's Original and Lay's Barbeque, are considered separate brands. Additionally, brands with the same name and flavor but different shapes, such as Mission Round, Mission Triangle, and Mission Strips, are considered distinct. To contribute to the existing literature on chip demand, brand-level chip demand is estimated. It employs the multinomial logit model and applies Berry's (1994) inversion technique for using instrumental variables to address the endogeneity problem. The study analyzes chip demand for Dallas, Texas, using the data described in section 4 of the research, which consists of supermarket scanner data, including chip sales provided by Information Resources Inc. (IRI).

3. Theoretical Framework

In the multinomial logit model, an individual encounters more than two choices in a choice set and decides on one alternative, which leads to utility maximization. The decision is made based on product characteristics. The model is summarized here for exposition purposes, following the works of Berry (1994), Nevo (2000a), and Villas-Boas(2007b).

The indirect utility function belongs to consumer i, $i = 1, \dots, n$, who purchase one unit of brand j, $j = 1, \dots, J$, in market t, $t = 1, \dots, T$, is given by

$$U_{ijt} = d_j + d_t + \alpha_i p_{jt} + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt} \quad (1)$$

where d_j represents product fixed effect (brand-specific dummy variables), d_t represents quarterly dummy variables, p_{jt} denotes the price of product j at market t, x_{jt} is a K-dimensional vector of observed product characteristics, ξ_{jt} represents the unobserved (by econometrician) product characteristics, and ε_{ijt} is a mean zero stochastic term. α and β are the parameters to be estimated.

It is worth noting that following Villas-Boas (2007b), the indirect utility function given in equation (1) involves product fixed effect and quarterly dummy variables. This is because product fixed effects represent observable and unobservable product characteristics that remain constant over time. Furthermore, the model includes quarterly dummy variables to capture unobserved determinants of demand specific to each quarter. These dummy variables manage factors influencing consumer behavior during specific quarters, like holidays. The indirect utility function also includes ξ_{jt}, representing unobserved product characteristics. Without the inclusion of quarterly dummy variables, ξ_{jt} would include seasonal and non-seasonal unobserved product characteristics. However, by introducing quarterly dummies, ξ_{jt} includes only non-seasonal unobserved product characteristics, such as changes in shelf display or product packaging.

In addition, the model includes an outside good that represents all the remaining products. The decision maker can opt for the outside good, indicated as $j = 0$. In this case, if a consumer chooses the option of the outside good, her utility is normalized to be constant over time and equal to zero.

If consumer i decides to purchase one unit of brand j in market t, it means that she maximizes her utility within the choice set. Aggregating over all the consumers who choose brand j in market t corresponds to the market share of the brand j in market t. The market share is also equal to the probability of the jth product being chosen, and it is given by

$$P(J = j) = s_{jt}\left(p_{jt}, x_{jt}; \theta\right) = \int I\left[U_{ijt}\left(p_{jt}, x_{jt}; \theta\right) \geq U_{ikt}(p_{kt}, x_{kt}; \theta)\ \forall k\right] f(\varepsilon) d\varepsilon \quad (2)$$

where I is an indicator function and it is 1 if the statement is true, and it is 0 if otherwise. θ represents to parameters to be estimated where $\theta = (\alpha, \beta)$.

Within the multinomial logit model framework, consumer heterogeneity is introduced solely through the error term. This term is assumed to follow an independent and identically distributed (i.i.d.) pattern, corresponding to a type I extreme value distribution. The assumption allows for a closed-form solution of the integral given by equation (2), which can be solved analytically.

The indirect utility can be also expressed as:

$$U_{ijt} = \delta_{jt}\left(p_{jt}, x_{jt}, \xi_{jt}; \theta\right) + \varepsilon_{ijt} \quad (3)$$

where δ_{jt} is the mean utility from brand j, and ε_{ijt} is i.i.d. with type I extreme value density and $\theta = (\alpha, \beta)$.

Finally, the traditional multinomial logit model is given by

$$s_{jt} = \frac{\exp(\delta_{jt})}{\exp(\delta_{0t}) + \sum_{k=1}^{J} \exp(\delta_{kt})} = \frac{exp(\delta_{jt})}{1+\sum_{k=1}^{J} exp(\delta_{kt})} = \frac{\exp(d_j + d_t + \alpha p_{jt} + \beta x_{jt} + \xi_{jt})}{1+\sum_{k=1}^{J} \exp(d_j + d_t + \alpha p_{kt} + \beta x_{kt} + \xi_{jt})} \quad (4)$$

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

The market share function given by Equation (4) is the predicted market share function. The data involves observed market shares, which is $\hat{s}_{jt}$, $j = 1, \dots, J$, and α and β are the parameters to be estimated. The objective is to find values for α and β that minimize the distance between observed shares and predicted shares. Specifically, the goal is to minimize the following expression:

$$\min_{\alpha,\beta} \hat{s}_{jt} - s_{jt}(\delta_{1t}, \dots, \delta_{jt}), \text{ for } j = 1,2, \dots, J \quad (5)$$

where $\hat{s}_{jt}$ is the observed share for brand j at the market t and s_{jt} is the predicted share for brand j at the market t.

The outside good's market share is denoted by $\hat{s}_{0t} = 1 - \sum_{j=1}^{J} \hat{s}_{jt}$. This means that the market share of the outside good at the market t is obtained by subtracting the sum of all the brands' observed shares from 1. Consequently, the total market shares will add up to 1 when considering all brands and the outside good.

The next step is to employ the instrumental variables method because of the endogeneity problem. Before Berry's (1994) work, the IV method could not be implemented in differentiated goods demand estimation when using discrete choice models because of the nonlinearity of the variables in the model. However, Berry (1994) suggests taking the inverse of the market share function to make the variables linear, which enables the application of the IV method to address the endogeneity issue.

Inverting the market share function yields to find the implied mean utility levels, δ_{jt}, for each brand. Berry (1994) confirms there is a unique δ and it satisfies the following equation:

$$\hat{s}_{jt} = s_{jt}(\delta) \quad (6)$$

When the observes shares $\hat{s}_{jt}$ is equated to the predicted shares s_{jt}, there will be $J + 1$ nonlinear equations with $J + 1$ unknowns that are $\delta_{0t}, \delta_{1t}, \dots, \delta_{jt}$. It is given by:

$$\begin{aligned} \hat{s}_{0t} &= s_{0t}(\delta_{0t}, \dots, \delta_{jt}) \\ \hat{s}_{1t} &= s_{1t}(\delta_{0t}, \dots, \delta_{jt}) \\ &\vdots \\ \hat{s}_{jt} &= s_{jt}(\delta_{0t}, \dots, \delta_{jt}) \end{aligned} \quad (7)$$

Because $\sum_{j=0}^{J} \hat{s}_{jt}$ is the sum of all probabilities, it is equal to one. Accordingly, $\sum_{j=0}^{J} \hat{s}_{jt} = 1$, with $j = 0$ for the outside good. Therefore, the equations are linearly dependent, which requires the normalization of the mean utility to be zero for the outside good. Thus, there will be J equations and the system of equations is now able to be inverted to solve $\delta_{1t}, \dots, \delta_{jt}$ as functions of the observed market shares $\hat{s}_{0t}, \dots, \hat{s}_{jt}$, such that

$$\hat{\delta}_{jt} = \delta_{jt}(\hat{s}_{0t}, \dots, \hat{s}_{jt}) \quad (8)$$

Now, equating the observed shares to the predicted market shares corresponds to the following system of equations:

$$\begin{aligned}
\hat{s}_{0t} &= \frac{1}{1+\sum_{k=1}^{J} exp\ (\delta_{kt})} \\
\hat{s}_{1t} &= \frac{exp\ (\delta_{1t})}{1+\sum_{k=1}^{J} exp\ (\delta_{kt})} \\
&\vdots \\
\hat{s}_{jt} &= \frac{exp\ (\delta_{jt})}{1+\sum_{k=1}^{J} exp\ (\delta_{kt})}
\end{aligned} \tag{9}$$

If the natural logarithm are applied to both sides, the system of linear equations can be expressed as follows:

$$\begin{aligned}
ln\ \hat{s}_{0t} &= 0 - ln\ (1+\sum_{k=1}^{J} exp(\delta_{kt})) \\
ln\ \hat{s}_{1t} &= \delta_{1t} - ln\ (1+\textstyle\sum_{k=1}^{J} exp(\delta_{kt})) \\
&\vdots \\
ln\ \hat{s}_{Jt} &= \delta_{J} - ln\ (1+\sum_{k=1}^{J} exp(\delta_{kt}))
\end{aligned} \tag{10}$$

Rearranging the system of equations yields:

$$\begin{aligned}
ln\ \hat{s}_{1t} - ln\ \hat{s}_{0t} &= \delta_{1t} \\
ln\ \hat{s}_{2t} - ln\ \hat{s}_{0t} &= \delta_{2t} \\
&\vdots \\
ln\ \hat{s}_{jt} - ln\ \hat{s}_{0t} &= \delta_{jt}
\end{aligned} \tag{11}$$

Consequently, the inversion denotes $\delta_{jt}{}'s$ as functions of observed shares $\hat{s}_{0t}$,..., $\hat{s}_{jt}$. Thus, the indirect utility function, $\delta_{jt} = d_j + d_t + \alpha p_{jt} + \beta x_{jt} + \xi_{jt}$, can be written as follows:

$$ln\ \hat{s}_{jt} - ln\ \hat{s}_{0t} = d_j + d_t + \alpha p_{jt} + \beta x_{jt} + \xi_{jt} \tag{12}$$

where $ln\ \hat{s}_{jt} - ln\ \hat{s}_{0t}$ represents the dependent variable, p_{jt} and x_{jt} are the independent variables, ξ_{jt} is the error term.

Because prices and product characteristics are potentially correlated with the error term, Ordinary Least Squares (OLS) estimation of α and β are inconsistent. To deal with the endogeneity problem, a Two Stage Least Squares estimator is used to obtain consistent estimations for α and β.

After estimating the parameters, the price elasticities is calculated using the following equation:

$$\eta_{jk} = \frac{\partial s_j}{\partial p_k}\frac{p_k}{s_j} = \begin{cases} \alpha p_{jt}(1-s_{jt}) & if\ j = k \\ -\alpha p_{kt}s_{kt} & if\ j \neq k \end{cases} \tag{13}$$

There are two observations with multinomial logit model elasticities. First, own-price elasticities are proportional to prices. Secondly, cross-price elasticities exhibit the independence from irrelevant alternatives (IIA) property. For instance, 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 and it can be written as:

$$\begin{aligned} \eta_{21} &= -\alpha p_{1t} s_{1t} \\ \eta_{31} &= -\alpha p_{1t} s_{1t} \\ &\vdots \\ \eta_{j1} &= -\alpha p_{1t} s_{1t} \end{aligned} \tag{14}$$

Despite these limitations, the multinomial logit model is still preferred due to its closed-form solution and the ease of estimating it analytically, simplifying the estimation process. Furthermore, the model effectively solves the dimensionality problem. Its compatibility with the IV procedure also addresses the endogeneity concern, making it a practical approach.

4. The Data

This paper uses supermarket scanner data provided by Information Resources Inc. (IRI). The data consists of weekly salty snack sales from December 27, 2010, to December 25, 2011, covering 52 weeks in Dallas, Texas. The IRI data provides unit sales, dollar sales, corresponding volume equivalents, and universal product codes that are unique for different brand sizes, volumes, and packaging. The data are available for many metropolitan areas. The geographical area chosen for this study is Dallas, Texas, based on arbitrary selection, assuming that salty snack sales across different geographical regions are independent. Brands of the same product in different geographical areas are not considered close substitutes (Besanko, 2004).

The sample contains 52 chip brands/products, including potato chips, tortilla chips, corn chips, extruded corn snacks, and multigrain chips at the brand level. Examples of these brands include Pringles Original, Pringles Sour Cream and Onion, Funyuns, Calidad Tortilla Chips Triangle, Doritos Nacho Cheese, Ruffles Reduced Fat, and Baked Cheetos Cheese. The selection of these 52 brands is based on their weekly volume sales and, eventually, those with higher market shares. Each period is considered a separate market in the industrial organizations' context. Since there are 52 weeks in the available data, there are 52 markets. It creates a balanced panel where each week consists of 52 brands, resulting in an observation size of 52 by 52, which amounts to 2704 observations.

The data does not directly provide information on volume sales, prices, and market shares. When unit sales are multiplied by their corresponding volume equivalents, volume sales are gathered. The dollar sales of each brand are summed up and divided by its corresponding aggregated volume sales for each market. Therefore, the price of the particular brand in a specific period/market is calculated.

To calculate the market shares for the brands, the first step is to calculate the potential market size. It is an approximate value obtained by multiplying the geographical area's population by the per capita consumption of salty snacks. It includes potato chips, corn chips, tortilla chips, extruded corn snacks, and multigrain chips. However, it excludes ready-to-eat popcorn, pork rinds, pretzels, nuts and seeds, and other salty snacks. Once the potential market size is calculated, the market shares for each brand are computed for each period. Additionally, the market share of the outside goods is calculated by subtracting the sum of the market shares of the 52 brands from one for each market. It is important to note that the outside good represents all the other brands that are not included in the sample, and its utility is normalized to zero.

Table 1 presents the descriptive statistics of chip sales in Dallas, Texas, in 2011, provided by IRI. The average weekly dollar sales for the chip market are 222,701.8 U.S. dollars. Approximately 102,221 items are sold weekly on average, and the average weekly volume sales reach approximately 875 thousand ounces. Furthermore, Table 2 represents summary statistics of the prices per ounce, the weekly market shares, and nutritional characteristics of the brands included in the sample.

Table 1: Descriptive Statistics of the Data

Weekly Data	Observation	Mean	Std. Dev.	Min	Max
Dollar sales ($)	52	222701.8	26613.42	152252.5	269278.5
Unit sales	52	102221.2	11507.28	66233	121166
Volume sales	52	874728.2	101474.8	580714.7	1117884

Source: Information Resources Inc. 2011

Table 2: Summary Statistics for Brands in the Sample

Variable	Observation	Mean	Std. Dev.	Min	Max
Price per ounce	2704	0.28391	0.07543	0.10167	0.53994
Market share	2704	0.00183	0.00223	0.00002	0.01737
Calories	2704	148.6538	11.4424	120	170
Sodium (mg)	2704	165.9423	61.61416	49	420
Total fat (g)	2704	8.115385	1.965481	3	11

Source: Own calculations from the IRI Data for price and market share. Nutritional information is collected from each brand's website. Calories, sodium, and total fat per serving (1 ounce).

Table 3 shows chip brands' market shares and prices in Dallas, Texas. The sample includes 52 brands produced by seven manufacturers. Frito-Lay, owned by PepsiCo, dominates the market with a 42.97% market share and 38 brands. Calidad Food Inc. and Mission Food Inc. are produced under the Gruma company, which holds a total market share of 4.37%, with four brands in the sample. Furthermore, Truco Enterprises holds a 2.16% market share with its two brands, and Proctor & Gamble is the next player with a 2.03% market share and four brands. Additionally, Barcel USA and El Milagro have one brand, with market shares of 1.13% and 0.52%, respectively. Lastly, Kettle, owned by Diamond Foods, holds 0.47% of the market share with its two brands.

The products by type in the sample include twenty-two potato chips, seventeen tortilla chips, six corn snacks, four corn chips, and three multigrain chips brands. Regarding total sales by type, approximately 20.79% are contributed by tortilla chips, 16.09% by potato chips, 8.45% by corn snacks, 7.38% by corn chips, and 1.47% by multigrain chips in the sample.

Besides, when looking at the brands specifically, Cheetos Cheese captures the highest market share with about 5.26% of total sales. The second leading brand is Doritos Nacho Cheese, which holds about 5.2% of the market share. Both brands are produced under Frito-Lay by PepsiCo. The most expensive brand in the sample is Funyuns, an extruded corn snack also produced by Frito-Lay. On average, its price is about 50 cents per ounce. Furthermore, baked products such as Baked Lay's Original, Baked Tostitos Scoops, and Baked Lay's Barbecue are among the other expensive brands. The least expensive brands by type are tortilla chips. The cheapest brand in the sample is Calidad Triangle, priced at 12.33 cents per ounce. Besides its affordability, Calidad Triangle holds a significant market share, ranking fifth with approximately 2.69% of total sales. Other inexpensive brands in the sample include Santitas Original, Mission Rounds, Mission Strips, and Mission Triangle, all of which are tortilla chips. Their prices range below 20 cents per ounce.

Table 3: Market Shares and Prices for Chips Brands in the Sample

No	Name	Type	Manufacturer	Market Share	Price ($/Oz.)
1	CHEETOS CHEESE	CORN SNACK	FRITO LAY	5.2647 %	0.2820
2	DORITOS NACHO CHEESE	TORTILLA CHIP	FRITO LAY	5.1952 %	0.2504
3	FRITOS ORIGINAL	CORN CHIP	FRITO LAY	3.5844 %	0.2603
4	SANTITAS ORIGINAL	TORTILLA CHIP	FRITO LAY	2.7370 %	0.1671
5	CALIDAD TRIANGLE	TORTILLA CHIP	CALIDAD FOODS INC	2.6896 %	0.1333
6	FRITOS SCOOPS ORIGINAL	CORN CHIP	FRITO LAY	2.6340 %	0.2458
7	WAVY LAY'S ORIGINAL	POTATO CHIP	FRITO LAY	2.5118 %	0.2450
8	CHEETOS FLAMIN' HOT	CORN SNACK	FRITO LAY	1.7698 %	0.2960
9	LAY'S BARBECUE	POTATO CHIP	FRITO LAY	1.6783 %	0.2566
10	ON THE BORDER TRIANGLE	TORTILLA CHIP	TRUCO ENTERPRISES	1.6701 %	0.2191
11	LAY'S SOUR CREAM & ONION	POTATO CHIP	FRITO LAY	1.5872 %	0.2546
12	RUFFLES ORIGINAL	POTATO CHIP	FRITO LAY	1.5482 %	0.3317
13	DORITOS COOL RANCH	TORTILLA CHIP	FRITO LAY	1.5330 %	0.2365
14	LAY'S CLASSIC	POTATO CHIP	FRITO LAY	1.4569 %	0.2906
15	BARCEL TAKIS FUEGO	TORTILLA CHIP	BARCEL USA	1.1250 %	0.2701
16	TOSTITOS SCOOPS	TORTILLA CHIP	FRITO LAY	0.9642 %	0.2587
17	PRINGLES ORIGINAL	POTATO CHIP	PROCTER & GAMBLE	0.9365 %	0.2682
18	DORITOS SPICY NACHO	TORTILLA CHIP	FRITO LAY	0.9004 %	0.2308
19	FRITOS CHILI CHEESE	CORN CHIP	FRITO LAY	0.8525 %	0.2493
20	WAVY LAY'S HICKORY BBQ	POTATO CHIP	FRITO LAY	0.7366 %	0.2586
21	LAY'S CHEDDAR & SOUR CREAM	POTATO CHIP	FRITO LAY	0.6640 %	0.2518
22	MISSION ROUNDS	TORTILLA CHIP	MISSION FOODS INC	0.6472 %	0.1711
23	LAY'S LIMON	POTATO CHIP	FRITO LAY	0.6330 %	0.2718
24	MISSION STRIPS	TORTILLA CHIP	MISSION FOODS INC	0.6217 %	0.1726
25	PRINGLES SOUR CREAM & ONION	POTATO CHIP	PROCTER & GAMBLE	0.6039 %	0.2466
26	RUFFLES CHEDDAR & SOUR CREAM	POTATO CHIP	FRITO LAY	0.5966 %	0.3672
27	FUNYUNS	CORN SNACK	FRITO LAY	0.5230 %	0.5046
28	WAVY LAY'S RANCH	POTATO CHIP	FRITO LAY	0.5190 %	0.2521
29	EL MILAGRO	TORTILLA CHIP	EL MILAGRO	0.5154 %	0.2391
30	ON THE BORDER ROUNDS	TORTILLA CHIP	TRUCO ENTERPRISES	0.4920 %	0.2162
31	DORITOS TOASTED CORN	TORTILLA CHIP	FRITO LAY	0.4441 %	0.2282
32	CHEETOS CHEDDAR JALAPENO	CORN SNACK	FRITO LAY	0.4397 %	0.2693
33	LAY'S CHILE LIMON	POTATO CHIP	FRITO LAY	0.4163 %	0.2664
34	MISSION TRIANGLES	TORTILLA CHIP	MISSION FOODS INC	0.4052 %	0.1762
35	FRITOS TWIST HONEY BBQ	CORN CHIP	FRITO LAY	0.3207 %	0.2342
36	TOSTITOS ORIGINAL	TORTILLA CHIP	FRITO LAY	0.3201 %	0.2501
37	SUNCHIPS ORIGINAL	MULTIGRAIN CH	FRITO LAY	0.3190 %	0.3249
38	SUNCHIPS GARDEN SALSA	MULTIGRAIN CH	FRITO LAY	0.3184 %	0.3267
39	DORITOS SALSA VERDE	TORTILLA CHIP	FRITO LAY	0.3161 %	0.2313
40	LAY'S GARDEN TOMATO & BASIL	POTATO CHIP	FRITO LAY	0.3158 %	0.2616
41	SUNCHIPS HARVEST CHEDDAR	MULTIGRAIN CH	FRITO LAY	0.3107 %	0.3299
42	KETTLE KRINKLE SALT AND PEPPER	POTATO CHIP	KETTLE	0.2717 %	0.3131
43	PRINGLES CHEDDAR CHEESE	POTATO CHIP	PROCTER & GAMBLE	0.2690 %	0.2421
44	RUFFLES QUESO	POTATO CHIP	FRITO LAY	0.2537 %	0.3676
45	RUFFLES REDUCED FAT	POTATO CHIP	FRITO LAY	0.2407 %	0.3891
46	BAKED CHEETOS FLAMIN' HOT	CORN SNACK	FRITO LAY	0.2342 %	0.3531
47	BAKED LAY'S ORIGINAL	POTATO CHIP	FRITO LAY	0.2306 %	0.4292
48	BAKED CHEETOS CHEESE	CORN SNACK	FRITO LAY	0.2202 %	0.3468
49	PRINGLES BBQ	POTATO CHIP	PROCTER & GAMBLE	0.2159 %	0.2495
50	BAKED TOSTITOS SCOOPS	TORTILLA CHIP	FRITO LAY	0.2032 %	0.4246
51	KETTLE SEA SALT	POTATO CHIP	KETTLE	0.2023 %	0.3091
52	BAKED LAY'S BARBECUE	POTATO CHIP	FRITO LAY	0.1860 %	0.4192

Source: Own calculations from the IRI Data. Notes: MULTIGRAIN CH=Multigrain Chip, Frito Lay by PepsiCo.; Calidad Foods and Mission Foods are both produced under Gruma; Barcel USA by Grupo Bimbo; Kettle by Diamond Foods.

In the analysis of chip demand, the instrumental variables are included as the final part of the data to deal with the endogeneity problem. Two instrumental variables are used: gasoline prices and the federal funds rate are obtained from The U.S. Energy Information Administration and The Federal Reserve Bank of St. Louis, respectively. These instrumental variables are multiplied by brand-specific dummy variables to capture brand variations. 52 brand-specific dummy variables are multiplied by gasoline prices and the federal funds rate, resulting in 104 instrumental variables. This approach aims to address the endogeneity issue in the analysis.

5. Empirical Results

This section presents the empirical results of the demand for the chips market in Dallas, Texas. Because prices and unobserved product characteristics are potentially correlated, there is a need to use instrumental variables. Before Berry (1994), instrumental variables could not be implemented when analyzing demand for differentiated goods using a discrete choice model because the variables are not linear. Berry's inversion technique linearizes the variables, enabling the use of instrumental variables. Consequently, a Two-Stage Least Squares (2SLS) estimator can be employed, as the Ordinary Least Squares (OLS) estimator is inconsistent due to endogeneity. Even if OLS is tested further and confirmed to be inconsistent, it is necessary to examine different sets of variables that explain market shares using OLS. Instrumental variables can be used after selecting the best model, referring to 2SLS. Furthermore, own-price and cross-price elasticities are presented and discussed.

Table 4 presents the results obtained through Ordinary Least Squares estimation using different models. Model 1 is the baseline, featuring only price as the explanatory variable. This baseline model accounts for just 19% of the variation in market shares. In model 2, introducing nutritional characteristics leads to a slight increase in the price coefficient. With this addition, the variables explain up to 31% of the variation. Model 3 takes a step further by incorporating quarterly dummy variables to address seasonal variations in demand analysis. In model 4, brand-name dummies are introduced. They refer to brand names without distinguishing specific flavors, baking types, and shapes. Besides brand name dummies, model 5 also includes quarterly dummy variables. In both model 4 and model 5, the price parameter estimates noticeably increase compared to other models. The variables explain up to 50% of the variation in market shares.

Model 6 incorporates product-specific dummy variables besides price. There is no need to add nutritional characteristics because these dummy variables include observed and unobserved product characteristics. Containing them substantially boosts goodness of fit, and all variables explain 92.7% of the variation in market shares. Taking it a step further, model 7 incorporates quarterly dummy variables. Notably, the estimated price parameter is the lowest among all the other models in model 7. All of the variables ultimately explain 93.1% of the variation. This model slightly improves the goodness of fit, and quarterly dummy variables are highly significant compared to model 3 and model 5. They account for seasonal changes; hence, the error term include only non-seasonal changes of demand. Further testing about exogeneity will show the need to use instrumental variables to deal with endogenous prices. Instrumental variables need to be uncorrelated with the error term. Villas-Boas (2007b) suggests input prices as good candidates because non-seasonal changes, such as changes in shelf and display, are not correlated with input prices. Because of all these reasons, model 7 is the preferred choice for further modeling and estimation. Nevo (2000) strongly recommends using brand-specific dummy variables whenever possible instead of using only nutritional characteristics because they account for all product characteristics, either observable or unobservable by researchers.

Table 4: Multinomial Logit Estimates Under Different Specifications using OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-5.662***	-5.123***	-5.169***	-2.584***	-2.702***	-8.357***	-8.776***
	(0.220)	(0.237)	(0.237)	(0.419)	(0.425)	(0.185)	(0.184)
Calories	---	0.036***	0.036***	-0.042***	-0.042***	---	---
		(0.004)	(0.004)	(0.005)	(0.005)		
Sodium	---	0.002***	0.002***	-0.005***	-0.005***	---	---
		(0.000)	(0.000)	(0.000)	(0.000)		
Total fat	---	-0.073***	-0.072***	0.474***	0.472***	---	---
		(0.023)	(0.023)	(0.030)	(0.030)		
Cheetos	---	---	---	0.971***	0.973***	---	---
				(0.111)	(0.111)		
Barcel Takis	---	---	---	2.175***	2.168***	---	---
				(0.216)	(0.216)		
Calidad	---	---	---	0.900***	0.883***	---	---
				(0.126)	(0.127)		
Doritos	---	---	---	0.790***	0.785***	---	---
				(0.084)	(0.084)		
El Milagro	---	---	---	-0.599***	-0.603***	---	---
				(0.120)	(0.120)		
Fritos	---	---	---	0.520***	0.521***	---	---
				(0.087)	(0.087)		
Lay's	---	---	---	0.007	0.011	---	---
				(0.072)	(0.072)		
Kettle	---	---	---	-1.474***	-1.468***	---	---
				(0.100)	(0.100)		
Funyuns	---	---	---	1.833***	1.852***	---	---
				(0.165)	(0.166)		
Mission	---	---	---	-0.540***	-0.552***	---	---
				(0.093)	(0.093)		
On The Border	---	---	---	0.166*	0.160*	---	---
				(0.091)	(0.091)		
Pringles	---	---	---	-0.746***	-0.745***	---	---
				(0.079)	(0.079)		
Ruffles	---	---	---	-0.159	-0.145	---	---
				(0.096)	(0.096)		
Santitas	---	---	---	1.712***	1.695***	---	---
				(0.125)	(0.126)		
Sunchips	---	---	---	0.171**	0.173**	---	---
				(0.084)	(0.084)		
q1	---	---	-0.012	---	0.014	---	-0.052***
			(0.043)		(0.037)		(0.013)
q2	---	---	-0.114***	---	-0.076**	---	-.168***
			(0.043)		(0.037)		(0.014)
q3	---	---	-0.052	---	-0.029	---	-.085***
			(0.043)		(0.037)		(0.013)
Product Dummies	---	---	---	---	---	Yes	Yes
Constant	-5.105***	-10.400***	-10.328***	-2.822***	-2.742***	-4.759***	-4.573***
	(0.064)	(0.439)	(0.44)	(0.573)	(0.576)	(0.060)	(0.061)
Adj-R^2	0.1961	0.3140	0.3154	0.5001	0.5008	0.9276	0.9315
F	660.43	310.38	178.90	143.31	124.27	667.04	669.41
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The dependent variable is $ln\,\hat{s}_{jt} - ln\,\hat{s}_{0t}$. * p<0.1; ** p<0.05, *** p<0.01. Standard errors in parentheses. 2704 observations. Brand names such as Cheetos and Lay's refer to brands without distinguishing flavor, baking type, and shape. Product dummies refer to product-specific dummy variables such as Lay's Classic and Lay's Limon.

Table 5 represents two-stage least square results based on model 7 from the previous table. The regression includes a constant term, price, quarterly dummy variables, and brand-specific dummy variables. As expected, the price parameter is negative, indicating that consumers' utility decreases as the price of a chip brand increases. The quarterly dummy variables correspond to the four seasons in the year, and there are 52 brand-specific dummy variables. One quarter and one brand are excluded to avoid full rank, resulting in 3 quarterly dummy variables and 51 brand-specific dummy variables in the estimation. The constant term, the price parameter, and the quarterly dummy variables are all statistically significant at the 1% level.

On the other hand, Baked Cheetos Cheese, Cheetos Cheddar Jalapeno, Kettle Krinkle Salt and Pepper, Lay's Chile Limon, and Pringles Sour Cream and Onion brands do not exhibit statistical significance. Baked Cheetos Flamin' Hot is significant at 5%, while the remaining brands demonstrate significance at 1%. Consumers strongly favor Cheetos Cheese brand, which positively affects their utility compared to other brands. Funyuns are the second brand, positively impacting consumer utility. In contrast, the Mission Triangles brand carries a negative value in the mean utility of consumers.

The Wooldridge robust score test result rejects exogeneity, indicating that OLS is not a consistent estimator. To address the endogeneity issue, instrumental variables are employed. Following Villas-Boas (2007b), input prices are multiplied by brand-specific dummy variables to serve as instrumental variables. The first-stage R^2 indicates that these instruments are not weak; they are highly correlated with prices, fulfilling the first requirement that instruments must have a high correlation with the endogenous variable.

The second requirement is that instrumental variables must be uncorrelated with the error term. As emphasized by Villas-Boas (2007b), using seasonal dummies accounts for seasonal changes, and including brand-specific dummy variables addresses time-invariant observed and unobserved product characteristics. Consequently, the error term only includes non-seasonal changes in demand. Variables like gasoline prices and interest rates are potentially uncorrelated with non-seasonal changes, such as changes in shelves, displays, and product packaging. Hence, they are suitable candidates for instrumental variables. In addition, to ensure variation across brands, brand-specific dummy variables are multiplied by brand-specific variables (Villas-Boas, 2007b).

Table 6 presents summary statistics of own-price elasticities for the chip brands implied by the multinomial logit model. Elasticities are calculated for each week, and the table shows that variation. On average, own-price elasticities range between -5.0412 and -1.4251, implying that all brands are elastic; thus, consumers are highly sensitive to chip prices. Moreover, tortilla chip brands are less elastic than potato chip brands, and consumers are relatively more responsive to the price changes of baked chips. Funyuns is an onion-flavored corn chip with the most elastic demand with an own-price elasticity of -5.0412. If there is a 10% increase in Funyuns' price, the quantity demanded of the brand will decrease by 50.41%, ceteris paribus. Besides, Calidad Triangle (-1.4251) has the least elastic demand. For example, a 10% price increase in Calidad Triangle results in a 14.25% decrease in its quantity demanded, ceteris paribus. Consumers are the least responsive to the price changes of the Calidad Triangle brand.

Table 5: Multinomial Logit Demand Parameter Estimates Using 2SLS

Variable	Parameter Estimate	Std Error	Variable	Parameter Estimate	Std Error
Price	-9.994***	0.616	Lay's Limon	0.403***	0.045
Baked Cheetos Cheese	0.044	0.065	Lay's SC & Onion	1.157***	0.035
Baked Cheetos Flamin' Hot	0.161**	0.067	Mission Rounds	-0.662***	0.072
Baked Lay's Barbecue	0.607***	0.104	Mission Strips	-0.676***	0.069
Baked Lay's Original	0.920***	0.110	Mission Triangles	-1.116***	0.077
Baked Tostitos Scoops	0.740***	0.107	On The Border Rounds	-0.493***	0.056
Barcel Takis Fuego	0.861***	0.054	On The Border Triangle	0.761***	0.059
Calidad Triangle	0.376***	0.082	Pringles Ched Cheese	-0.785***	0.044
Cheetos Ched Jalapeno	-0.014	0.040	Pringles Original	0.760***	0.042
Cheetos Cheese	2.591***	0.039	Pringles SC & Onion	0.066	0.046
Cheetos Flamin' Hot	1.634***	0.047	Pringles BBQ	-0.938***	0.039
Doritos Cool Ranch	0.908***	0.037	Ruffles Cheddar & SC	1.308***	0.081
Doritos Nacho Cheese	2.263***	0.036	Ruffles Original	1.865***	0.059
Doritos Salsa Verde	-0.722***	0.043	Ruffles Queso	0.394***	0.087
Doritos Spicy Nacho	0.316***	0.042	Ruffles Reduced Fat	0.580***	0.097
Doritos Toasted Corn	-0.406***	0.043	Santitas Original	0.756***	0.070
El Milagro	-0.191***	0.041	Sunchips Garden Salsa	0.261***	0.058
Fritos Chili Cheese	0.440***	0.040	Sunchips Harvest Ched	0.264***	0.062
Fritos Original	1.946***	0.047	Sunchips Original	0.241***	0.057
Fritos Twist Honey BBQ	-0.686***	0.042	Tostitos Original	-0.561***	0.046
Fritos Scoops Original	1.498***	0.044	Tostitos Scoops	0.560***	0.072
Funyuns	2.486***	0.154	Wavy Lay's Hickory BBQ	0.414***	0.037
Kettle Krinkle S&P	-0.056	0.052	Wavy Lay's Original	1.503***	0.037
Kettle Sea Salt	-0.407***	0.051	q1	-0.066***	0.015
Lay's Barbecue	1.233***	0.035	q2	-0.187***	0.016
Lay's Cheddar & SC	0.248***	0.035	q3	-0.096***	0.012
Lay's Chile Limon	-0.060	0.045	Constant	-4.244***	0.169
Lay's Classic	1.371***	0.070	First Stage R^2	0.8998	
Lay's Garden T&B	-0.476***	0.089	Robust Score Test (p-value) (Wooldridge)	4.6427 (p = 0.0312)	

Note: The dependent variable is $ln\,\hat{s}_{jt} - ln\,\hat{s}_{0t}$. * p<0.1; ** p<0.05, *** p<0.01. There are 2704 observations. Wooldridge robust score test rejects the null hypothesis that price is exogenous; hence, OLS is not a consistent estimator. It requires the use of instrumental variables. The model is estimated using 2SLS, including instrumental variables that consist of input prices multiplied by the brand-specific dummy variables following Villas-Boas(2007b). Ched: Cheddar; SC: Sour Cream; S&P: Salt and Pepper; T&B: Tomato and Basil.

Table 6: Summary Statistics of Own-Price Elasticities

Brands	Name	Mean	Std. Dev.	Min	Max
1	BAKED CHEETOS CHEESE	-3.4699	0.1343	-3.6242	-3.1315
2	BAKED CHEETOS FLAMIN' HOT	-3.5284	0.1028	-3.6241	-3.1998
3	BAKED LAY'S BARBECUE	-4.2033	0.1679	-4.4295	-3.7732
4	BAKED LAY'S ORIGINAL	-4.2998	0.1662	-4.5400	-3.8410
5	BAKED TOSTITOS SCOOPS	-4.2468	0.1558	-4.4296	-3.8198
6	BARCEL TAKIS FUEGO	-2.7003	0.0962	-2.9839	-2.3433
7	CALIDAD TRIANGLE	-1.4251	0.1761	-1.5822	-1.0054
8	CHEETOS CHEDDAR JALAPENO	-2.7454	0.2761	-3.2640	-2.1903
9	CHEETOS CHEESE	-2.8335	0.2350	-3.2267	-2.3247
10	CHEETOS FLAMIN' HOT	-2.9809	0.2569	-3.4668	-2.4606
11	DORITOS COOL RANCH	-2.4239	0.2758	-2.9974	-1.9693
12	DORITOS NACHO CHEESE	-2.5287	0.2632	-3.0425	-2.0724
13	DORITOS SALSA VERDE	-2.3905	0.3084	-3.0604	-1.8329
14	DORITOS SPICY NACHO	-2.3720	0.2877	-2.9200	-1.8913
15	DORITOS TOASTED CORN	-2.3675	0.3265	-3.1185	-1.8457
16	EL MILAGRO	-2.3878	0.0095	-2.4076	-2.3560
17	FRITOS CHILI CHEESE	-2.5273	0.2585	-3.0347	-2.0539
18	FRITOS ORIGINAL	-2.5880	0.1902	-3.0238	-2.1896
19	FRITOS TWIST HONEY BBQ	-2.3999	0.2646	-2.9651	-1.9587
20	FRITOS SCOOPS ORIGINAL	-2.4510	0.1451	-2.6796	-2.1356
21	FUNYUNS	-5.0412	0.2084	-5.3914	-4.7094
22	KETTLE KRINKLE SALT AND PEPPER	-3.1706	0.2952	-4.1218	-2.7291
23	KETTLE SEA SALT	-3.1257	0.2479	-3.9894	-2.5789
24	LAY'S BARBECUE	-2.6755	0.3551	-3.2873	-1.7390
25	LAY'S CHEDDAR & SOUR CREAM	-2.6205	0.3327	-3.2939	-1.8591
26	LAY'S CHILE LIMON	-2.7881	0.4268	-3.5868	-1.8721
27	LAY'S CLASSIC	-3.0598	0.3310	-3.5582	-1.9264
28	LAY'S GARDEN TOMATO & BASIL	-2.7109	0.3636	-3.3257	-1.7422
29	LAY'S LIMON	-2.8105	0.3978	-3.5037	-1.8693
30	LAY'S SOUR CREAM & ONION	-2.6547	0.3594	-3.3445	-1.6942
31	MISSION ROUNDS	-1.7353	0.1257	-1.9202	-1.1543
32	MISSION STRIPS	-1.7610	0.1431	-1.9934	-1.0896
33	MISSION TRIANGLES	-1.7896	0.1541	-2.0309	-1.1609
34	ON THE BORDER ROUNDS	-2.1889	0.1357	-2.5430	-1.7857
35	ON THE BORDER TRIANGLE	-2.2209	0.1366	-2.5268	-1.8457
36	PRINGLES CHEDDAR CHEESE	-2.5249	0.2347	-2.8110	-1.9110
37	PRINGLES ORIGINAL	-2.8094	0.3537	-3.2938	-2.1618
38	PRINGLES SOUR CREAM & ONION	-2.5824	0.2708	-2.9353	-1.9863
39	PRINGLES BBQ	-2.5435	0.1965	-2.7765	-2.0203
40	RUFFLES CHEDDAR & SOUR CREAM	-3.7736	0.4020	-4.7835	-2.9210
41	RUFFLES ORIGINAL	-3.3567	0.2544	-3.8066	-2.7069
42	RUFFLES QUESO	-3.7269	0.3344	-4.5719	-3.0199
43	RUFFLES REDUCED FAT	-3.9287	0.3888	-4.7876	-2.9754
44	SANTITAS ORIGINAL	-1.6635	0.0915	-1.7848	-1.2767
45	SUNCHIPS GARDEN SALSA	-3.3448	0.3293	-3.7961	-2.5334
46	SUNCHIPS HARVEST CHEDDAR	-3.3924	0.3279	-3.8640	-2.6458
47	SUNCHIPS ORIGINAL	-3.3209	0.3294	-3.8256	-2.5763
48	TOSTITOS ORIGINAL	-2.5325	0.1747	-2.7538	-2.2046
49	TOSTITOS SCOOPS	-2.7739	0.3786	-3.4196	-2.2368
50	WAVY LAY'S HICKORY BBQ	-2.6586	0.3391	-3.3159	-1.8587
51	WAVY LAY'S ORIGINAL	-2.5337	0.3324	-3.2006	-1.6802
52	WAVY LAY'S RANCH	-2.6137	0.3494	-3.3058	-1.7848

Table 7 shows the elasticity matrix, including both own-price and cross-price elasticities of nine selected brands among the 52 brands. The actual elasticity matrix, on average, includes all 52 brands, resulting in 2704 elasticities (the square of 52). Among these, 52 are own-price elasticities, and 2652 are cross-price elasticities. To ease the demonstration, only the selected nine brands are presented here. The elasticity matrix's diagonal represents the selected brands' own-price elasticities. As mentioned above, the magnitudes of own-price elasticities indicate that consumers are highly responsive to price changes. Compared to the magnitudes of own-price and cross-price elasticities, the cross-price elasticities are significantly smaller in absolute value. It implies that consumers exhibit brand loyalty and are more likely to shift their demand from chips to an outside good.

Kuchler et al. (2005) examine salty snack demand at a highly aggregated level, not at the brand level. Their findings indicate that potato chips' demand is inelastic, with an own-price elasticity of -0.45, and similarly, the entire chips category shows inelastic demand, with an own-price elasticity of -0.22. Another study by Arnade et al. (2011) estimates the demand for the potato chip market using a city-specific AIDS model. Their results show that approximately 60% of the own-price elasticities fall within the range of -1.5 to -0.9, indicating elastic demand. Moreover, their study highlights a significant substitution level among different chip brands. Another study by Staudigel and Anders (2018) examines 20 potato and tortilla chip brands and shows that all own-price elasticities are negative, ranging from -4.9 to -2.1. They find that Baked Lay's Original has the most elastic demand while Tostitos Hint of Lime has the least elastic demand among the brands.

Cross-price elasticities are positive, as expected, indicating that chip brands are substitutes. It means that one would buy more of a chip brand if the price of its substitute increases. They range between 0.0010 and 0.0263, on average. For instance, the cross-price elasticity of all brands with respect to Cheetos Cheese is the same as shown in Table 7, equal to 0.0263. It indicates that if there is a 10% increase in Cheetos Cheese price, the quantity demanded of all brands, such as Ruffles Original and Lay's Original, will increase by 0.263%, ceteris paribus.

The results indicate that cross-price elasticities hold for the independence from irrelevant alternatives (IIA) property of the multinomial logit model, as expected. In the sample, Calidad Triangle and on the Border Triangle are tortilla chips in the same shape, while Pringles Original is a potato chip brand. On The Border brand is a closer substitute to Calidad than Pringles due to their product characteristics. However, the IIA assumption implies that an increase in Calidad Triangle's price results in both on the Border's and Pringles' (and all the remaining brands') market shares being equally affected, assuming all other factors remain the same. It means that all brands are equally affected by a brand's price change, regardless of their product characteristics and how close substitutes they are. Nevo (2010) points out that the IIA problem arises because there is no variation around the mean utility, and consumer heterogeneity enters the model through only the i.i.d. random shock (Nevo, 2000a).

Table 7: The Elasticity Matrix of Selected Chips Brands

	Calidad	Cheetos	Doritos	Fritos	Funyuns	Lay's	Border	Pringles	Ruffles
Calidad	-1.4251	0.0263	0.0231	0.0165	0.0047	0.0075	0.0065	0.0045	0.0091
Cheetos	0.0064	-2.8335	0.0231	0.0165	0.0047	0.0075	0.0065	0.0045	0.0091
Doritos	0.0064	0.0263	-2.5287	0.0165	0.0047	0.0075	0.0065	0.0045	0.0091
Fritos	0.0064	0.0263	0.0231	-2.588	0.0047	0.0075	0.0065	0.0045	0.0091
Funyuns	0.0064	0.0263	0.0231	0.0165	-5.0412	0.0075	0.0065	0.0045	0.0091
Lay's	0.0064	0.0263	0.0231	0.0165	0.0047	-3.0598	0.0065	0.0045	0.0091
Border	0.0064	0.0263	0.0231	0.0165	0.0047	0.0075	-2.2209	0.0045	0.0091
Pringles	0.0064	0.0263	0.0231	0.0165	0.0047	0.0075	0.0065	-2.8094	0.0091
Ruffles	0.0064	0.0263	0.0231	0.0165	0.0047	0.0075	0.0065	0.0045	-3.3567

Notes: The diagonal of the elasticity matrix is shaded and represents own-price elasticities. Calidad=Calidad Triangle; Cheetos=Cheetos Cheese; Doritos=Doritos Nacho Cheese; Fritos=Fritos Original; Lay's=Lay's Classic, Border=On the Border Tringle; Pringles=Pringles Original; Ruffles=Ruffles Original.

6. Conclusion

The U.S. chip market represents oligopolistic competition, primarily due to the presence of only a few major companies. A significant feature of this market is product differentiation, where there are numerous products that are similar but have distinguishing characteristics. The presence of numerous brands in the market makes it challenging to use traditional demand estimation models like the Rotterdam model due to the high dimensionality problem. To overcome this issue, the study employs the multinomial logit model, which uses product characteristics to estimate demand by projecting products onto a characteristics space.

Neglecting important brands during the analysis of the chip market can result in an incomplete analysis. The main objective of this study is to include relevant types and, ultimately, the relevant brands in the analysis. The goal is to calculate elasticities using the multinomial logit model to identify and interpret the substitutability between different brands.

Since this paper relies on the multinomial logit model, which takes into account product characteristics, it seeks to identify which product characteristics better explain chip demand. After evaluating various models, it becomes clear that the most appropriate approach involves using brand-specific dummy variables and seasonal dummies. This choice also helps identify appropriate instrumental variables. It is necessary because prices are potentially correlated the error term. Ignoring the issue of endogeneity may result in inconsistent parameter estimates, as highlighted in the existing literature.

To address the endogeneity problem, it is crucial to identify instrumental variables that must be highly correlated with the endogenous variable (price) and not correlated with the error term. Villas-Boas (2007b) recommends using input prices, commonly employed in the marketing literature, because they are potentially not correlated with non-seasonal changes in demand. Because brand-specific dummy variables and seasonal dummies are employed, they encompass time-invariant observed and unobserved product characteristics and seasonal demand factors, respectively. Therefore, the error term exclusively includes non-seasonal demand factors, and input prices potentially do not correlate with non-seasonal factors, such as shelf placement and display changes. Additionally, to ensure variation across brands, input prices are multiplied by brand-specific dummy variables (Villas-Boas, 2007b), and the results indicate that they serve as strong instruments for explaining prices while being uncorrelated with the error term.

Addressing the endogeneity and dimensionality problems of demand estimations, the multinomial logit model is used for estimating chip demand in Dallas, Texas, at the brand level, using IRI supermarket scanner data from 2011. There are 52 chip brands produced by seven companies, including potato chip, tortilla chip, corn chip, extruded corn snack, and multigrain chip brands. The empirical results of chip demand show that all brands are elastic, indicating that consumers are highly responsive to chip prices. Own-price elasticities range between -5.0412 and -1.4251, on average. Notably, tortilla chip brands have less elastic demand than potato chip brands. Moreover, baked chip brands are highly elastic, meaning consumers' responsiveness to price changes for these brands is higher than for other brands.

Furthermore, the results show that Funyuns, an onion-flavored extruded corn snack brand, has the most elastic demand with an own-price elasticity of -5.0412. It means that a 10% price increase in Funyuns would result in a significant decrease, 50.41%, in the quantity demanded, holding all other factors constant. Conversely, Calidad Triangle, a tortilla chip brand, exhibits the least elastic demand, with an own-price elasticity of -1.4251. In this case, a 10% price increase in Calidad Triangle would lead to a smaller decrease (14.25%) in the quantity demanded, assuming everything else remains unchanged. For example, one study by Staudigel and Anders (2018) examines 20 potato and tortilla chip brands, and it finds that the own-price elasticities range between -4.9 (Tostitos Hint of Lime) and -2.1 (Baked Lay's Original).

All estimated cross-price elasticities are positive; hence, chip brands are substitutes, meaning consumers would buy more of other brands if a particular chip brand's price increases. However, the magnitudes of the cross-price elasticities are notably smaller than the own-price elasticities, indicating that consumers exhibit strong brand loyalty. Even though they are pretty sensitive to price changes for their chosen chip brands, they prefer switching to the outside good rather than opting for different chip brands. The magnitudes of cross-price elasticities range between 0.0010 and 0.0263. For instance, the cross-price elasticity of all brands with respect to Doritos Nacho is 0.0231. If the price of Doritos Nacho increases by 10%, the quantity demanded of Barcel Takis, Calidad Triangle, and Cheetos Cheese would each increase by 0.231%. It confirms that the cross-price elasticities exhibit the independence from irrelevant alternatives (IIA) property.

The sample of 52 chip brands includes different types such as potato chips, tortilla chips, and extruded corn snacks with various flavors such as barbecue, sour cream and onion, cheddar cheese, and ranch. Additionally, they are differentiated based on cooking methods, salt content, packaging, and other factors. While all the chip brands are considered substitutes, there could be closer substitutes within specific brand categories. For example, among the potato chip brands, Pringles and Lay's both offer the same flavor, sour cream and onion. Despite being packaged differently (Pringles in cylindrical containers and Lay's in regular chip bags) and having distinct chip shapes in the packages, these two brands might be more closely related to each other than to Doritos Spicy Nacho, which belongs to the flavored tortilla chip category. Given that the cross-price elasticities exhibit the IIA property, any price change in Pringles Sour Cream & Onion will equally impact both Lay's Sour Cream & Onion and Doritos Spicy Nacho brands even though two potato chip brands with the same flavor might be closer substitutes. Nevo (2010) proposes addressing the IIA property by incorporating consumer heterogeneity, which leads to a systematic divergence in the mean utility. For future research, it would be more relevant to include consumer characteristics, as the demand for differentiated goods depends on subjective tastes and preferences.

This research provides insights into the demand for chips in the U.S., including a wide range of brands and analyzing them at the brand level. This study considers different flavors within the same brand as separate entities, for example, distinguishing between Pringles Original and Pringles Sour Cream and Onion. The same brand names and flavors but different shapes, like Tostitos Original and Tostitos Scoops, are treated as distinct brands. In contrast to previous studies that focus solely on potato chip demand, include only potato and tortilla chips, or approach the goods at a highly aggregated level, this research takes a more inclusive approach. It examines various chip types, such as corn chips, extruded corn snacks, and multigrain chip brands, alongside potato chips and tortilla chip brands, while analyzing them at the brand level. Ignoring significant types and brands would cause an incomplete representation of the chips market. As previously noted, a further extension of the current research could include consumer heterogeneity. Moreover, considering the brands at the package size level may be more relevant. Furthermore, this study highlights the versatility of demand analysis, as it facilitates various evaluations, including tax implications, product targeting, product launches, pricing tactics, promotional strategies, and welfare analysis. Future research that examines the pricing behavior of chip companies could provide a fruitful area of study.

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