DISSERTATION

ANALYZING THE U.S. DAIRY AND NONDAIRY MILK MARKETS: THREE ESSAYS ON CONSUMER DEMAND, PRODUCT SEPARABILITY, LABELING, AND WELFARE

Submitted by

Armen Ghazaryan

Department of Agricultural and Resource Economics

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2020

Doctoral Committee:

Advisor: Alessandro Bonanno

Dawn Thilmany McFadden
Marco Costanigro
Laura Bellows

ABSTRACT

ANALYZING THE U.S. DAIRY AND NONDAIRY MILK MARKETS: THREE ESSAYS ON CONSUMER DEMAND, PRODUCT SEPARABILITY, LABELING, AND WELFARE

This dissertation is comprised of three main chapters, presenting empirical analyses of different aspects of the U.S. dairy and nondairy milk markets. In Chapter 2, two different empirical analyses are performed: 1) tests for weak separability in an Exact Affine Stone Index (EASI) milk demand system that includes dairy and nondairy milks; 2) tests of aggregability of dairy and nondairy milk products in the context of demand analysis by implementing an empirical test based on the Generalized Composite Commodity Theorem (GCCT). We use state-level point-of-sale weekly scanner data of dairy and nondairy milk products' sales from 2012 to 2017. To our knowledge, this is the first study to implement weak separability tests for the linear-approximate EASI model. The goal of Chapter 3 is to estimate consumers' valuation of the "milk" label on nondairy milks, and, as a result, how much producers of nondairy milks may be seeking to capitalize on consumers' preference using dairy terminology. We use one year of monthly point-of-sale scanner data from 2013 to analyze the demand for dairy and nondairy milks using a random coefficients logit model. Additionally, we estimate the welfare implications of the presence of the "milk" label. In Chapter 4, we first use the concept of diversion ratios to assess whether strategic price changes by nondairy milk producers can constitute a threat for dairy milk producers (in terms of market shares) and vice versa. Then, we assess how changes in the market definition of nondairy milks may affect the milk market.

ACKNOWLEDGEMENTS

Now that I have time to look back at the past four years of my studies at Colorado State University, I want to take a moment and thank the people who have made this journey not only possible but also pleasant. First, I want to thank my advisor and supervisor, Alessandro, for all his mentorship, support, flexibility, and encouragement. The Ph.D. journey is a tough one, and, at times, when even I had hard times believing in myself, he continued believing in me, engaging me in multiple fascinating projects, and guiding me through the academic life, all while being extremely friendly and treating my like a colleague, rather than a student. I also want to thank Becky and Andi, for involving me in some of their projects, teaching me numerous applied skills and tools, and guiding me on my career path. My committee members—Dawn, Marco, and Laura, have all been incredibly helpful and supportive, each bringing a different perspective, and making me see the bigger picture while pursuing my research, for which I am extremely grateful. Additionally, I want to thank Hayley, for creating a warm, accommodating, and a welcoming environment in the Department, and all the professors, for sharing their wisdom and making me a better economist. Special thanks to Denise, Donna, and Kathy, for all their administrative support throughout these years.

During my Ph.D. studies, I was lucky to continue my long-time friendships and meet amazing new friends from the Department, the Fort Collins community, and all around the world. I want to thank each and every one of them for all the shared memories and all the positive ways in which they have impacted my life. I am particularly thankful to Kelvin and Sachintha for the countless long study nights, and to Eleni for always cheering me up. Most importantly, I want to thank my family, without listing any particular reasons, because an entire dissertation would not be enough.

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Chapter 1: Introduction [1]

As American consumers have become more health- and environmentally conscious, many of them seek alternatives to traditional food products, such as dairy-free cheese and yogurt, plant-based meat, and dairy alternative beverages (Mäkinen et al., 2016; O'Connor, 2019). Within the alternative product categories, nondairy milks have particularly stood out due to the rapid increase in sales and popularity they have garnered (Packaged Facts, 2020). This growth is likely driven by a number of different factors, such as: lactose-intolerance and allergic reactions to dairy milk; the variety of tastes and textures offered by nondairy milk (Ferreira, 2019); consumer concerns about the dairy industry's handling of animals (McCarthy et al., 2017); and the sector's active promotion of nondairy products as more nutritious and/or tasty alternatives to dairy milk (Packaged Facts, 2018). In short, dairy alternative milks have transitioned from being "fringe" products, sold mostly in health stores and/or in the specialty aisle of grocery stores, to being mainstream products, available in most coffee shops and stores, alongside dairy milk (Franklin-Wallis, 2019). These market changes are part of a bigger trend, which Franklin-Wallis (2019) summarizes with the following: "almond and oat milk are the next wave in a fundamental shift towards a more conscious, sustainable way of living.".

Initially, there was little competition among the different types of nondairy milks. This, however, has changed as producers have been introducing new varieties to the market and trying to highlight the various nutritional and environmental/sustainability characteristics within the

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[1] The findings and conclusions in this study are those of the author(s) and should not be construed to represent any official USDA or U.S. Government determination or policy. This study was supported in part by the U.S. Department of Agriculture, Economic Research Service. The analyses, findings, and conclusions expressed in this study also should not be attributed to Information Resources, Inc. (IRI).

category of nondairy milks (Packaged Facts, 2018). Some oat milk producers, for example, point out the environmentally-focused claim that the production of oats requires up to 90 percent less water than that of almond (Packaged Facts, 2018). In terms of health-related claims, many almond and coconut milks are labeled as soy-free, while other alternatives indicate that they are both dairy-, lactose-, soy-, and nut-free. Moreover, the industry has continuously innovated in terms of new flavors and new plant-derived bases, such as flax, cashew, hemp, macadamia, to name a few, and in terms of new production processes and "milking" technologies that improve the mouthfeel, taste, and scent of nondairy milks (Bizzozero, 2019; Packaged Facts, 2018). Even though the nondairy milk sales have been rising in the United States, their market share was just 7.6 percent as of 2015 (ERS, 2018).

At the same time, U.S. dairy milk sales have been declining for decades. While some of the decline is attributed to the rising popularity of dairy alternatives, there are other factors that have negatively affected the demand for dairy milk. These factors include the availability of new packaged smoothies and shakes, soft drinks, bottled tea, coffee, and water (Franklin-Wallis, 2019). In addition, there are other market disruptions influencing consumption patterns, including: declining sales of cereal, lack of innovations, and changes in the global milk market, such as European Union's abolition of milk quotas in 2015, Russia's ban on imports, and China's weakening demand for milk (Wiener-Bronner, 2019).

In response to the rapid market growth of nondairy milks, the National Milk Producers Federation (NMPF) and other stakeholder groups are opposing the use of dairy terminology (e.g. milk, cheese, yogurt) by nondairy alternatives, as it may affect negatively sales of dairy products (NMPF, 2019). The NMPF argues that, using dairy terminology, nondairy milks benefit from the value some consumers place on products in the broadly defined dairy category. As a result, the

Defending Against Imitations and Replacements of Yogurt, Milk, and Cheese To Promote Regular Intake of Dairy Everyday (DAIRY PRIDE) Act was introduced by Senator Baldwin of Wisconsin in January 2017, to promote the adoption of a stricter legal definition of milk in the United States and it is supported by the NMPF. Similar bills were later introduced in different states.

At the same time, the Plant Based Foods Association (PBFA), which represents the interests of plant-based meat- and dairy alternative manufacturers, with 130 member-producers of different size, argues that such a policy would not only unfairly favor the dairy industry, but also impede innovation, create unjustified costs for its members ranging between 50,000 to 200,000 USD per Stock Keeping Unit (SKU), and eventually be found unconstitutional (Nilson, 2020; PBFA, 2019; Sibilla, 2019). Several courts have dismissed lawsuits which claimed that nondairy milk producer deceive consumers by using dairy terminology, with one judge noting that (PBFA, 2019):

> *... it is simply implausible that a reasonable consumer would mistake a product like soymilk or almond milk with dairy milk from a cow. The first words in the products' names should be obvious enough to even the least discerning of consumers. And adopting Plaintiffs' position might lead to more confusion, not less...*
>
> *Under Plaintiffs' logic, a reasonable consumer might also believe that veggie bacon contains pork, that flourless chocolate cake contains flour, or that e-books are made out of paper.*

Additionally, the Association has established voluntary labeling guidance, recommending that *"... labels clearly identify the main ingredient as part of the word 'milk' or be labeled as a* *'plant-based milk,' along with a clear disclosure of the main ingredient. We also recommend that the principal display panel contain the words 'dairy-free' or 'non-dairy'…"*(PBFA, 2019). Others have argued that nondairy milk producers would have already removed the "milk" term had consumers thought their products contained dairy milk, because many consumers specifically seek to purchase nondairy milk due to the dietary- and moral issues associated with dairy milk (Weijers & Munn, 2019).

Similar policy discussions have also been taking place in other countries, such as Australia and New Zealand (Neo, 2020), while the European Union (EU) banned the use of the dairy terminology on nondairy products in 2017 (Pisanello & Ferraris, 2018). In its ruling, the European Court of Justice concluded that, under EU law, only products of animal origin can be labeled as "milk", "cream", "butter", "cheese" and "yogurt" (Pisanello & Ferraris, 2018). However, the court decision has a list of exceptions, such "coconut milk". Even though the "milk" designation is not allowed on almond beverages, the French, Spanish and Italian terms "lait d'amandes", "leche de almendras" and "latte di mandorla" are allowed.

Within the context of the dairy and nondairy milk products and the impact of labeling on market outcomes, there are four major groups of market players that collectively affect the broadened milk market. The government, setting and enforcing food products' standards of identity; producers (broadly defined, including dairy farmers and/or processors), deciding on how much to innovate, what products to offer through push and/or pull strategies, what labels to use, who to target, and how to market their products (including the pricing decisions); retailers, optimizing store-wide shelf-space allocation; and consumers, making purchase decisions. While there is a vast applied economic literature analyzing dairy milk market's different components, the literature on the broadened milk market, which includes nondairy milks has been lacking, despite the latter’s rapidly increasing popularity and sales. Thus, this study attempts to fill in the gap by focusing on dairy and nondairy milk demand and the structure and nature of consumer preferences in terms of demand separability and aggregability; the preference for the milk label; and counterfactual simulations based on a set of different labeling scenarios.

Particularly, the goal of Chapter 2 of this dissertation is to assess whether consumers first allocate part of their budget to a broad category of milk, which includes both dairy and nondairy milks, and then make their purchase decision, or rather they allocate a part of their budget separately to each category and then make a purchase decision. In other words, we analyze whether dairy and nondairy milks compete for consumers’ expenditure directly or indirectly. To do that, two different empirical analyses are performed: 1) tests for weak separability in an Exact Affine Stone Index (EASI) milk demand system that includes dairy and nondairy milks; 2) tests of aggregability of dairy and nondairy milk products in the context of demand analysis by means of an empirical application of the Generalized Composite Commodity Theorem (GCCT). We use state-level point-of-sale weekly scanner data of dairy and nondairy milk products’ sales from 2012 to 2017. To our knowledge, this is the first study to implement weak separability tests for the linear-approximate EASI model. All the null hypotheses of separability considered in this chapter are rejected, suggesting that nondairy milks compete with dairy milks for the same portion of consumers' budgets, which are allocated to a broadly defined milk category. The results of the GCCT tests also suggest that when analyzing milk demand, it is possible to include dairy and nondairy milks as separate product categories or, alternatively, as one aggregate category, depending on the objectives of a study.

The goal of Chapter 3 is to estimate consumers’ valuation of the “milk” label on nondairy milks, and, as a result, how much producers of nondairy milks may capitalize on the use of dairy terminology. Providing a valuation of the "milk" label, for nondairy milks, will provide the first assessment as of whether the NMPF's claim that producers of nondairy milks benefit from dairy milk's reputation by using dairy terminology is valid. The analysis performed in Chapter 3 uses one year of monthly state-level point-of-sale scanner data from 2013 to analyze the demand for dairy and nondairy milks using a random coefficients logit model. Additionally, we estimate the welfare implications of the presence of the "milk" label on nondairy milks for both consumers and dairy and nondairy milk producers. The results from this chapter suggest that consumers value the "milk" label on nondairy milks positively, and that soy milk producers benefit the most from the use of dairy terminology, followed by almond milk, and other nondairy milk producers. The policy implication is that if the Food and Drug Administration (FDA) recognizes the use of dairy terminology on nondairy milks as deceitful/confusing, then consumers are potentially overpaying for nondairy milks with a "milk" label, while only a fraction of that amount is captured by producers of nondairy milks, resulting in large deadweight losses.

In Chapter 4, we first use the concept of diversion ratios, widely used in establishing market definition in horizontal merger analysis, to assess whether strategic price changes by nondairy milk producers can constitute a threat for dairy milk producers and vice versa. Then, we assess how changes in the market definition of nondairy milks may affect the milk market. Particularly, we simulate counterfactual scenarios measuring changes in milk prices, market shares, dairy and nondairy milk producer profits, and consumer welfare in case nondairy milks are banned from using dairy terminology. The simulation results have two policy implications. First, if the use of "milk" by nondairy milk products is not misleading, and these products are forced to be de-labeled (i.e. they are banned from using milk terminology), the most likely effects will be an increase (decrease) in the profits of dairy (nondairy) milk producers, and a drop in consumer surplus. Thus, such a policy may potentially be unintentionally overall welfare-reducing. Second, if consumers are, indeed, confused by the dairy terminology on nondairy milks, then such a policy would increase both consumers' and dairy milk producers' welfare while decreasing that of nondairy milk producers. Therefore, the policy may potentially be overall welfare-improving.

In conclusion, the findings of this dissertation suggest that: (a) in a multi-stage budgeting context, consumers consider all milk types (dairy and nondairy) when making a milk purchase decision; (b) on average, consumers positively value the "milk" label on nondairy milks; and (c) nondairy milk producers may be able to capitalize on the average consumer's preferences when they use dairy terminology. We also find that dairy milk producers' welfare can increase as a result of stricter enforcement of milk's legal definition. However, whether the overall welfare will increase or decrease as a result of such a policy depends on whether consumers' positive valuation of the "milk" label on nondairy milks comes from confusion or a clear understanding of nutritional differences between dairy and nondairy milks.

Chapter 2: Got Milk or Mylk? Testing for Separability of Demand in a Broadened Milk Category

Introduction

The consumption of dairy milk alternative beverages, such as almond milk and soy milk, commonly referred to as nondairy milk, has experienced rapid growth in recent years. As the U.S. consumers have become more health- and environmentally-conscious, many of them seek alternative products such as dairy-free cheese and yogurt, nondairy milks, and plant-based meat (Mäkinen et al., 2016; O'Connor, 2019). Within the nondairy milk market, preferences have changed significantly. While soy milk was the pioneer product and the leader in terms of volumes of sales in the nondairy milk market through 2014, almond milk has become the product with the largest sales (O'Connor, 2019). This shift is likely due to almond milk's low caloric content, taste, absence of saturated fat, and high-content of vitamin E (Copeland, 2016; Gulseven & Wohlgenant, 2014; O'Connor, 2019).

Nondairy milks also compete with dairy milks for shelf space in stores, as many of nondairy milk products are found in the dairy aisle (Gulseven & Wohlgenant, 2014; Haddon & Parkin, 2018). While sales of nondairy milk have been increasing, volume sales of products in the dairy milk category fell 15 percent during 2012-2017 (Mintel Group Ltd., 2017). According to Haley and Jones (2017), the per capita consumption of dairy milk has been declining at an increasing rate since 1995. Even the sales of organic dairy milk, which were increasing until 2016, started to drop, which can be partly explained by the rising popularity of nondairy milks (Haddon & Parkin, 2018). These market changes have attracted interest of dairy milk producers, policy makers, and academics.

The Defending Against Imitations and Replacements of Yogurt, Milk, and Cheese to Promote Regular Intake of Dairy Everyday (DAIRY PRIDE) Act was introduced in January 2017. The bill proposes to limit the use of dairy terminology on nondairy milks in the United States and it is supported by the National Milk Producers Federation (NMPF). In a press release dated on October 30, 2018, the NMPF President and CEO Jim Mulhern called on the U.S. Food and Drug Administration (FDA) to: "*end deceptive labeling of fake-dairy products*", arguing that consumers are confused about nutritional properties of dairy and nondairy milk products, with many consumers believing that the two categories are nutritionally equivalent (NMPF, 2018). In addition, in February 2019 the NMPF filed a petition with the FDA proposing to label nondairy milk products as "milk substitutes", "milk alternatives", and "imitation milk", depending on the nutritional profile of the beverage (NMPF, 2019).

Several researchers have studied the demand for dairy and nondairy milk beverages, demographic and socio-economic factors affecting their consumption, and preferred attributes (B. Chen et al., 2018; X. Chen et al., 2017; Choi et al., 2013; Copeland & Dharmasena, 2015; Dhar & Foltz, 2005; Dharmasena & Capps, 2014). However, to our knowledge, all previous studies assume either explicitly (B. Chen et al., 2018; Choi et al., 2013; Dhar & Foltz, 2005; X. Li et al., 2018) or implicitly (Dharmasena & Capps, 2014; Dharmasena et al., 2017) that the expenditure on demand for dairy milk is weakly separable from that of nondairy milks, and other consumer goods and beverages. If the demand for dairy milk is in fact weakly separable from that of nondairy milks, then, consumer preferences for products in the dairy milk category are independent of the quantities (purchased) in other categories (nondairy milk). In the context of the DAIRY PRIDE Act, this implies that the bill is based on an incorrect assumption. In other words, the underlying assumption of the DAIRY PRIDE Act is that when making a milk purchase decision, consumers consider all milk types (dairy and nondairy) simultaneously, rather than allocating a part of their budget separately to dairy milks, another part—to nondairy milks, and then making a product choice from each or one of the categories (dairy and/or nondairy).

In this analysis we use a revealed-preference approach to test the assumption of weak separability between dairy and nondairy milk products' demand along three dimensions. In grouping (1), we hypothesize that the demand for dairy milks is weakly separable from the demand for nondairy milks. The logic behind this grouping is that, as shown earlier, many previous studies assumed separability along this dimension, while under the DAIRY PRIDE Act, one of the implicit assumptions is that the demand for dairy milk is not separable from that of nondairy. In separable grouping (2), we assume that the demand for dairy milk and soy milk demand is jointly weakly separable from the demand for almond and other nondairy milk products. The logic for this grouping is that soy milk fortified with calcium, vitamin A, and Vitamin D is currently the only nondairy milk included by the Department of Health and Human Services (DHHS) and USDA as part of the dairy group in the 2015–2020 Dietary Guidelines for Americans (DHHS & USDA, 2015). In grouping (3), the hypothesis is that dairy skim milk and nondairy milk demand is jointly separable from the demand for reduced fat and whole fat dairy milk. The logic behind this grouping is that the fat content in many nondairy milks is lower than that in dairy milk (Vanga & Raghavan, 2018), while many popular blogs[2] suggest that skim milk can be substituted with multiple types of nondairy milks, which might lead to consumers believing that skim milk and nondairy milks are more similar categories of milk. The results of the weak separability tests will shed light on how consumers allocate their milk expenditures.

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[2] An example of a popular blog focused on dairy-free lifestyle is https://www.godairyfree.org/dairy-substitutes/how-to-substitute-milk-skim-low-fat-whole.

This information will be useful for policy makers involved in the current policy debate regarding restricting the use of milk terminology on nondairy milks. Particularly, it will illustrate whether the underlying assumption of the DAIRY PRIDE Act is valid.

To that end, we develop a weak separability test for the linear-approximate Exact Affine Stone Index (LA-EASI) demand model of Lewbel and Pendakur (2009), which is an additional contribution to the literature. Additionally, we apply the Generalized Composite Commodity Theorem (GCCT) tests of Lewbel (1996) to further investigate the aggregability of dairy and nondairy milk products in the context of demand analysis, which is also important since miss-specified aggregation can lead to biased results (Davis et al., 2000). Given the different levels of aggregation used in the recent literature for the milk category (Alviola & Capps, 2010; B. Chen et al., 2018; Dharmasena & Capps, 2014; Gulseven & Wohlgenant, 2014; X. Li et al., 2018), the results of the GCCT tests will guide future research analyzing milk demand on the correct level of product aggregation.

Following the existing literature (Dhar et al., 2003; Nayga & Capps, 1994; Sellen & Goddard, 1997), we specify an incomplete demand system, focusing only on the demand for dairy and nondairy milk and assume that the demand for these goods (in aggregate) is separable from that for all other goods. We use the Information Resources Incorporated (IRI) point-of-sale (PoS) data on dairy and nondairy milk products from 2012 to 2017 and estimate the demand for these products using the LA-EASI model. The data access was provided by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA) through a third-party agreement.

We find that all three weak separability structures can be rejected, thus suggesting that consumers allocate their budget to all six milk types (dairy skim, dairy reduced fat, dairy whole fat, almond, soy, and other nondairy milks) when making a purchase decision. The implications of this finding are twofold. First, studies which assume weak separability of dairy milk demand from nondairy milk demand in the U.S. may report biased estimates. Second, coupled with the sign and magnitude of the cross-price elasticities (discussed below), this finding supports the NMPF claim that nondairy milks compete with dairy milks for consumers' budget allocated to the category of milk. Our results suggest that, in most cases, an increase in nondairy milk prices leads to higher sales of dairy milks and lower sales of nondairy milks, in that dairy milks are considered substitutes for nondairy milks, whereas nondairy milks are seen as complements. In contrast, a price increase in most dairy milks leads to higher sales of both other dairies and nondairy milks – thus, dairy and nondairy milks are mostly substitutes for each dairy milk product.

Based on the GCCT test, we find that to minimize the risk of misspecification when estimating U.S. milk demand, researchers could either aggregate all dairy milks (skim, reduced fat, and whole fat) together, all nondairy milks (almond, soy, other nondairy) together, or all six milk types (dairy and nondairy) together as one category. In short, the levels of aggregation appropriate to use (two categories, or one broader category), will depend upon the objectives of the study.

Market Outlook and Literature Review

The nondairy milk category has grown rapidly. The value of U.S. sales of soy and almond milk alone rose from 1.44 billion USD in 2010 to 2.25 billion USD in 2018 and is expected to further grow to 2.36 billion USD by 2024 (O'Connor, 2019). The increased consumption of nondairy milk products is not solely due to the increase in the number of consumers being vegetarians or vegans. Consumer beliefs regarding food issues, such as mistreatment of animals, animal-based products being less healthy, and use of hormones in dairy milk have contributed more broadly to this growth (McCarthy et al., 2017). Among many reasons, consumers may also purchase nondairy milk because of allergic reactions to dairy milk, lactose-intolerance, or because they like different taste, texture, or want additional nutrients offered by nondairy milks (Ferreira, 2019). Given the large variety of nondairy milks, they offer the same functionality as dairy milk and are used both as drinks and in coffee, cereal, cooking, and smoothies and shakes (Ferreira, 2019; PBFA, 2019). From 2013 to 2015, dairy milk's market share dropped from 94.33% to 92.37%, while the nondairy milk products' market share rose proportionally—with almond milk leading the growth (ERS, 2018).

Along with nondairy milk products, several dairy milk categories have also been experiencing growth in sales. In the U.S. market, organic milk sales have been growing since the mid-1990s (Alviola & Capps, 2010), reaching 1.37 billion USD of sales in 2017 (Haddon & Parkin, 2018). Lactose-free milk has also become popular, with sales reaching an estimated 881.1 million USD in 2017 (Copeland, 2016). Lactose-free is a desirable product attribute for consumers of both dairy and nondairy milk (McCarthy et al., 2017). Overall, the individual factors that have boosted the demand for nondairy milks, might also be responsible for the increased sales of specialty dairy milks.

Few studies have analyzed the demand for nondairy milk products and/or characterized the nondairy milk consumers. Younger household heads and part-time employed household heads (vs full-time employed), are more likely to purchase soy milk (Copeland, 2016;

Dharmasena et al., 2017; Gulseven & Wohlgenant, 2014). Household heads employed part-time purchase more almond milk than the unemployed household heads, while full-time employed household heads purchase less almond milk than the unemployed ones (Copeland, 2016). Black, Asian, and Hispanic households have a higher probability of purchasing soy milk and almond milk[3] than non-Hispanic white households (Copeland, 2016; Dharmasena et al., 2017; Gulseven & Wohlgenant, 2014). Households with children are also more likely to purchase soy milk (Dharmasena et al., 2017; Gulseven & Wohlgenant, 2014). Household heads with higher education levels are also more likely to purchase soy and almond milk (Copeland, 2016).

Most of these studies, however, either explicitly or implicitly assume that the expenditures on dairy milk demand are weakly separable from those of nondairy milks. According to Sellen and Goddard (1997): "*…weak separability implies that the marginal rate of substitution between two consumption goods in one group is independent of quantities of goods consumed from outside the group.*" In the context of multi-stage budgeting, this means that consumers first devote their budget to a broad category of goods, and then, based on product prices and expenditures, allocate their expenditure among sub-categories of goods. Thus, demand studies including only conventional dairy milk products, assume implicitly that nondairy and dairy milk markets are separable. Similarly, demand analyses focusing only on dairy milks and one or two nondairy milks (e.g. soy milk) assume that the demand for those products is separable from that of other emerging nondairy milks not included in the study. While the assumption of

[3] This might be due to perceived or actual lactose intolerance among these populations. According to Bailey et al. (2013), perceived or actual lactose intolerance is one of the main reasons why both African Americans and Hispanic Americans consume less than the recommended levels of dairy foods.

weak separability is necessary for multi-stage budgeting and estimating conditional demand systems, the convenience of an assumption cannot substitute the truth (Moschini et al., 1994).

Demand analysis results, which are often used in calculating consumer welfare changes due to policy or price changes, can be biased if the underlying weak separability assumptions cannot be justified (LaFrance, 1993). Previous studies have tested for weak separability in multiple markets, focusing primarily on the demand for meat products. For example, Eales and Unnevehr (1988), using U.S. annual data from 1965 to 1985, rejected the hypothesis that consumers first allocate expenditures to animal product aggregates (e.g. beef or chicken), and then among products within an aggregate category. At the same time, they failed to reject the null that consumers allocate expenditure across all meat products at once or between high-quality and low-quality products from different animals (Eales & Unnevehr, 1988). Thus, they suggested that tests for structural change based on meat aggregates and the resulting policy implications may be biased (Eales & Unnevehr, 1988). In contrast, Nayga and Capps (1994), using weekly scanner data from a retail food firm in Houston from 1986 to 1988, rejected the null that consumers select among various cuts or qualities of a particular meat type; or that they select among meat types of similar quality. Boonsaeng and Wohlgenant (2009), analyzed demand separability between imported and domestic meats in the U.S. In their study, which used quarterly time-series data from 1971 to 2002, the null of demand separability between domestic and imported meats was rejected, in spite of many previous studies having assumed such a separable structure for the ease of modeling (Boonsaeng & Wohlgenant, 2009). Lakkakula et al. (2016) used a test for weak separability of U.S. caloric sweetener demand using data from 1975 to 2013 to establish an appropriate commodity aggregation level. They found that all commodities (sugar, high fructose corn syrup, and glucose) should be included in the demand system (Lakkakula et al., 2016).

A Model of Demand for Dairy and Nondairy Milks

For our analysis of the demand for dairy and nondairy milk products, we use the EASI demand system, developed by Lewbel and Pendakur (2009). Besides sharing all the desirable properties of Deaton and Muellbauer (1980) widely-used Almost Ideal Demand System (AIDS) and its variations (e.g. Banks et al. (1997); Bollino (1987); and Hovhannisyan and Gould (2012)), EASI provides two additional benefits. First, it is not limited by the rank-three restriction of Gorman (1981), thus allowing the shape of the Engel curve to be fully unrestricted and determined by the data (Lewbel & Pendakur, 2009). Second, it accounts directly for unobserved consumer heterogeneity, which is expressed in the error term (Zhen et al., 2013).

We illustrate the derivation of the EASI model following the notation used by Pendakur (2009). Consider a consumer who maximizes utility given a linear budget constraint. Let the minimum nominal total expenditure required for obtaining a utility level, u, be

(2.1) $$x = C(\mathbf{p}, u),$$

where x is the nominal total expenditure, $C(\cdot)$ is the cost function, and $\mathbf{p} = [p_1, ... p_J]$ is a vector of prices of the J goods included in the bundle consumers can choose from. Let $\mathbf{w} = [w_1, ..., w_J]$ be the vector of budget/expenditure shares defining the bundle of goods chosen by the consumer. The compensated (Hicksian) budget-share functions, in turn, can be written as

(2.2) $$\boldsymbol{w}(\mathbf{p}, u) = \left[w_1(\mathbf{p}, u), ..., w_j(\mathbf{p}, u) \right]$$

Based on Shephard's Lemma, the compensated budget-share functions are equivalent to the price elasticity of the cost function:

(2.3) $$w_j(\mathbf{p},u) = \frac{\partial \ln C(\mathbf{p},u)}{\partial \ln p_j}.$$

However, since the budget-share is still expressed in terms of unobserved utility, it cannot be used in applied demand analysis. Assuming that the compensated budget-share functions are uncorrelated across goods, they can be written as

(2.4) $$w_j(\mathbf{p},u) = m_j(u) \text{ for all } j = 1,\ldots,J .$$

Using duality, the cost function takes the following form:

(2.5) $$\ln C(\mathbf{p},u) = u + \sum_{j=1}^{j=J} m_j(u) \ln p_j .$$

Unobserved consumer characteristics, $\boldsymbol{\varepsilon} = [\varepsilon_1,\ldots,\varepsilon_J]$, can be incorporated as an argument of the cost function as follows

(2.6) $$\ln C(\mathbf{p},u,\varepsilon) = u + \sum_{j=1}^{j=J} m_j(u) \ln p_j + \sum_{j=1}^{j=J} \varepsilon_j \ln p_j ,$$

where $E[\boldsymbol{\varepsilon}] = \mathbf{0}_J$. By Shephard's Lemma, the compensated budget-share functions become

(2.7) $$w_j(\mathbf{p},u,\varepsilon) = m_j(u) + \varepsilon_j .$$

Given that budget/expenditure shares, $w_j = w_j(\mathbf{p},u,\varepsilon)$, and expenditure, x, can be can be calculated from data, the utility function can be rewritten in terms of observables. Thus, replacing $w_j(\mathbf{p},u,\varepsilon)$ with w_j, and $C(\mathbf{p},u,\varepsilon)$ with x, we have

(2.8) $$u = \ln x - \sum_{j=1}^{j=J} w_j \ln p_j \,.$$

Further replacing u in (2.4) with (2.8) results in implicit Marshallian demand expressed as

(2.9) $$w_j = m_j\left(\ln x - \sum_{j=1}^{j=J} w_j \ln p_j\right) + \varepsilon_j = m_j\left(y\right) + \varepsilon_j \,,$$

where $y = \ln x - \sum_{j=1}^{j=J} w_j \ln p_j$ is implicit utility and ε_j can be interpreted as unobserved consumer preference heterogeneity. The Marshallian demand is implicit because budget-shares are on both sides of the equation. In the Marshallian budget-share functions, y is not constrained by the rank-three restriction of Gorman (1981) and can take any shape. However, at this stage, prices enter the demand equations only through implicit utility, y, which creates an unrealistic situation, where prices do not affect the uncompensated budget-share functions. If the price vector is $\mathbf{1}_J$, resulting in a log-price vector of $\mathbf{0}_J$, then $y = \ln x - \sum_{j=1}^{j=J} w_j \ln p_j$ reduces to $y = \ln x$, making y log real-expenditures. Given the Stone index, $\Pi_{j=1}^{j=J}\left(p_j\right)^{w_j}$, which is the exact deflator, nominal expenditures become real expenditures.

To capture the effect of prices on compensated budget shares, a quadratic form in log-prices can be added to (2.6), yielding an EASI cost function

(2.10) $$\ln C\left(\mathbf{p}, u, \boldsymbol{\varepsilon}\right) = u + \sum_{j=1}^{j=J} m_j\left(u\right) \ln p_j + \frac{1}{2} \sum_{j=1}^{j=J} \sum_{k=1}^{k=J} \alpha_{jk} \ln p_j \ln p_k + \sum_{j=1}^{j=J} \varepsilon_j \ln p_j \,.$$

Compensated budget-share functions are obtained using Shephard's Lemma and take the following form

(2.11) $$w_j\left(\mathbf{p}, u, \boldsymbol{\varepsilon}\right) = m_j(u) + \sum_{k=1}^{k=J} \alpha_{jk} \ln p_k + \varepsilon_j \,,$$

with $\alpha_{jk} = \alpha_{kj}$ for all j,k. Proceeding as illustrated above, and replacing $\ln C(\mathbf{p},u,\boldsymbol{\varepsilon})$ with $\ln x$, and $w_j(\mathbf{p},u,\boldsymbol{\varepsilon})$ with w_j, the implicit utility becomes

$$(2.12) \qquad y = u = \ln x - \sum_{j=1}^{j=J} w_j \ln p_j + \frac{1}{2}\sum_{j=1}^{j=J}\sum_{k=1}^{k=J} \alpha_{jk} \ln p_j \ln p_k \ ,$$

where the log of the deflator that exactly converts nominal into real expenditure is given by

$$(2.13) \qquad \sum_{j=1}^{j=J} w_j \ln p_j - \frac{1}{2}\sum_{j=1}^{j=J}\sum_{k=1}^{k=J} \alpha_{jk} \ln p_j \ln p_k \ ,$$

which is an Affine transformation of the Stone Index. By replacing u in (2.11) with y from (2.12), implicit uncompensated budget/expenditure shares become

$$(2.14) \qquad w_j = m_j(y) + \sum_{k=1}^{k=J} \alpha_{jk} \ln p_k + \varepsilon_j \ ,$$

where $\alpha_{jk} = \alpha_{kj}$ for all j,k.

Weak Separability

We follow the approach of Eales and Unnevehr (1988); Lakkakula et al. (2016); Nayga and Capps (1994); Sellen and Goddard (1997) to characterize weak separability of the direct utility function. Let $\mathrm{q} = (q_1,...,q_J)$ denote the vector of consumption goods. These goods can be ordered in *Z* separable groups and form Z sub-utility functions, such that the utility function, $U(\mathbf{q})$, can be represented as:

$$(2.15) \qquad U(\mathrm{q}) = U_0\left[U_1(q_1), U_2(q_2), ..., U_Z(q_Z)\right]$$

According to Goldman and Uzawa (1964), this separable structure limits the substitution patterns of goods in different groups. Thus, the Slutsky substitution term, S_{ik}, between two goods *j* and *k* in different groups, respectively, *G* and *H*, is proportional to the product of the income effects (Goldman & Uzawa, 1964):

$$(2.16) \qquad S_{ik} = \mu_{GH}(\mathbf{p}, M)\frac{\partial q_i(\mathbf{p}, M)}{\partial M}\frac{\partial q_k(\mathbf{p}, M)}{\partial M} \text{ for all } i \in G, \;\; k \in H, \;\; G \neq H$$

where $\mathbf{p} = (p_1, ..., p_n)$ is the vector of nominal prices; M denotes income; $\mu_{GH}(\mathbf{p}, M)$ is the proportionality term, which measures the degree of substitutability between the two groups; and *G* and *H* are separable groupings of goods. These conditions are necessary and sufficient for weak separability (Moschini et al., 1994).

If the direct utility function is weakly separable, then from (2.16) it follows that:

$$(2.17) \qquad \frac{S_{ik}}{\frac{\partial q_i(\mathbf{p}, M)}{\partial M}} = \frac{S_{jk}}{\frac{\partial q_j(\mathbf{p}, M)}{\partial M}} \text{ for all } i, j \in G, \; k \in H, \; G \neq H \; .$$

Based on (2.17), weak separability can also be expressed in terms of the elasticities of substitution, σ_{ik} and σ_{jk}, between the goods in *G* and *H*; and the expenditure elasticities, τ_i and τ_j:

$$(2.18) \qquad \frac{\sigma_{ik}}{\sigma_{jk}} = \frac{\tau_i}{\tau_j} \text{ for all for all } i, j \in G, \; k \in H, \; G \neq H \; .$$

If weak separability holds, then the ratio of expenditure elasticities should be equal to the ratio of compensated cross-price elasticities of two goods within *G* (in this case, good *i* and good *j*), with respect to a good from group *H* (good *k*).

From an empirical standpoint, the weak separability also allows to test for the proper product aggregation level, which is important for demand estimation. To do so, it is necessary to impose additional restrictions so that the model is consistent with the assumption of homothetic preferences (Sellen & Goddard, 1997). In the EASI demand context, this means that the functions $m_j(y)$ are independent of y. In other words, to represent homothetic preferences within the EASI demand system, one should exclude y from the model. However, one of the advantages of the EASI demand model is that the functions of $m_j(y)$ are fully unrestricted in their dependence on y (Pendakur, 2009). That is, the EASI model allows the data to determine y's proper degree of polynomial. Thus, if non-homothetic preferences are confirmed by the estimated parameters, it will be counterintuitive to use the weak separability test for defining a proper aggregation level within the demand system. Thus, we turn to Lewbel (1996)'s GCCT to define the aggregation level. This procedure relies on data time-series properties and is therefore less restrictive than the separability tests.

Generalized Composite Commodity Theorem

The GCCT allows to establish proper aggregation levels within a demand system by means of statistical testing. Finding the right aggregation level is important for reducing possible misspecification errors in demand analysis (Davis et al., 2000). Given the interest in U.S. milk demand analysis, a goal of this study is to establish a proper milk aggregation level within a demand system.

Below we follow the approach taken in Lewbel (1996); Reed et al. (2005); Schulz et al. (2012) . According to the GCCT, logged elementary (product-level) prices, $\ln \mathbf{p}$, and logged income, $\ln M$, comprise the functions of J elementary share equations, such that the *j*th elementary budget/expenditure share is $w_j (j = 1,..., J)$. Following Lewbel (1996),

$g_j : (\ln \mathbf{p}, \ln M) \to w_j (j = 1,..., J)$, such that

(2.19) $$w_j = g_j(\ln \mathbf{p}, \ln M) + \varepsilon_j,$$

where $E\left(\varepsilon_j \mid \ln \mathbf{p}, \ln M\right) = 0 \Rightarrow E\left(w_j \mid \ln \mathbf{p}, \ln M\right) = g_j(\ln \mathbf{p}, \ln M)$. Given that g_j make up a valid elementary demand system, they satisfy some general restrictions, namely Engel aggregation (or adding-up) $\left(\Sigma g_j = 1\right)$, homogeneity $\left(g_j\left(\ln \mathbf{p} - k, \ln M - k\right) = g_j\left(\ln \mathbf{p}, \ln M\right) \text{for all } j\right)$, and Slutsky symmetry $\left(i.e., \left(\partial g_k / \partial \ln \boldsymbol{p}_j\right) + \left(\partial g_k / \partial \ln M\right) g_j = \left(\partial g_j / \partial \ln \boldsymbol{p}_k\right) + \left(\partial g_j / \partial \ln M\right) g_k\right)$.

The Hicksian demands also meet the requirement of negative semi-definiteness. In addition, the GCCT maintains the existence of a system of aggregate (composite) share equations. The $D(< J)$ aggregate shares $W_I = \sum_{j \in I} w_j \left(I = 1,..., D\right)$ are functions of logged income, $\ln M$, and logged aggregate prices $\ln \mathbf{P}$, such that

(2.20) $$W_I = G_I(\ln \mathbf{P}, \ln M) + v_I,$$

where $E\left(v_I \mid \ln \mathbf{P}, \ln M\right) = 0 \Rightarrow G_I\left(\ln \mathbf{P}, \ln M\right) = E\left(W_I \mid \ln \mathbf{P}, \ln M\right)$. Further, let $G_I^*\left(\ln \mathbf{p}, \ln M\right)$ be the sum of conditional means of group I 's elementary demands (Lewbel, 1996), such that

(2.21) $$G_I^*\left(\ln \mathbf{p}, \ln M\right) = \sum_{j \in I} g_j\left(\ln \mathbf{p}, \ln M\right).$$

The j th relative price can be defined as $\rho_j = \ln \boldsymbol{p}_j - \ln \boldsymbol{P}_I$, while the vector of the relative prices can be defined as $\boldsymbol{\rho} = \ln \mathbf{p} - \ln \mathbf{P}^*$, where $\ln \mathbf{P}^*$ is the vector of group prices. Therefore,

$$v_I = \sum_{j \in I} \varepsilon_j + G_I^* \left(\boldsymbol{\rho} + \ln \mathbf{P}^*, \ln M \right) - G_I \left(\ln \mathbf{P}, \ln M \right), \tag{2.22}$$

which suggests that the errors from the composite model are correlated with relative elementary prices. According to Lewbel (1996), aggregation is valid when the vector of relative prices is statistically independent of aggregate prices and income. Therefore,

$$G_I \left(\ln \mathbf{P}, \ln M \right) = E\left[G_I^* \left(\ln \mathbf{P}^* + \boldsymbol{\rho}, \ln M \right) | \ln \mathbf{P}, \ln M \right] = \int G_I^* \left(\ln \mathbf{P}^* + \boldsymbol{\rho}, \ln M \right) dF\left(\boldsymbol{\rho} \right), \tag{2.23}$$

which, as Reed et al. (2005) noted, shows that *"the conditional expectation of the Ith composite share equals an unconditional expectation of sums of the elementary demand functions in the Ith composite",* when the elementary prices, $\ln \mathbf{p}$, can be replaced by the deviations from the group price indexes, $\ln \mathbf{P}^* + \boldsymbol{\rho}$.

Using (2.23), Lewbel (1996) obtains results that are applicable to demand system estimation. First, $G_I \left(\ln \mathbf{P}, \ln M \right) \left(I = 1, ..., D \right)$ is a valid system of composite demand equations since it meets the Engel aggregation, homogeneity, and Slutsky symmetry conditions through the elementary demands. Second, $G_I \left(\ln \mathbf{P}, \ln M \right)$ produces elasticities which are the best, unbiased estimates of within-group sums of elementary demand elasticities. Third, based on (2.22) and (2.23), $(G_I^* - G_I)$ is a function of $\boldsymbol{\rho}$, the bias term which occurs as a result of aggregation. Since this bias can be found in v_I, relative prices will be correlated with the GCCT-justified aggregate demand system's errors. However, if the demand system is based on preferences, such that $G_I^* = G_I$, and $v_I = \sum_{j \in I} \varepsilon_I$, then the aggregate demand errors will not be correlated with relative prices.

Data

For this study, we utilize weekly point-of-sale scanner data from 2012 to 2017, originally supplied by Information Resource Incorporated (IRI) to the ERS, USDA[4]. The sales data are collected through in-store scanners of affiliated retailers and are recorded at the Universal Product Code (UPC) level. Some affiliates provide data at the store level, others—at a retail marketing area (RMA) level[5]. Given the scope of this research, we use the store-level data.

From the product dictionary we identified 14,668 UPCs for dairy and nondairy milks sold in retailers which provide store-level data for the years of 2012-2017. The UPCs were aggregated into six products: dairy non-flavored skim milk, dairy non-flavored reduced fat milk (e.g. 1% and 2%), dairy non-flavored whole fat milk, non-flavored almond milk, non-flavored soy milk, and non-flavored other nondairy[6] milk. By focusing on non-flavored milk sales, we still capture about 87.48 percent of dollar sales from the data. The primary reason for excluding flavored milks is that the variety of flavors is very large, leading to us arbitrarily combining different flavors and making additional assumptions about aggregability and separability: given

[4] Access to data was granted via Third Party Access Agreement with IRI in cooperation with the USDA/ERS.

[5] RMAs are geographic areas defined by the retailer (Muth et al., 2016). RMA sales data are aggregated from all stores in the retailer-defined region and reported at the UPC-level for each week (Muth et al., 2016). These regions can cross state borders so using these data for state-level analysis requires additional assumptions.

[6] Examples of other nondairy milk include rice, cashew, coconut, flax, hazelnut, walnut, grain, pecan milk, and other milks.

the goals of this paper, it is something we want to avoid[7]. The sales data are further aggregated at the week and state level (contiguous U.S.), including the District of Columbia.

Aggregating the data by state, week, and year yields 15,288 observations (6 years x 52 weeks x 49 states)[8]. Data include the number of units sold for each product at the week, state, and year level, as well as the total expenditure on those units. These are used to construct the variables of interest, which will be discussed in the next section. Summary statistics are presented in Table 2.1.

Table 2.1: Summary statistics

Variable	Mean	SD	Min	Max
Weekly sales (1000 USD), 2012-207				
Skim milk	200.028	46.277	138.879	304.231
Reduced fat milk	668.955	60.064	566.949	806.391
Whole fat milk	399.617	33.663	338.779	511.615
Other nondairy milk	15.852	5.835	4.870	28.077
Soy milk	17.156	3.236	12.241	25.373
Almond milk	39.095	11.809	16.184	62.337
Average weekly expenditure shares				
Skim milk	0.141	0.024	0.104	0.186
Reduced fat milk	0.513	0.014	0.485	0.535
Whole fat milk	0.296	0.027	0.254	0.350
Other nondairy milk	0.011	0.004	0.003	0.020
Soy milk	0.011	0.001	0.009	0.015
Almond milk	0.026	0.008	0.010	0.041
Average weekly price (USD) per 64 oz.				
Skim milk	2.085	0.318	1.155	3.028
Reduced fat milk	1.990	0.262	1.169	2.813
Whole fat milk	2.060	0.248	1.274	2.683
Other nondairy milk	3.631	0.305	2.459	6.202
Soy milk	3.289	0.229	2.455	4.807

[7] No aggregation would result in an overly large number of products, which leads to computational difficulties when estimating a demand system.

[8] Given that there were 53 weeks in 2012 and 2015, we dropped the 30th week (end of July, when there are no major holidays or events) from those years to have a balanced panel.

Almond milk	3.277	0.219	2.478	4.300

Source: Authors' calculations based on the 2012-2017 IRI PoS data from the U.S.

Expenditure shares for the six products over the years of 2012-2017 are presented in Figure 2.1. In the period included in the analysis, the data show that the largest expenditure share belongs to reduced fat milks, although it is declining. Whole milk shows the second largest expenditure share, which seems to grow over time, while skim milk is third, exhibiting the largest drop in budget shares among all milk types. As for nondairy milks, almond milk's expenditure share has increased the fastest, reaching almost 3.8% in 2017 from 1.4% in 2012. While soy milk had the fifth largest expenditure share until 2014, its value declined and was outpaced by other nondairy milks which showed a sharp increase in their expenditure share.

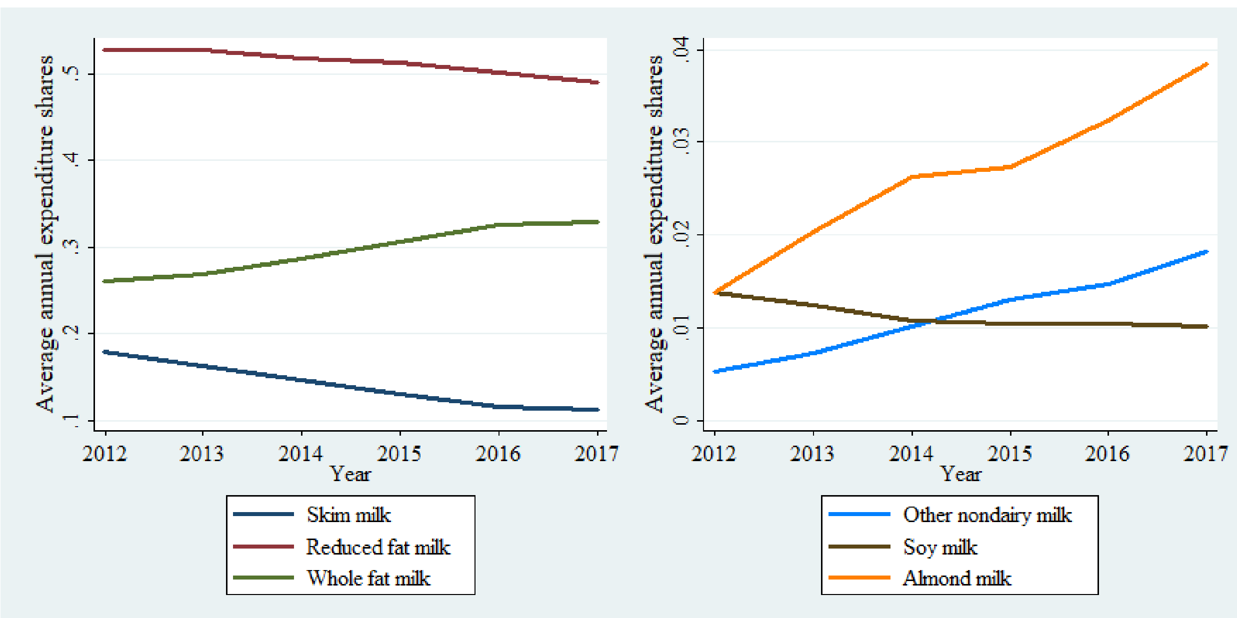

Figure 2.1: Average Annual Milk Expenditure Shares

Demand Estimation and Identification

Model Specification

The empirical specification of the demand model can be formalized as:

$$\text{(2.24)} \quad w_{jsrt} = \alpha_{j0} + \sum_{l=1}^{l=L} \beta_{jl} y_{srt}^{l} + \sum_{i,j=1}^{i,j=J} \alpha_{ij} \ln\left(p_{jsrt}\right) + \sum_{s=1}^{s=48} \lambda_{js} State_{s} + \sum_{r=1}^{r=51} \eta_{jr} Week_{r} + \sum_{t=1}^{t=5} \phi_{jt} Year_{t} + \varepsilon_{jsrt}$$

where w_{jsrt} is the expenditure share of milk *j* in state *s,* week *r*, and year *t*; *J* is the number of products; y_{srt}^{l} denotes the Stone price-deflated real expenditure, with *L* being the highest order of polynomial in y_{srt}^{l}, to be determined empirically; p_{jsrt} denotes the unit price of product *j* in state *s,* week *r*, and year *t*; *State, Week,* and *Year* are the state, week, and year fixed effects, respectively; α_{ij}, β_{il}, λ_{js}, η_{jr}, and ϕ_{jt} are the parameters to be estimated; and ε_{jsrt} is the model's residual, which can be interpreted as unobserved consumer heterogeneity. Note that y_{srt} takes the following form:

$$\text{(2.25)} \quad y_{srt} = \ln(x_{srt}) - \sum_{j=1}^{J} w_{jsrt} \ln(p_{jsrt})$$

where x_{srt} denotes consumer milk expenditure in state *s,* week *r*, and year *t*. This specification of the real expenditure yields the linear approximate (LA) EASI model, where the Stone price index is the correct deflator of income by design (Hovhannisyan et al., 2019; Lewbel & Pendakur, 2009; Zhen et al., 2013).

Expenditure Endogeneity

Since y_{srt} is constructed using expenditure shares, it is likely endogenous. However, Lewbel and Pendakur (2009) and Zhen et al. (2013) found that this is not a concern when using an incomplete demand system, such as EASI. To control for endogeneity of the Stone price-deflated real expenditure, we follow the approach of Dhar et al. (2003) and Lakkakula et al. (2016) and estimate a reduced form equation for the real expenditure.

We follow Zhen et al. (2013) and construct the following instrumental variable

$$\tilde{y}_{srt} \equiv \ln x_{srt} - \sum_{j=1}^{j=J} \bar{w}_j \ln \tilde{p}_{jsrt} , \tag{2.26}$$

where $\bar{w}$ is the average expenditure share of the *j*th good, and $\tilde{p}_{jsrt}$ is the Hausman-type instrument[9] (Hausman, 1996) for p_{jsrt}.[10] The reduced form equation includes state, week, and

[9] This instrumental variable represents the log of the average price of a given product sold in other states in the same week and year. The idea is that if an event happens in one state (e.g. city- or state-wide promotion of one category of milk) and it affects demand locally, it is unlikely to affect milk demand in other states. The underlying assumption is that local demand shocks are uncorrelated across space, while supply shocks are correlated (since products can come from the same plants in multiple cities). This assumption is not too heroic, given that milk markets are regional in nature (Gould, 2010), and the U.S. fluid milk processing industry (including cooperatives) has a relatively high CR4 (Shields, 2010).

[10] Some studies that have used the EASI demand model, such as Zhen et al. (2013), or variations of the AIDS model, such as Lakkakula et al. (2016) have also controlled for price endogeneity. To make our results comparable to those of the existing dairy and nondairy milk demand literature, we do not control for price endogeneity, because most of them have not controlled for it either, regardless of the model used (e.g. variations of AIDS (B. Chen et al., 2018; Davis et al., 2012; X. Li et al., 2018), Tobit (Davis et al., 2011), or discrete choice (Choi et al., 2013)) or data used (e.g. household scanner (B. Chen et al., 2018; Choi et al., 2013; Davis et al., 2012; Davis et al., 2011) or retail scanner (X. Li et al., 2018)). However, as a robustness check, we tried to control for price endogeneity by estimating a reduced form equation for each price by including Hausman-type instrumental variables and/or cost-shifters. The results based on these specifications were implausible, producing positive own-price elasticities. Additionally, finding input prices shifting each product's price uniquely was challenging.

year fixed effects. Predicted values of the real expenditure from the reduced form equation are then included in the model in place of the observed y_{srt} from the data.

We perform the Durbin–Wu–Hausmann (DWH) test, where the null hypothesis is that parameter estimates are consistent without controlling for endogeneity (Dhar et al., 2003). The test statistic, *DWH,* is computed as

$$DWH = (\vartheta_{exog} - \vartheta_{endog})[VAR(\vartheta_{exog}) - VAR(\vartheta_{endog})]^{-1}(\vartheta_{exog} - \vartheta_{endog})' \tag{2.27}$$

where ϑ_{exog} is the vector of estimated coefficients without controlling for endogeneity, and ϑ_{endog} is the vector of estimated coefficients after replacing price and real expenditure with the respective predicted values from the reduced form equations. *DWH* is asymptotically distributed as a chi-square statistic, $\chi^2(k)$, where k is the degrees of freedom equal to the number of positive diagonal elements of matrix $[VAR(\vartheta_{exog}) - VAR(\vartheta_{endog})]$ (Lakkakula et al., 2016).

Estimation

The fixed-effects LA-EASI model with imposed theoretical restrictions (adding-up, symmetry, and homogeneity) is estimated using the seemingly unrelated regression (SUR) estimation (Zellner, 1962), which assumes that the error terms are correlated across the equations. We estimate a system of five equations. Estimates of the sixth equation can be recovered through the above-mentioned theoretical restrictions. The reduced-form expenditure equation is estimated via ordinary least squares (OLS). To determine the proper degree of expenditure polynomials, we started with $l = 1$ and incrementally increased the degree of the polynomial function[11] up to $l=5$. We tested the incremental change in the explanatory power of models with higher polynomial structures through a Likelihood Ratio (LR) test

(2.28) $$LR = 2(LL_{UR} - LL_R),$$

where $LL_{UR}(LL_R)$ is the optimal value of the log-likelihood function for the unrestricted (restricted) model. The *LR* statistic is asymptotically distributed as a $\chi^2(k)$, where k is the degrees of freedom equal to the difference in the number of estimated parameters under the restricted and unrestricted specifications.

Price and Expenditure Elasticities

Following Zhen et al. (2013), we calculate LA-EASI expenditure elasticities as follows:

(2.29) $$E = \left(diag(W)\right)^{-1}\left[\left(I_J + BP'\right)^{-1} B\right] + 1_J,$$

where *W* is a $J \times 1$ vector of observed expenditure shares; I_J is a $J \times J$ identity matrix; *B* is a $J \times 1$ vector with the *i*th element equal to $\sum_{l=1}^{l=L} l\beta_{il} y^{l-1}$; P $(J \times 1)$ is the vector of log prices; and 1_J is a *J* x 1 vector of ones.

Hicksian elasticities for the LA-EASI model can be calculated using the following formula (Zhen et al., 2013):

(2.30) $$\in_{ij}^{H} = \frac{\alpha_{ij}}{w_i} + w_j - \delta_{ij}, \forall i, j = 1, ..., J,$$

---

[11] According to Pendakur (2009), in order for the demand system to converge, it is required that *L* < *J*.

where $\in_{ij}^{H}$ is the Hicksian elasticity of demand for product *i* with respect to the price of product *j*, δ_{ij} is the Kronecker delta, which equals 1 if $i = j$, and 0 otherwise.

The Marshallian elasticities can then be calculated based on the Hicksian and expenditure elasticities as follows (Zhen et al., 2013):

(2.31) $$\in_{ij}^{M} = \in_{ij}^{H} - w_j \tau_i$$

where $\in_{ij}^{M}$ is the Marshallian elasticity of demand for product *i* with respect to price of product *j*, and τ_i is the expenditure elasticity of product *i* equal to the *i*th element of the expenditure elasticity vector *E*.

Testing for Weak Separability

In this work we develop a test for weak separability using estimated LA-EASI parameters. In our derivation of the test we follow Moschini et al. (1994), which developed the weak separability test for the full nonlinear AIDS model, and Lakkakula et al. (2016) which instead derived the necessary restrictions of the test for the Quadratic AIDS model.

According to Moschini et al. (1994), the elasticity of substitution, σ_{ik}, between goods *i* and *k* is given by the following equation:

(2.32) $$\sigma_{ik} = \frac{\in_{ik}^{H}}{w_k} = \frac{\in_{ik}^{M} + \tau_i w_k}{w_k} = \frac{\in_{ik}^{M}}{w_k} + \tau_i .$$

For the LA-EASI demand model, for *i* is not equal to *k*, we have

(2.33) $$\in_{ik}^{H} = \frac{\alpha_{ik}}{w_i} + w_k - 1, \quad \forall i, k = 1, ..., J; \quad i \neq k .$$

Replacing $\in_{ij}^{H}$ in the elasticity of substitution equation with (2.33) results in

$$\sigma_{ik} = \frac{\left(\frac{\alpha_{ik}}{w_i} + w_k - 1\right)}{w_k} = \frac{\alpha_{ik}}{w_i w_k} - \frac{1}{w_k} + 1 \tag{2.34}$$

To test for non-homothetic weak separability, we impose the constraint in (2.18) and compare the results to those from the baseline model. Substituting the terms σ_{ik}, σ_{jk}, τ_i, and τ_j into equation (2.18) and further simplifying the equation gives

$$\frac{\left[\left(\alpha_{ik} - w_i\right) / \left(w_i w_k\right) + 1\right]}{\left[\left(\alpha_{jk} - w_j\right) / \left(w_j w_k\right) + 1\right]} = \frac{\left[\left(\sum_{l=1}^{l=L} l\beta_{il} y^{l-1}\right) / \left(w_i + w_i \ln p_i \sum_{l=1}^{l=L} l\beta_{il} y^{l-1}\right) + 1\right]}{\left[\left(\sum_{l=1}^{l=L} l\beta_{jl} y^{l-1}\right) / \left(w_j + w_j \ln p_j \sum_{l=1}^{l=L} l\beta_{jl} y^{l-1}\right) + 1\right]}. \tag{2.35}$$

We follow existing studies that test for weak separability in demand and perform only tests of local separability at the mean, because the global equivalents are too restrictive, as they require homotheticity for the separable groups as well as unitary income elasticities of goods in separable groups, which is not a necessary condition even under homotheticity (Lakkakula et al., 2016; Moschini et al., 1994; Sellen & Goddard, 1997). Given that prices are normalized to be one at the mean, $w_i \ln p_i \sum_{l=1}^{l=L} l\beta_{il} y^{l-1}$ drops out, because the log of one is equal to zero. Additionally, expenditure shares are replaced by their respective intercept values, which we use as proxies for the average predicted expenditure shares in a given year, state, and week. We follow Hovhannisyan et al. (2019), who interpret the intercept values in the LA-EASI demand model as predicted budget/expenditure shares. Thus, the weak separability restrictions take the following form:

(2.36) $$\frac{\left[\left(\alpha_{ik}-\alpha_{io}\right)/\left(\alpha_{io}\alpha_{ko}\right)+1\right]}{\left[\left(\alpha_{jk}-\alpha_{jo}\right)/\left(\alpha_{jo}\alpha_{ko}\right)+1\right]}=\frac{\left[\left(\sum_{l=1}^{l=L} l\beta_{il}\bar{y}^{l-1}\right)/\left(\bar{w}_i\right)+1\right]}{\left[\left(\sum_{l=1}^{l=L} l\beta_{jl}\bar{y}^{l-1}\right)/\left(\bar{w}_j\right)+1\right]},$$

where $\bar{y}$ is the average real expenditure[12]. The above separability restriction is non-homothetic. It is imposed on the LA-EASI demand system and tested against the unrestricted model using the LR test. The test is also implemented using the size-corrected LR. The test is based on χ^2 statistic with degrees of freedom equal to the number of restrictions.

We apply the separability test to three product groupings, presented below in Table 2.2. Particularly, we test whether: (a) consumers allocate their budget to dairy and nondairy milks separately, that is, whether the demand for dairy milks is weakly separable from that of nondairy milks; (b) whether the demand for dairy milks and soy milk is jointly weakly separable from that of almond milk and other nondairy milk; and (c) whether the demand for soy, almond, other nondairy, and dairy skim milk is jointly separable from that of dairy reduced fat (1% and 2% fat combined) and dairy whole fat milks. These three test results will help inform marketers as well as the current policy debate by illustrating how consumers allocate their expenditure and make milk choices across a system of market choices.

Table 2.2: Structure of Separable Demand Models

	Separable Groupings		
Product	(1)	(2)	(3)
Dairy: skim milk	A	A	A

[12] Ideally, expenditure shares should be replaced by $\hat{w}_j=\alpha_{j0}+\sum_{l=1}^{l=L}\beta_{jl}\bar{y}_{srt}^{l}+\sum_{s=1}^{s=49}\lambda_{js}\overline{State}_s+\sum_{r=1}^{r=52}\eta_{jr}\overline{Week}_r+\sum_{t=1}^{t=6}\phi_{jt}\overline{Year}_t$, where $\overline{State}_s$, $\overline{Week}_r$, and $\overline{Year}_t$ represent the average values of state, week, and year, respectively. However, due to the large number of fixed effects and software limitations, we replaced them with the intercept values. As a robustness check, we also impose the restrictions replacing expenditure shares with their respective average values observed in the data.

Dairy: reduced fat milk	A	A	B
Dairy: whole fat milk	A	A	B
Nondairy: almond milk	B	B	A
Nondairy: soy milk	B	A	A
Nondairy: other milk	B	B	A
No. of product groups	2	2	2
No. of nonredundant restrictions	8	7	7

Note: In each grouping, all milks with the same letter are assumed to belong to the same group. Milks with different letters are assumed weakly separable.

When formulating weak separability tests, it is helpful to determine the number of nonredundant weak separability restrictions, *R*, which can be calculated using the following formula (Moschini et al., 1994; Nayga & Capps, 1994; Sellen & Goddard, 1997):

$$R = \left(\frac{N^2 + N - O^2 + O - \Sigma_o (n_o^2 + n_o)}{2} \right) \tag{2.37}$$

where *N* is the number of products in the separable groupings; *O* is the number of separable groups; and n_o represents the number of products within group *o*. For our first grouping, the number of separability restrictions should be 8 (*N*=6; *O*=2; n_1=3 for dairy milk products; and n_2 =3 for nondairy milk products). For the second and third groupings, the number of required weak separability restrictions is 7.

Testing for GCCT

The GCCT can be empirically tested by analyzing whether relative elementary prices ρ_j, are statistically independent of an aggregate price index for that group, $\ln \boldsymbol{P}_I$ (Lewbel, 1996). Since the test is based on the time series properties of the data, we averaged all prices across states and created a database of average milk sales by week and year. Then, using unit root tests, we determined the stationarity of ρ_j and $\ln \boldsymbol{P}_I$. Following studies that have used the GCCT test for determining proper product aggregation level, such as Lewbel (1996), Reed et al. (2005), and Schulz et al. (2012), we use the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and the Kwaitkowski, Phillips, Schmidt, and Shin (KPSS) (Kwiatkowski et al., 1992) tests to test for stationarity of ρ_j and $\ln \boldsymbol{P}_I$. The former test is based on the null of nonstationarity, while the latter is based on the null of stationarity, therefore introducing the possibility of contradicting results. If such a contradiction occurred, we relied on the joint confirmation hypothesis (JCH) of a unit root (Carrion-i-Silvestre et al., 2001; Schulz et al., 2012).

If both ρ_j and $\ln \boldsymbol{P}_I$ are stationary, then a test of independence, such as Spearman's rank correlation test is needed. Product *j* can be included in the aggregate group *I,* when ρ_j and $\ln \boldsymbol{P}_I$ are uncorrelated. If both ρ_j and $\ln \boldsymbol{P}_I$ are nonstationary, then a test of independence, such as a cointegration test is needed. We used the Engle-Granger test (Engle & Granger, 1987) to test for cointegration under the null that ρ_j and $\ln \boldsymbol{P}_I$ are not cointegrated. If they are not cointegrated, then aggregation of product *j* into group *I* is appropriate. When either ρ_j or $\ln \boldsymbol{P}_I$ is stationary, while the other one is nonstationary, then aggregation is valid. No test of independence is needed in this case, because they cannot be cointegrated if one is stationary and the other one is not (Granger & Hallman, 1988).

Results and Discussion

The results of the test based on equation (2.28) and presented in Table 2.3 indicate that the LA-EASI specification with a fifth polynomial in real expenditure (i.e. *L*=5) is sufficient to capture the curvature of the Engel curves. This is consistent with the results of Zhen et al. (2013), who estimated the demand for 23 food and beverage categories, including whole milk, and also found that the proper degree of the income polynomial is five.

Table 2.3: Model Specification Tests

Hypothesis:	LR	df	p-value
(a) Linear EASI (i.e. linear Engel curve)			
vs Quadratic EASI	1396.370	5	0.000
(b) Quadratic EASI vs Cubic EASI	101.930	5	0.000
(c) Cubic EASI vs Quartic EASI	223.770	5	0.000
(d) Quartic EASI vs Quintic EASI	485.410	5	0.000
DWH specification test χ^2 =	877.900	340	0.000

Notes: Model specification test outcomes indicate that quintic EASI significantly enhances the explanatory power of the quartic EASI at the 0.01 significance level. The null hypothesis of exogenous expenditures may be rejected based on the Durbin-Wu-Hausman test statistic value.

The value of the DWH statistic DWH=877 and $k = 340$ lead us to reject the null of consistent parameter estimates of the model which does not control for endogeneity. Therefore, controlling for endogeneity of real expenditure is necessary to obtain consistent parameter estimates.

Parameter estimates from the demand equations are presented in Table 2.4. All intercept coefficients are statistically different from zero. Most week and state fixed-effects' coefficients are also statistically significant but omitted for brevity. The coefficients on year dummies, all of which are statistically significant, suggest that, compared to 2012, the expenditure shares on skim, reduced fat, and soy milks (not shown in the table) decrease at an increasing rate with every following year, while those for whole fat, almond, and other nondairy milks increase at an increasing rate.

Table 2.4: Parameter Estimates from the LA-EASI Model

Variable	Skim		Reduced Fat		Whole		Other Nondairy		Almond	
Ln(p) skim	-0.033	***	0.110	***	-0.106	***	0.004	***	0.014	***
	(0.004)		(0.004)		(0.003)		(0.001)		(0.001)	
Ln(p) reduced fat	0.110	***	-0.342	***	0.238	***	0.012	***	-0.009	***
	(0.004)		(0.006)		(0.004)		(0.001)		(0.001)	
Ln(p) whole fat	-0.106	***	0.238	***	-0.124	***	-0.009	***	0.004	***
	(0.003)		(0.004)		(0.004)		(0.001)		(0.001)	
Ln(p) other nondairy	0.004	***	0.012	***	-0.009	***	-0.004	***	-0.003	***
	(0.000)		(0.001)		(0.001)		(0.000)		(0.000)	
Ln(p) soy	0.011	***	-0.009	***	-0.003	***	-0.001	***	0.000	
	(0.001)		(0.001)		(0.001)		(0.000)		(0.000)	
Ln(p) almond	0.014	***	-0.010	***	0.004	***	-0.002	***	-0.006	***
	(0.001)		(0.001)		(0.001)		(0.000)		(0.000)	
y	0.024	***	-0.020	***	-0.008	***	0.001	***	0.002	***
	(0.000)		(0.001)		(0.001)		(0.000)		(0.000)	
y^2	0.010	***	-0.009	***	-0.001	***	-0.000	*	-0.001	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
y^3	-0.003	***	0.007	***	-0.004	***	0.000	***	0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
y^4	-0.001	***	0.001	***	-0.000	***	0.000	***	0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
y^5	0.000	***	-0.001	***	0.001	***	-0.000	***	-0.000	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
2013	-0.013	***	-0.001	*	0.007	***	0.002	***	0.006	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
2014	-0.027	***	-0.008	***	0.022	***	0.004	***	0.012	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
2015	-0.042	***	-0.017	***	0.041	***	0.008	***	0.013	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
2016	-0.058	***	-0.027	***	0.061	***	0.009	***	0.018	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
2017	-0.064	***	-0.033	***	0.064	***	0.012	***	0.024	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Intercept	0.125	***	0.579	***	0.269	***	0.009	***	0.013	***
	(0.001)		(0.002)		(0.002)		(0.000)		(0.000)	

Source: Authors' own estimation.
Notes: Standard errors are in parenthesis. *, **, *** identify parameter estimates that are statistically different from 0 at the 0.01, 0.05, and 0.10 significance levels, respectively. The coefficients on state and week fixed effects are omitted for brevity.

The Marshallian and Hicksian price elasticities, estimated at the observation level and averaged across all observations, are presented in Table 2.5. Marshallian own-price elasticities capture both the income effects and the substitution effects of a change in price, while Hicksian elasticities capture only the substitution effect. As expected, all own-price elasticities are negative and statistically different from zero at the 1% probability level. Based on the Marshallian elasticities, reduced fat milk has the highest (in absolute value) own-price elasticity (-1.67), followed by other nondairy (-1.63), whole fat (-1.45), skim (-1.30), and almond (-1.30) milks. Soy milk has the lowest own-price elasticity of demand (-0.85) and is the only milk type with inelastic demand.

The elasticity magnitudes are consistent with others' findings. Davis et al. (2012) reported elasticities in the range of -3.82 to -1.07, with non-flavored skim milk being the most responsive to own price changes among other non-flavored milk types. Dhar and Foltz (2005) estimated the elasticities for the categories of rBST free, organic, and unlabeled milk, and reported own-price uncompensated elasticities in the range of -4.40 to -1.04. Chouinard et al. (2010) estimated the demand for four types of milk (1%, 2%, skim, and whole) and reported elasticities ranging from -2.05 for 1% milk, to -0.628 for nonfat milk. Dharmasena and Capps (2014) found the own-price elasticity of soy milk to be -0.30.

Table 2.5: Marshallian and Hicksian Price Elasticity Estimates

Marshallian Elasticities						
	With Respect to the Price of					
Quantity of	Skim	Reduced fat	Whole fat	Other nondairy	Soy	Almond
Skim	**-1.297**	0.864	-0.946	0.035	0.094	0.113
	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
Reduced fat	0.219	**-1.666**	0.474	0.024	-0.018	-0.018
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

Whole fat	-0.390	0.926	**-1.450**	-0.033	-0.010	0.016
	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)
Other nondairy	0.621	1.699	-1.413	**-1.634**	-0.112	-0.403
	(0.007)	(0.019)	(0.015)	(0.007)	(0.001)	(0.004)
Soy	1.178	-0.908	-0.261	-0.074	**-0.853**	0.008
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Almond	0.691	-0.537	0.162	-0.137	0.002	**-1.296**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)

Hicksian Elasticities

	With Respect to the Price of					
Quantity of	Skim	Reduced fat	Whole fat	Other nondairy	Soy	Almond
Skim	**-1.138**	1.445	-0.606	0.048	0.107	0.143
	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
Reduced fat	0.358	**-1.160**	0.766	0.035	-0.007	0.008
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Whole fat	-0.258	1.408	**-1.169**	-0.022	0.001	0.041
	(0.001)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)
Other nondairy	0.795	2.339	-1.043	**-1.621**	-0.098	-0.372
	(0.007)	(0.020)	(0.015)	(0.007)	(0.001)	(0.004)
Soy	1.310	-0.442	0.005	-0.063	**-0.842**	0.033
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Almond	0.849	0.036	0.493	-0.124	0.015	**-1.268**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)

Notes: Standard errors are in parenthesis. All elasticity estimates are statistically significant at 1% significance level. Own-price elasticities are in bold.

Based on the cross-price elasticities, all milk types are substitutes for skim milk, except for whole fat milk (a complement), with the closest substitute being soy milk. For reduced fat milk, the substitutes are skim, whole fat, and other nondairy milks (the closest substitute), while other milk types are found to be complements. Reduced fat (the closest substitute) and almond milks, are substitutes for whole fat milk. For other nondairy milk, the only substitutes are skim (the closest substitute) and reduced fat milks. Skim and almond milks are substitutes for soy milk, with skim milk being the closest substitute, while the other milks are complements for soy milk. For almond milk, the closest substitute is also skim milk, followed by whole fat and soy milks.

Overall, the signs and magnitudes of cross-price elasticities suggest that when prices of nondairy beverages increase, there is some substitution among nondairy milks, while most substitution happens toward dairy milk types. On the contrary, when the price of a particular dairy milk increases, there is substitution toward both other dairy and nondairy milks. Of six cross-price elasticities among nondairy milks, four suggest complementarity. However, only two cross-price elasticities suggest complementarity among dairy milks.

Table 2.6 shows the expenditure elasticities, which represent the percent change in the quantity of a particular milk demanded when the U.S. total expenditures on milk (milk types included in the study) increases by 1%. Expenditure elasticities are all positive and range from 0.91 (soy milk) to 1.24 (other nondairy milks). Only the expenditure elasticities for reduced fat, whole fat, and soy milk are less than unitary elastic.

Table 2.6: Expenditure Elasticities

Product	Expenditure Elasticity	
Skim	1.136	***
	(0.001)	
Reduced fat	0.985	***
	(0.000)	
Whole fat	0.941	***
	(0.000)	
Other nondairy	1.242	***

	(0.003)	
Soy	0.910	***
	(0.001)	
Almond	1.114	***
	(0.001)	

Notes: Standard errors are in parenthesis. *, **, *** identify statistical significance at the 0.01, 0.05, and 0.10 significance levels, respectively.

The results of non-homothetic weak separability tests are in Table 2.7. The unrestricted model (with imposed homogeneity and symmetry) is tested against each model where we impose restrictions consistent with the separable groups mentioned in Table 2.2. Both LR and size-corrected LR test results suggest that non-homothetic weak separability is rejected for all separability structures tested. This implies that consumers consider all types of milks when formulating their ultimate demand and purchases, rather than allocating expenditure to specific sub-categories before making a purchase.

The implication of these results for researchers is that the common practice of excluding nondairy milk subcategories when estimating U.S. milk demand, may actually lead to biased results because of misspecification, since the demand for dairy milk is not separable from that of nondairy milks.

Table 2.7: Results of Non-Homothetic Weak Separability Tests

Separable Grouping	Number of Restrictions	LR Test Statistic	Size-Corrected LR Test Statistic	Critical Value $\chi_{0.5}$
(1)	8	3530.0	3502.5	15.507
(2)	7	2186.1	2169.1	14.067
(3)	7	155.7	154.5	14.067

Notes: Non-homothetic separability restrictions were imposed on the demand system. Test results where expenditure shares were replaced with the respective average values instead of respective intercept coefficients produce almost identical results.

Table 2.8 summarizes the results of the GCCT tests for three aggregation scenarios: (a) all dairy milk types can be aggregated into one category; (b) whether all nondairy milk types can be aggregated into one category; and (c) whether all dairy and nondairy milk types can be aggregated into one category. In all three aggregation groups, the aggregate prices are nonstationary based on the ADF and KPSS tests results. Of 12 relative prices, 11 are nonstationary, and one is stationary. Where relative prices are nonstationary, we rely on the Engel Granger test of cointegration. For the one stationary relative price, the aggregation is considered valid. The Engle Granger test failed to reject the null of a spurious regression for all of the individual price comparisons, therefore, there was no need to perform family-wise tests (Davis et al., 2000). These test results suggest that each of the three aggregation structures are valid. Thus, when estimating milk demand, researchers can aggregate all dairy (skim, reduced fat, and whole fat) non-flavored milk types into one composite. Similarly, all nondairy (almond, soy, and other nondairy) milk types into one category, as well as all dairy and nondairy milk types into an aggregate category of milk.

Table 2.8: GCCT Test Results

Group and relative prices	ADF Test H0: I(1)[a]	KPSS Test H0: I(0)[b]	I(0) or I(1)	Engel-Granger Test H0: Not Cointegrated (NC)	Aggregation Valid
ln ***P*** (nf. dairy)	-2.171 (6)	0.309*** (12)	I(1)		
ρ (skim)	-3.263* (3)	0.385*** (12)	I(1) JCH[c]	-3.068 (4)	Yes
ρ (red fat)	-3.030 (4)	0.377*** (12)	I(1)	-3.259 (5)	Yes
ρ (whole)	-1.923 (4)	0.252*** (12)	I(1)	-2.067 (5)	Yes

ln $\boldsymbol{P}$ (nf. nondairy)	-2.105 (7)	0.216*** (11)	I(1)		
ρ (other nondairy)	-6.205*** (3)	0.085 (11)	I(0)	NC	Yes
ρ (soy)	-2.018 (7)	0.160** (11)	I(1)	-2.116 (8)	Yes
ρ (almond)	-1.796 (11)	0.341*** (11)	I(1)	-2.704 (6)	Yes
ln $\boldsymbol{P}$ (nf. milk)	-1.978 (5)	0.307*** (12)	I(1)		
ρ (skim)	-2.983 (3)	0.430*** (12)	I(1)	-2.851 (4)	Yes
ρ (red fat)	-2.653 (4)	0.410*** (12)	I(1)	-3.019 (5)	Yes
ρ (whole)	-1.923 (4)	0.284*** (12)	I(1)	-1.986 (5)	Yes
ρ (other nondairy)	-2.205 (7)	0.290*** (12)	I(1)	-2.853 (8)	Yes
ρ (soy)	-2.335 (7)	0.252*** (12)	I(1)	-3.276 (8)	Yes
ρ (almond)	-2.830 (2)	0.388*** (12)	I(1)	-2.167 (8)	Yes
10% critical values	-3.130	0.119	(-3.391, 0.114)	-3.519	

Notes: *, **, *** denote rejection of the null at the at the 0.01, 0.05, and 0.10 significance levels, respectively.

[a] The test statistics of the null hypothesis of I(1) are the augmented Dickey and Fuller (1979) (ADF) t-values of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged-differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by STATA 15.1.

[b] The test statistics in the second column are the Kwiatkowski et al. (1992) (KPSS) t-statistics. They are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. The test's denominator is automatically calculated using the Bartlett kernel. The maximum lag order (bandwidth) presented in parentheses is derived from an automatic bandwidth selection routine provided by STATA 15.1.

[c] When the ADF and KPSS tests conflict, the inferences is based on the joint confirmation hypothesis (JCH) of a Unit Root are used (Carrion-i-Silvestre et al., 2001).The joint critical values of (–3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

Discussion and Policy Implications

The results presented above have several policy implications in the context of the DAIRY PRIDE Act. First, the separability test results suggest that consumers do not allocate their budgets to different categories of milk (dairy and nondairy) and then make a choice from each category, rather they consider all milks when making a purchase decision. While this does not tell managers and policymakers anything specific about consumer confusion regarding the varying nutritional properties of dairy and nondairy milks, it does suggest that dairy and nondairy milks may not be perceived by consumers as completely different product categories when making a purchase decision. This supports PBFA's argument that "a consumer who puts almond milk in their coffee instead of dairy milk is making a conscious choice to use one type of milk instead of another." (PBFA, 2019)

As for consumer confusion about the labeling, representative survey results suggest that both with and without looking at product front labels, the majority of American consumers (over 70 percent) understand correctly that nondairy milks do not contain cow's milk, while only 10 percent believes they do (IFIC, 2018). In another survey, when asked whether consumers associate a product with dairy milk after seeing images of dairy and nondairy milk products, less than 32 percent of the respondents were found to associate nondairy milk brands with dairy milk (Jackson & Newall, 2018). According to PBFA (2019), the majority of both dairy (64 percent) and nondairy milk (71 percent) consumers believe that the "milk" term best identifies nondairy milk products, as it sets correct expectations about the product and its functionality. Additionally, consumers do not prefer terms such as "drink" or "beverage" on nondairy milks, as those labels are more closely associated with soft drinks and alcohol (PBFA, 2019).

It is worth noting that some of the nondairy milks that make up the aggregate nondairy milk categories (almond, soy, and other nondairy milks) included in this study, did not carry the term milk on their labels during the study period, but rather, were labeled as beverage or drink. This suggests that even if the nondairy milks are banned from using dairy terminology, which is the primary goal of the DAIRY PRIDE Act, it may not serve its purpose of making dairy and nondairy milks more clearly delineated by consumers as different product categories in their purchase decisions.

Interestingly, as Sibilla (2019) notes, several federal courts have rejected the argument that calling nondairy milk "milk" is misleading. For example, the U.S. Court of Appeals for the Ninth Circuit dismissed a lawsuit against Blue Diamond Growers, which claimed that company *"mislabeled its almond beverages as 'almond milk' when they should be labeled 'imitation milk' because they substitute for and resemble dairy milk but are nutritionally inferior to it"* ("Cynthia Cardarelli Painter v. Blue Diamond Growers," 2018). In an unpublished opinion, it is further stated that:

"Painter's complaint does not plausibly allege that a reasonable consumer would be deceived into believing that Blue Diamond's almond milk products are nutritionally equivalent to dairy milk based on their package labels and advertising… Nor can Painter plausibly allege that Blue Diamond's almond milk products are mislabeled in violation of federal law." ("Cynthia Cardarelli Painter v. Blue Diamond Growers," 2018).

Additionally, the court concludes that it is not likely that a reasonable consumer would *"assume that two distinct products have the same nutritional content*" or that almond milk is nutritionally inferior to dairy milk, because the two products have different nutritional characteristics ("Cynthia Cardarelli Painter v. Blue Diamond Growers," 2018). Later, a federal court in California blocked a similar lawsuit against another nondairy milk producer (Sibilla, 2019). On a related note, in July 2019, Arkansas Eastern District Court blocked Arkansas from enforcing a state law, which prohibited firms from labeling their non animal-based products with meat terminology, such as "burger", "sausage", or "roast" (Watson, 2019). Particularly, the judge wrote that “*The State appears to believe that the simple use of the word 'burger,' 'ham,' or 'sausage' leaves the typical consumer confused, but such a position requires the assumption that a reasonable consumer will disregard all other words found on the label….That assumption is unwarranted* ” (Watson, 2019). More recently, Virginia Governor Ralph Northam vetoed house bill NO. 119 intended to prevent producers of nondairy milk from continuing to label their products as “milk” (Vozzella, 2020). According to the Governor’s spokeswoman Alena Yarmosky: “*While the Governor is very supportive of the dairy industry, he is concerned this bill is unconstitutional and could violate commercial freedom of speech…*” (Vozzella, 2020).

Thus, combined with previous survey results and the court decisions, which conclude that consumers are unlikely to be confused about the nutritional differences between dairy and nondairy milks, the separability test results for consumers suggest choices are intentional. Given the underlying data (i.e. some nondairy milks not being labeled milk), U.S. consumers appear to consciously choose between almond, soy, other nondairy, skim, reduced fat, and whole fat milks, rather than as a result of confusion about the respective nutritional profiles.

Additionally, the magnitudes and signs of the cross-price elasticities suggest that there is some substitutability (and complementarity) among different types of dairy and nondairy milk, but nondairy milks are more likely to be substituted with dairy milks in case of a price increase in the former, than are dairy milks to be substituted with nondairy milks when the price of a particular dairy milk increases. That is, depending on the product, when the price of one type of dairy milk increases, consumers are mostly switching to other dairy milks. In contrast, when the price of one type of nondairy milk increases, consumers are more likely to switch to dairy milks.

Lastly, the GCCT test results suggest that all milks (dairy and/or nondairy) can be aggregated into one product category, which illustrates that from marketing and demand analysis perspectives, dairy and nondairy milks comprise one category of product—milk. Combined with the previous results and keeping in mind that some of the products that are included in the aggregate nondairy milk types were not labeled as milk, these findings suggest that the DAIRY PRIDE Act may not only be ineffective but might also lead to market outcomes that are the opposite of what it is intended to do.

Conclusions and Limitations

In this study, we used weekly point-of-sale data from 2012 to 2017 on dairy and nondairy milk products in the U.S. and estimated the demand for these products via the LA-EASI demand model. To our knowledge, this is the first study to extend the weak separability restrictions for the LA-EASI model. The magnitudes and signs of the estimated cross-price elasticities suggest that there is some substitutability and complementarity among the products included in this study (skim, reduced fat, whole fat, soy, almond, and other nondairy milks). We find that a price increase (decrease) among nondairy milks results in higher (lower) sales of most dairy milks and lower (higher) sales of nondairy milks, since the latter are mostly complements to each other. However, the effects of a price change of a dairy milk are more complex since most dairy and nondairy milks are substitutes for dairy milks. All three weak separability tests are rejected, suggesting that, in a multi-stage budgeting context, dairy and nondairy milks are not considered separate categories of products, rather, all six types of milk are considered by consumers when making a purchase decision.

The implications of these findings are twofold: (a) researchers estimating U.S. milk demand systems should include both nondairy and dairy milks in the analysis. Previous studies that either explicitly or implicitly assumed weak separability of dairy milk demand from that of nondairy milks (or the other way around) may have produced results that incorporate model misspecification errors; (b) policymakers siding with or against the DAIRY PRIDE Act should take into account the complex structures of substitutability and complementarity between different types of milk as well as the finding that the demand for dairy and nondairy milks is not separable.

The GCCT results suggest that when estimating milk demand, almond, soy, and other nondairy milks can be aggregated into one category; skim, reduced fat, and whole fat milks can also be aggregated into one category; and all six milk types can be incorporated into one category of milk. Given the increasing availability of and propensity to use syndicated data, reducing the number of products included in demand analysis is usually necessary, and researchers often make arbitrary assumptions about what products can be represented by a composite good. Thus, this study illustrates features of milk demand providing foundation for future studies to reduce the number of products based on empirical evidence.

One limitation of this study is the exclusion of flavored milk, as well as products such as goat milk, buttermilk, and bottled milk shakes from the analysis. Thus, future studies may either focus on those products or include them in addition to the six products included in this study. Another limitation is that we did not control for price endogeneity for two main reasons: (a) we wanted to make our results comparable to those of existing studies analyzing milk demand in the U.S., most of which have not controlled for price endogeneity either, regardless of the model or data used; and (b) while trying to control for price endogeneity as a robustness check, the results from these specifications were implausible (e.g. large and positive own-price elasticities). Also, due to the data structure, we could not test for demand separability between dairy and nondairy milks not labeled as “milk”. That is, this research does not answer whether labeling nondairy products as milk changes the separability structure of demand. Therefore, from a policy perspective, this analysis should be complemented by one performed using more disaggregated product category, and it is informative only in part. Potential extensions include analysis of milk demand and weak separability for countries, where nondairy milk products, such as soy milk, have been in the market longer than in the U.S. (e.g. China).

Chapter 3: To Milk or not to Milk? Valuing the Milk Label on Non-Dairy Beverages

Introduction

In recent years, the dairy industry has faced stiff competition from nondairy milk alternatives, such as almond milk and soy yogurt (Mäkinen et al., 2016). In response to the rapid market growth of plant-based dairy alternatives, the National Milk Producers Federation (NMPF) is contesting the use of dairy terminology (e.g. milk, cheese, yogurt) for the marketing of plant-based food and drinks. In January 2017, Senator Baldwin of Wisconsin introduced the "Defending Against Imitations and Replacements of Yogurt, milk, and cheese to Promote Regular Intake of Dairy Everyday" (DAIRY PRIDE) Act, a bill intended to promote the enforcement of a stricter use of the already existing legal definition of milk in the United States.

According to the Food and Drug Administration (FDA) standards of identity, milk is defined as "…the lacteal secretion, practically free from colostrum, obtained by the complete milking of one or more healthy cows" (Carvalho et al., 2001). Except for fortified soy milk, which nutritionally resembles dairy milk, the Department of Health and Human Services (DHHS) and the United States Department of Agriculture (USDA) do not include nondairy beverages in the dairy group, since their nutritional content is different from that of dairy milk (DHHS & USDA, 2015). The FDA has not yet enforced that manufacturers of nondairy milk stop using "dairy" terminology. If enforced, several nondairy beverages currently referred to as "milk" (that is, almond milk, soy milk, etc.) will no longer be allowed to be sold as such in the U.S. market. This may change consumers' perception of these products and result in re-organization of the market.

Even though there are several studies characterizing the demand for nondairy "milk" products (Dharmasena & Capps, 2014; McCarthy et al., 2017; Mintel Group Ltd., 2017; Packaged Facts, 2017), no study has assessed the potential value of carrying the "milk" label on dairy-alternative beverages. If using the term milk results in a price premium for nondairy products, producers of dairy-alternative beverages capitalizing on such premia may be heavily affected by the DAIRY PRIDE Act, if it comes to pass. This study analyzes the demand for dairy and nondairy milk products, focusing on the valuation of the "milk" label on nondairy milk products and related consumer and producer welfare implications. This allows one to assess the validity of the NMPF's claim that nondairy milk producers use dairy terminology to benefit from the latter's good reputation; and provides a framework to analyze the potential welfare effects of the DAIRY PRIDE Act.

To that end, we use the IRI InfoScan point-of-sale weekly data on dairy and nondairy milk products for the year 2013 combined with the "Purchase to Plate Crosswalk", a novel dataset developed by USDA (Carlson et al., 2019). We utilize the Berry, Levinsohn, and Pakes random coefficients logit model (Berry et al., 1995), commonly known as BLP, which has been widely adopted in studies modeling consumer choice behavior with aggregate data within a differentiated product industry (Hirsch et al., 2018; Lopez & Lopez, 2009).

Our main contributions are threefold. First, to our knowledge, this is the first study to analyze and assign a monetary value to the "milk" label on nondairy beverages. Second, to the best of our knowledge, this is the first study to simulate the potential welfare effects of the DAIRY PRIDE Act. Third, this study adds to the literature on milk demand by estimating a highly disaggregate demand model, thus delineating consumer preferences for a variety of product attributes. Particularly, (a) unlike other studies which combine all flavored milk under one category, we control for chocolate- and vanilla-flavor attributes separately; (b) we also control for product location in store (dairy aisle vs other), given that dairy and nondairy milk products compete for store space; and (c) we control for product familiarity (measured in terms of the number of years since product's launch) which may affect the demand for these products.

This chapter proceeds as follows: first, a discussion of the recent developments in the U.S. dairy market is provided. Then, we describe our model, which includes a discussion of assumptions made about consumers' and producers' behavior, as well as the procedures used in the welfare simulation of the DAIRY PRIDE Act. This is followed by a discussion of the utilized data and the steps taken to empirically estimate the model. Finally, we illustrate the results of this study, discuss their implications and provide conclusions.

Background: The U.S. Dairy Industry and the Emergence of Nondairy Alternatives

The U.S. dairy industry, along with the meat, grain, and other food processing sectors, has faced major structural changes and consolidations in the past several decades (Ollinger et al., 2005). The concentration ratio of the four largest fluid milk processing firms (CR4) increased from 22 percent in 1992 to 42.6 in 2002 (Shields, 2010). Similarly, the CR4 of dairy cooperatives involved in the marketing of U.S. farm milk increased from 24 percent in 1980 to 40 percent in 2008 (Gould, 2010). However, these values are likely to be higher at the regional level because milk markets are regional in nature (Gould, 2010).

Despite the dairy industry's efforts to attract consumers by introducing new flavors and varieties of milk, such as probiotic milk, vitamin-, mineral-, protein-, and antioxidant-enriched milks, per capita milk consumption has been declining (Copeland, 2016). From 2012 to 2017, sales volume in the dairy milk category fell 15 percent (Mintel Group Ltd., 2017). The per capita consumption of cow's milk has been declining annually, from a -0.9 percent decline in the 1995-

2010 period to -2.6 in 2010-2016 (Haley & Jones, 2017). Organic dairy milk sales reached their peak of $1.42 billion in 2016, falling to $1.37 billion in 2017 according to Nielsen data—experiencing a decline for the first time since 2013 (Haddon & Parkin, 2018). This decline is, in part, attributed to the rising popularity of plant-based beverages (Haddon & Parkin, 2018). Additionally, the increase in retail milk prices over the last decade (Bolotova & Novakovic, 2016), may have also contributed to the decline in dairy milk consumption.

The decline in milk sales can be primarily attributed to lower consumption of skim / reduced fat milk. Particularly, from 2010 to 2018, the sales volumes of skim, 1% fat, and 2% fat milks have decreased by about 52.5, 13.2, and 18.1 percent, respectively (ERS, 2018). The market for other dairy milks have instead experienced an increase: from 2010 to 2018, whole milk sales volume increased by about 10.1 percent (ERS, 2018), which is due to consumers changing their attitude toward more holistic and natural nutrition (Mintel Group Ltd., 2017). Flavored milk sales have grown 18 percent from 2012 to 2017, making it the fastest growing dairy milk category (Mintel Group Ltd., 2017). Another dairy milk category that has seen an expansion in sales is lactose-free[13] milk, which showed a year-over-year growth rate of 11.9 percent from 2018 to 2019 (DairyFoods, 2020)

According to Haley and Jones (2017), dairy milk's market share of all milk beverages dropped form 94.33 percent in 2013 to 92.37 percent in 2015, in favor of increased sales of nondairy alternatives; in the same period, the market share of soy beverages dropped from 1.82 to 1.38 percent, whereas almond and other alternative milks' share rose from 3.85 to 6.26 percent (Haley & Jones, 2017). The switch from soymilk to other plant-based beverages could be due to

[13] This is not surprising, since an estimated 30 to 50 million American adults are lactose intolerant (DHHS, 2006).

the amount of saturated fat and calories in soymilk (Copeland, 2016), its taste, the presence of phytoestrogens and estrogen-like compounds (Franklin-Wallis, 2019), soy avoidance, and increased variety of nondairy milks, among other reasons. According to an online-survey, consumers purchase soymilk for its taste, low amount of preservatives, and low risk of food-borne illnesses; while its lesser important attributes (as ranked by respondents) were "lactose-free" and "casein-free" (Zheng, 2011).

Based on the IRI household scanner data, the percent of consumers who purchased dairy milk and alternative beverages in 2015 was 92.2 and 32.2, respectively; most of the consumers who purchased a dairy analog also purchased dairy milk (Haley & Jones, 2017). Survey results from 2018 show that 91 percent of respondents had, at some point, bought dairy milk and 56 percent—nondairy milk, with 87 and 42 percent having bought dairy and/or nondairy milk in the preceding six months, respectively (DMI, 2019).

Among nondairy milk products, almond, soy, and coconut milks account for 64, 13, and 12 percent of the market, respectively; moreover, other plant-based alternatives—pecan, quinoa, flax, and cashew are quickly gaining popularity (Dharmasena & Capps, 2014). In 2016, the category of plant-based dairy beverages grew to approximately $6 billion globally, 25 percent of the overall sales of dairy beverages: this figure is expected to further increase to 40 percent in 2021 (J. Li & Dharmasena, 2016).

Several factors explain this expansion, including the wide range of flavors, beliefs about animal mistreatment, lactose-intolerance, convenient packaging, and consumers' perception of plant-based drinks as healthier and more environmentally-friendly alternatives to dairy beverages (McCarthy et al., 2017; Packaged Facts, 2017). However, the motivations behind buying dairy and/or nondairy milk seem to vary. Specifically, those who only buy dairy milk, indicated that the most important reasons for purchasing dairy milk are that it is a good source of calcium, it tastes good, it is healthy, nutritious, and a good source of vitamins and minerals (DMI, 2019). For those who purchase only nondairy milk, the most important reasons are that it is healthy, nutritious, lactose-free, flavorful, tasty, and is good for those with milk allergies (DMI, 2019). The order of preference is similar for those buying both dairy and nondairy milks, indicating that consumers purchase dairy and nondairy milks for somewhat different reasons and product attributes. Thus, nondairy milks are consumed by different consumer segments: some that consume nondairy milks for their organoleptic properties or for nutritional reasons; others because of dietary restrictions. Both segments are likely to have contribute to the growth of the nondairy milk market.

According to McCarthy et al. (2017), nondairy milk consumers' most preferred type is almond milk, and the most desirable package size is a half-gallon. While sweetness is an important attribute for nondairy and lactose-free milk preferences (Palacios et al., 2009), nondairy milk consumers prefer naturally-sweetened plant beverages, or beverages with zero added sugar (McCarthy et al., 2017).

The NMPF claims that the producers of plant-based milk alternatives use dairy terminology, such as "milk" to benefit from dairy milk's reputation as a healthy product (Ellefson, 2018). The dairy industry argues that using dairy terminology for plant-based products may mislead consumers[14], because they may think of plant-based milk alternatives as perfect substitutes for dairy milk (Ellefson, 2018). Results from a recent survey suggest that about 55

[14] In fact, a product name or description (statement of identity) is argued to be a common source of confusion among North American consumers (Katz et al., 2005).

percent of respondents believe that nondairy milk is a good substitute for dairy milk (DMI, 2019). At the same time, over 50 percent of nondairy milk buyers believe that the main ingredient in plant-based milks is the plant itself (i.e. soy, nuts, grain, etc.), followed by water, while acknowledging (over 70 percent of nondairy milk buyers) that the nutrition content and ingredients vary in nondairy milks by brand and type (DMI, 2019), suggesting that consumers are not confused about the nutritional differences between dairy and nondairy milks. Even so, nondairy milks compete with dairy milk products not only for consumers' dairy expenditure but also for shelf space at stores, since they are usually located in the stores' dairy section[15] (Gulseven & Wohlgenant, 2014). In another survey, when asked to choose why a manufacturer would label a product "milk" even though it does not contain dairy milk, about 53 percent of respondents chose "Nutrition is similar to dairy milk", 46 percent chose *"It tastes like dairy milk"*, 43 percent chose "Quality is similar to dairy milk", followed by 41 percent choosing "Substitutable for cooking and baking" (Jackson & Newall, 2018).

The Plant Based Foods Association, wrote their counter-arguments to the NMPF's claims in response to FDA's call for comments on the labeling of plant-based products with names that include the names of dairy foods such as "milk," "cultured milk," "yogurt," and "cheese" (PBFA, 2019). One of their arguments is that for the PBFA members and consumers, these terms represent product functionality, taste, and form, rather than the primary source of the main ingredient. The PBFA also claims that their members use these terms in conjunction with appropriate clarifiers, such as "alternative", "dairy-free", "vegan", "plant-based", and/or

[15] For example, Kroger Co.'s spokeswoman reported dedicating more shelf space to plant-based alternatives at the expense of organic milk (Haddon & Parkin, 2018).

“nondairy” to convey their consumers that these products do not contain dairy milk, which is why consumers purchase nondairy products in the first place (PBFA, 2019).

The Model

In this section, we first describe the demand side of the model. Second, we describe the supply side of the model and the rationale behind the assumed market structure (Nash–Bertrand). Third, we discuss our approach for calculating the impact of the presence of “milk” terminology on nondairy beverages on consumer and producer welfare.

The Demand Side

We use the BLP demand model developed by (Berry et al., 1995). Let u_{ijt} denote the utility of consumer $i = 1,...,I$, for product $j = 1,...,J$, in market $t = 1,...,T$. Then,

(3.1) $$u_{ijt} = \alpha_i(y_i - p_{jt}) + \mathbf{x}'_{\mathrm{jt}}\boldsymbol{\beta}_i + \xi_{jt} + \varepsilon_{ijt}$$

where α_i is the marginal utility of income, y_i is individual income, p_{jt} is the price of product j in market t, $\mathbf{x}_{\mathrm{jt}}$ is a vector of product characteristics, $\boldsymbol{\beta}_i$ is a vector of coefficients, ξ_{jt} is the unobserved to the researcher product j’s characteristics in market t, and ε_{ijt} is an idiosyncratic error term. Consumer i also has an option of buying the outside option, referred to as $j = 0$, with the following normalized utility:

(3.2) $$u_{i0t} \equiv \alpha_i y_i + \varepsilon_{i0t}$$

We do not need to know consumer income, because quasilinear utility is linear in income, therefore it lacks income effects. In the BLP model, both α_i and $\boldsymbol{\beta}_i$ are assumed to be linear functions of a vector of consumer i's demographic characteristics, $\mathbf{D_i}$, and a vector of consumer i's unobservable characteristics, $\boldsymbol{v}_i$. In particular,

$$\begin{pmatrix} \boldsymbol{\beta}_i \\ \alpha_i \end{pmatrix} = \begin{pmatrix} \boldsymbol{\beta} \\ \alpha \end{pmatrix} + \mathbf{\Pi D_i} + \mathbf{\Sigma}\boldsymbol{v}_i \tag{3.3}$$

where α and $\boldsymbol{\beta}$ are the average values of α_i and $\boldsymbol{\beta}_i$ across consumers, respectively, while $\mathbf{\Pi}$ and $\mathbf{\Sigma}$ are parameters to be estimated. Even though both $\mathbf{D_i}$ and $\boldsymbol{v}_i$ are generally unobserved, their distributions are assumed to be known (Vincent, 2015). We assume that $\mathbf{\Sigma}\boldsymbol{v}_i \sim$ i.i.d. $\mathrm{N}(0,\mathbf{\Sigma\Sigma})$, where $\mathbf{\Sigma\Sigma}$ is the covariance matrix of the coefficients α_i and $\boldsymbol{\beta}_i$, conditional on $\mathbf{D_i}$. That is, $\mathbf{D}_i \sim \mathbf{P_D}(\mathbf{D})$, $\boldsymbol{v}_i \sim \mathbf{P}_v(\boldsymbol{v})$, where $\mathbf{P_D}$ and $\mathbf{P}_v$ are the distribution functions of $\mathbf{D}_i$ and $\boldsymbol{v}_i$, respectively.

Therefore, the utility in equation (3.1) can be decomposed into mean utility, δ_{jt}, and consumer-specific utility, μ_{ijt}, (Berry, 1994) as follows:

$$u_{ijt} = \alpha_i y_i + \delta_{jt}(\mathbf{x_{jt}}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(\mathbf{x_{jt}}, p_{jt}, \boldsymbol{v}_i, \mathbf{D_i}; \theta_2) + \varepsilon_{ijt}, \tag{3.4}$$

$$\delta_{jt} = \mathbf{x_{jt}}\boldsymbol{\beta} - \alpha p_{jt} + \xi_{jt}, \quad \mu_{ijt} = \left[-p_{jt}, \mathbf{x_{jt}}\right]\left(\mathbf{\Pi D_i} + \mathbf{\Sigma}\boldsymbol{v}_i\right),$$

where α_i is the utility from income, y_i is kept for consistency with equation (3.1) and will later drop out, since it does not affect consumer's choice; δ_{jt} is the mean utility, which is the same across all consumers; $\theta_1 = (\alpha, \boldsymbol{\beta})$ is a vector of linear parameters; μ_{ijt} is a heteroskedastic disturbance; $\theta_2 = \left(\mathbf{\Pi}, \mathbf{\Sigma}\right)$ is a vector of nonlinear parameters; and ε_{ijt} is a homoscedastic and independent and identically distributed (i.i.d.) disturbance.

Given $\mathbf{D_i}$ and $\boldsymbol{v}_i$, the probability of individual i selecting product j, in market t, can be defined as (Vincent, 2015):

$$\Pr_{ijt} = \int_{A_{ijt}} dF(\varepsilon_{it} \,|\, \mathbf{D_i}, \boldsymbol{v}_i) \tag{3.5}$$

where $A_{ijt} = \left(\varepsilon_{it} : u_{ijt} \geq u_{imt}, \forall m \neq j\right)$ is the set for which consumers choose product *j* over any other product; and $\varepsilon_{it} = \left(\varepsilon_{ij0}, ..., \varepsilon_{iJt}\right)$. According to Nevo (2000), to evaluate the integral in (3.5), one can assume that $\theta_2 = 0$, $\boldsymbol{\beta}_i = \beta$, and $\alpha_i = \alpha$ for all *i,* which means that ε_{ijt} is the only component capturing consumer heterogeneity. Then, equation (3.1) becomes $u_{ijt} = \alpha(y_i - p_{jt}) + \mathbf{x}'_{\mathrm{jt}}\boldsymbol{\beta} + \xi_{jt} + \varepsilon_{ijt}$ and since income is common to all options, it drops out. According to Nevo (2000), if, ε_{ijt} are i.i.d., following a type-I extreme-value distribution, and $\theta_2 = 0$, one arrives at the expression of the logit market shares, which are equal to:

$$s_{jt} = \frac{\exp\left(\mathbf{x'_{jt}\beta} - \alpha p_{jt} + \xi_{jt}\right)}{1 + \sum_{m=1}^{J} \exp\left(\mathbf{x'_{mt}\beta} - \alpha p_{mt} + \xi_{mt}\right)} \tag{3.6}$$

Compared to the logit model, the BLP has several advantages. First, unlike the logit model, the BLP does not restrict consumers' preferences to be homogeneous, since $\theta_2 \neq 0$. Second, BLP substitution patterns are not mostly dependent on the market shares, unlike the logit substitution patterns. (Nevo, 2000). In the logit model, the price elasticities of the market shares for the simple logit model are defined as:

$$e_{jmt} = \begin{cases} -\alpha p_{jt}(1 - s_{jt}) & \text{if } j = m \\ \alpha p_{mt} s_{mt} & \text{if } j \neq m \end{cases} \tag{3.7}$$

Since product market shares are usually small, the own-price elasticities are proportional to own price, which means that the demand for lower-priced products is automatically less elastic in terms of own-price elasticity (in absolute value). This leads to higher predicted markup over marginal costs for cheaper products, which is possible only in case the marginal cost of a lower-priced product is lower as a percentage of price than it is for a higher-priced product. Another limitation of the logit model is that it requires implausible constraints on the substitution patterns between products[16].

To overcome this problem of restricted cross-price elasticities due to the i.i.d. assumption of the error terms, the utilities in (3.1) need to correlated across brands. By adding $\mathbf{D_i}$ and/or just $\boldsymbol{v}_i$ in (3.3), a correlation between products that are similar in the characteristics space is introduced in the model. This also allows for consumers with the same demographic characteristics to have similar substitution patterns.

Thus, instead of assuming that $\theta_2 = 0$, $\boldsymbol{\beta}_i = \beta$, and $\alpha_i = \alpha$, one can integrate out the unobservable characteristics in equation (3.5). Then, the probability becomes:

(3.8) $$\Pr_{jt} = \int_{\mathbf{D_i}} \int_{\boldsymbol{v}_i} \Pr_{ijt} \, dF\left(\mathbf{D_i} \mid \boldsymbol{v}_i\right) dF(\boldsymbol{v}_i)$$

[16] The logit model restricts the increase in the sales of two products (product 1 and product 2) with different characteristics but similar market shares for a rise in the price of another product (product 3, which is similar to, say, product 1 in the characteristics space), to be the same. However, common sense would suggest that consumers would switch more between products that have similar characteristics and less between those with different characteristics.

where $\Pr_{jt}$ is the same across all consumers. Because the integrals in (3.8) cannot be evaluated analytically, we can approximate it by Monte Carlo integration with R random draws for $\mathbf{D_i}$ and/or $\boldsymbol{v}_i$ (Vincent, 2015).

Thus, the market share of product j can be written as:

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R}\Pr_{ijt} = \frac{1}{R}\sum_{i=1}^{R}\frac{\exp\left\{\delta_{jt} + \left(\mathbf{x'_{jt}}, -p_{jt}\right)\left(\mathbf{\Pi D_i} + \mathbf{\Sigma}\boldsymbol{v}_i\right)\right\}}{1+\sum_{m=1}^{J}\exp\left\{\delta_{mt} + \left(\mathbf{x'_{mt}}, -p_{mt}\right)\left(\mathbf{\Pi D_i} + \mathbf{\Sigma}\boldsymbol{v}_i\right)\right\}} \tag{3.9}$$

The Supply Side

Based on the industry structure described above and following previous literature analyzing differentiated product markets (Berry et al., 1995; Bonanno et al., 2015; Di Giacomo, 2008; Hirsch et al., 2018; Lopez & Lopez, 2009; Nevo, 2001), we assume that prices are the outcomes of a pure-strategy Nash-Bertrand price equilibrium and that U.S. milk manufacturers are oligopolistic firms selling differentiated products. For example, in the Northeast of the U.S., two firms—Dean Foods[17] and HP Hood process and bottle 90 percent of the fluid milk (Liu et al., 2016). Cai and Stiegert (2013) found that the fluid milk markets in California, New York, and Wisconsin are not perfectly competitive. While Chidmi and Segarra (2011) and Tian and Cotterill (2005) tested and found that Nash-Bertrand is a proper specification for the dairy milk markets in Dallas-Fort Worth and Boston, respectively. As for the nondairy milk industry, it is a

[17] After Dean Foods, the largest dairy producer in the U.S., filed for bankruptcy in November 2019, 44 of its facilities, as well as certain corporate functions were later acquired by Dairy Farmers of America (DFA). This was followed by an antitrust lawsuit filed in North Carolina against DFA by Food Lion and the Maryland and Virginia Milk Producers Cooperative Association, claiming that DFA is “an aspiring monopolist… With capability to wield market power at two levels of the supply chain, DFA now has both the ability and the incentive to wipe out any remaining pockets of competition,…” (Byington, 2020).

highly concentrated industry, where the largest four producers control more than 70 percent of the market[18] (O'Connor, 2019).

Suppose there are *N* firms; the *n*-th manufacturer produces a subset, ϑ_n, of the j=1,…,J different milk products. Each of the *n* manufacturer faces a profit-maximization problem:

$$\max_{p_j} \Pi_n = \sum_{j \in \vartheta_n} (p_j - mc_j) M s_j(p) - F_n \ , \tag{3.10}$$

where mc_j is product *j*'s (constant) short-run marginal cost; *M* is the market size; $s_j(p)$ is the market share of product *j,* as a function of product characteristics and prices of all products; and F_n is the long-run fixed cost of production.

Under the Nash-Bertrand assumption, the vector of first-order conditions (FOCs) solving (3.10) is expressed as:

$$p - mc = -\varpi^{-1} \mathbf{S}(\cdot) \ , \tag{3.11}$$

where *p-mc* is a vector of price-cost margins (PCM); $\mathbf{S}(\cdot)$ is a vector of market shares; ϖ is a $J \times J$ matrix with elements $\varpi_{jk} = \varpi^*_{jk} \frac{\partial s_j(\cdot)}{\partial p_k}$ and

[18] In April 2017, Danone acquired WhiteWave Foods and in April 2018 the merged company was named Danone North America—accounting for 52.8 percent of the industry revenue (O'Connor, 2019). After the purchase of WhiteWave Foods, which was also a large producer of organic dairy products, Danone North America has started using some of its organic milk in organic cheese, yogurt, or creamer production (Haddon & Parkin, 2018). Prior to this merger, WhiteWave Foods had purchased Silk, Alpro, and So Delicious, while Danone acquired Vega, another large producer of plant-based nutrition products, in 2015 (O'Connor, 2019). The second largest player in the market is Blue Diamond Growers, with 18.9 percent of industry revenue, selling its products under the Almond Breeze brand name (O'Connor, 2019).

$$\varpi^*_{jk} = \begin{cases} 1, \text{if } j,k \in \vartheta_n \\ 0, \text{otherwise} \end{cases} \quad (3.12)$$

Thus, based on the available data on *p,* the ownership matrix ϖ^*, and partial derivatives of the market share equation with respect to each element of the price vector, we can obtain estimates of PCM without needing cost data. PCMs calculated this way represent short-run margins (i.e. allocation of fixed costs is not considered). Therefore, they can be considered as upper bound estimates of the U.S. dairy and nondairy milk producers' profitability. We also calculate the percentage PCM (Lerner index), which measures the market power at the product level and can be obtained as $L_j = (p_j - mc_j) / p_j$.

Simulated Welfare Impact of the Presence of the "Milk" Claim on Nondairy Beverages

Once estimates of PCMs are obtained, we assess the potential welfare implications of the presence of the "milk" term on nondairy milk products by measuring how much consumers may be over/underpaying for nondairy beverages with a "milk" claim. Additionally, we measure the associated welfare losses/gains incurred by consumers, and how much of that amount is internalized by producers in terms of producer surplus.

Following Bonanno et al. (2015) and Bimbo et al. (2019) we include in the demand model a binary variable, $X_j^{milklabel}$ indicating the presence of a "milk" claim, which takes a value of one when the product's packaging contains "milk" term, and a value of zero otherwise. Thus, the coefficient $\beta^{milklabel}$ represents consumers valuation of the presence of the "milk" term. Considering consumers' marginal utility of income $\bar{\alpha} = \frac{1}{R}\sum_{i=1}^{i=R} \alpha_i$, the average monetary value attached to the "milk" label in nondairy beverages , is calculated as $\bar{\beta}^{milklabel} / \bar{\alpha}$ where

$\bar{\beta}^{milklabel} = \frac{1}{R}\sum_{i=1}^{i=R} \beta_i^{milklabel}$.

Suppose p_j^0 is product *j*'s price observed in the data. Then, if a nondairy beverage *j* is labeled as "milk", according to the logic of the proposed DAIRY PRIDE Act, such label should have been removed, which implies that consumers should have paid:

$$p_j^{milklabel} = p_j^0 - \bar{\beta}^{milklabel} / \bar{\alpha} \quad . \tag{3.13}$$

Based on this equation, if $\bar{\beta}^{milklabel}$ has a positive sign, it suggests that, under the proposed act, the product has a lower value and consumers are overpaying for a nondairy beverage because of the "milk" claim. The opposite is true if $\bar{\beta}^{milklabel}$ has a negative sign.

We can estimate the changes in an individual consumer's welfare for the consumption of each unit of the product using equivalent variation (Bimbo et al., 2019), which is given by

$$EV_i = \frac{\sum_{j=1}^{j=J} \ln\left(\sum_{i=1}^{i=I}\left(\exp\left(u_{ij}^{milklab}\right)\right)\right) - \sum_{j=1}^{j=J} \ln\left(\sum_{i=1}^{i=I}\left(\exp\left(u_{ij}^{0}\right)\right)\right)}{\alpha_i} \ , \tag{3.14}$$

where $u_{ij}^{milklab} = \alpha_i + \delta_j(\mathbf{x_j}, p_j^{milklab}, \xi_j; \theta_1) + \mu_{ij}(\mathbf{x_j}, p_j^{milklab}, \boldsymbol{v_i}, \mathbf{D_i}; \theta_2) + \varepsilon_{ij}$, whereas $u_{ij}^0 = \alpha_i + \delta_j(\mathbf{x_j}, p_j^0, \xi_j; \theta_1) + \mu_{ij}(\mathbf{x_j}, p_j^0, \boldsymbol{v_i}, \mathbf{D_i}; \theta_2) + \varepsilon_{ij}$ is the baseline scenario. Multiplying equation (3.14) by the market size, *M*, it gives the total change in consumer welfare.

Based on the observed prices and estimated markets shares, as well as the estimated $\bar{\beta}^{milklabel} / \bar{\alpha}$, the profits attributable to the presence of "milk" claims on nondairy beverages, given the higher price charged to consumers, internalized by producers can be calculated by

$$\Delta\Pi_n^{milklabel} = M \sum_{j \in \vartheta_f} s_j^0 \left(p_j^{milklabel} - p_j^0 \right) . \tag{3.15}$$

Data, Estimation, and Identification

Data

The primary data source is a barcode-level, point-of-sale weekly sales data for the year 2013, acquired by the Economic Research Service (ERS) from Information Resources Incorporated (IRI); access was granted via Third Party Access Agreement. About half of all grocery sales in the United States are covered by the IRI retail data (Levin et al., 2018). In addition, we use the Purchase to Plate Crosswalk (PPC)[19], a new dataset, developed by USDA, which links the 2013 InfoScan data to the 2011-12 Food and Nutrient Data for Dietary Studies (FNDDS) and Food Patterns Equivalent Database (FPED) (Carlson et al., 2019), which are used to construct additional instrumental variables, as illustrated below.

There are 7,491 Universal Product Codes[20] (UPCs) in the IRI InfoScan data for dairy and nondairy milk products. Of these 7,491 UPCs, 6,062 UPCs were matched with the PPC data. These UPCs were grouped based on 18 product attributes, which resulted in 2,235 "product aggregates". The aggregation of products based on product attributes is a common method used in demand analyses using highly disaggregated data (Bonanno, 2012; Hirsch et al., 2018; Miller & Weinberg, 2017; Nevo, 2001; Zhen et al., 2014). Since the number of products was still large once the UPCs were aggregated based on product attributes, we retained the top 75 percent of

[19] The PPC dataset covers 95 percent of InfoScan sales recorded at the bar-code level, excluding private label products not released at the UPCs level (Carlson et al., 2019).

[20] These UPCs do not include kefirs, nogs, goat milk, Bulgarian milk, buttermilk, smoothies, milk shakes, acidophilus milk, nor cultured milk products.

products by grocery sales volume (total ounces) and the next nine nondairy products which did not use the term "milk" on their packages[21]. The data were further aggregated from the store-week level to the state-month level and include sales of 72 products (54 dairy and 18 nondairy) in the contiguous United States, including the District of Columbia, resulting in 22,985 observations.

We define markets, *t*, as state-month pairs (12 months x 49 states=588 markets), and include producer fixed effects, τ_p, 13 binary product characteristics (including the presence of a "milk" claim), and three continuous product characteristics: the average size in ounces to account for consumers' preference over packaging size; average launch year, to capture consumers' familiarity with the product; and the log of the average number of items sold (*LnN*) in each market. We include *LnN* following Ackerberg and Rysman (2002), to control for the negative effect of congestion on demand, given that we have an unbalanced panel and a varying number of products in each market (ranging between 27 and 51, depending on the market). Summary statistics are presented in Table 3.1.

By including dummy variables (e.g. brand or market-specific, depending on the data), we can capture some aspects of the unobserved characteristics (Nevo, 2000). Thus, we also include state and month fixed effects, τ_{state} and τ_m, to capture time-invariant state characteristics and monthly unobserved determinants of demand, respectively. The structural error ξ_{jt} is likely still correlated with prices, as it includes product characteristics observed by consumers but not by the researcher.

[21] These nine products were added to enable us perfom couterfactual simulations, because all with the exception of one nondairy beverage in the top 75 percent carried the "milk" term.

The total market size, which is used to compute market shares, is calculated using the state-level population data for 2013, obtained from the U.S. Census Bureau (2016). The population size is then multiplied by 216.154, which is the average per-capita monthly consumption of milk by U.S. consumers, which we calculated based on U.S. fluid milk sales volume data[22] obtained from the ERS (2018). The construction of market size using these assumptions is a standard practice in studies using aggregate-data discrete-choice models (Berry et al., 1995; Bonanno et al., 2015; Chidmi & Lopez, 2007). The market share of product *j* in market *t* is calculated as $\text{Volume}_{jt}/\text{MarketSize}_t$, where Volume=total ounces sold. Following Bonnet and Bouamra-Mechemache (2016) and Hirsch et al. (2018), the unobservable characteristics[23] for 50 consumers for each market were randomly generated from a normal distribution with a mean of zero and standard deviation of one. Thus, the data include a total of 29,400 "generated" consumers across all markets (588 markets x 50 consumers).

Table 3.1: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Share	0.0029	0.0084	0.0000	0.1047
Share: dairy	0.0046	0.0105	0.0000	0.1047
Share: nondairy	0.0004	0.0005	0.0000	0.0036
Price	5.6360	2.3917	1.5256	14.9688
Ln(N)	3.6736	0.1221	3.2958	3.9318
Milk label	0.8054	0.3959	0.0000	1.0000
Years from launch	25.3006	6.8536	4.5000	35.0000

[22] ERS (2018) reports annual fluid beverage milk sales volume (millions of pounds) by product categories, including whole, reduced-fat (2 % milk fat), low-fat (1 % milk fat), skim, flavored whole, flavored-other than whole milks. After calculating the total sales of these products, we converted to ounces and divided by the population of the U.S. in 2013 and the number of months (12) to get an average per capita/per month milk consumption estimate.

[23] We tried including demographic variables, such as age, presence and/or age of children in the household, and others, randomly drawn from the Current Population Survey. However, due to the large number of products and computational limitations, the estimation would take unrealistic times to run and face nonconvergence issues.

Average unit size	71.0721	31.7424	12.0000	128.0000
Carton package	0.5349	0.4988	0	1
Dairy aisle	0.7798	0.4144	0	1
Flavor: vanilla	0.1209	0.3260	0	1
Flavor: chocolate	0.1245	0.3301	0	1
Type: almond	0.1581	0.3648	0	1
Type: other nondairy	0.1736	0.3788	0	1
Type: skim	0.1515	0.3585	0	1
Type: 1% fat	0.1189	0.3237	0	1
Type: 2% fat	0.2008	0.4006	0	1
Type: whole fat	0.1298	0.3361	0	1
Lactose free	0.2717	0.4448	0	1
Organic	0.2382	0.4260	0	1

Estimation

Following Nevo (2000), the own- and cross-price elasticities for the BLP using equation (3.8) become:

(3.16)
$$e_{jmt} = \begin{cases} -\dfrac{p_{jt}}{s_{jt}} \int \alpha_i \Pr_{ijt}\left(1-\Pr_{ijt}\right) dF(\mathbf{D_i}, \boldsymbol{v}_i) & \text{if } j = m \\ \dfrac{p_{mt}}{s_{jt}} \int \alpha_i \Pr_{ijt} \Pr_{imt}\, dF(\mathbf{D_i}, \boldsymbol{v}_i) & \text{if } j \neq m \end{cases}$$

Note, that ξ in equation (3.1) is most likely known to both consumers and producers, and producers may base their pricing decisions on the values of ξ. Therefore, it is a potential source of endogeneity for prices (Knittel & Metaxoglou, 2014). We follow previous literature (Knittel & Metaxoglou, 2014; Nevo, 2000, 2001; Vincent, 2015) and estimate the BLP model via an instrumental variable (IV) Generalized Method of Moments (GMM) (Hansen, 1982).

The unconditional moment restrictions can be presented as:

(3.17)
$$E\left(\mathbf{z_{jt}}\xi_{jt}\right) = 0$$

where $\mathbf{z_{jt}}$ is vector of instruments consisting of cost-shifters and product characteristics. The estimation of the GMM then takes the following steps. First, one needs to draw R random values for $\mathbf{D_i}$ and/or $\boldsymbol{v}_i$ for $i = 1,...,R$ from their respective distributions. Second, for a given vector of parameters θ_2, solve the vector of mean utilities δ_t, such that the predicted shares from (3.8) equal observed market shares. This system of equations is solved using contraction mapping, such that for each δ_t^n, the computation includes

(3.18)
$$\delta_t^{iter+1} = \delta_t^{iter} + \log\left(\frac{s_t}{s\left(\delta_t^n, \theta_2\right)}\right)$$

where $iter$ is the number of the iterations. This process continues, until $\| \delta_t^{iter} - \delta_t^{iter-1} \|$ is below an inner-loop tolerance level of 10^{-15} (Vincent, 2015). Third, after obtaining δ, we can infer the value of ξ from

(3.19)
$$\xi_{jt} = \delta_{jt} - \mathbf{x_j}\boldsymbol{\beta} - \alpha p_{jt}$$

where α and $\boldsymbol{\beta}$ are obtained using linear IVs.

The nonlinear GMM objective function takes the following form:

(3.20)
$$Q_T(\theta) = \{T^{-1}\xi(\theta)'\mathbf{Z}\}W_T\{T^{-1}\mathbf{Z}'\xi(\theta)\}$$

where $\mathbf{Z}$ is a matrix of instruments and W_T is a positive-definite weighting matrix independent of θ, assuming a sample size T.

Identification

Following previous literature (Berry & Haile, 2014; Hirsch et al., 2018; Reynaert & Verboven, 2014), we use two sets of instruments to correct for the endogeneity of price —input prices and "BLP-type" instruments, that is, the sums of the characteristics of other products. We assume that changes in input prices are correlated with product price changes and are uncorrelated with unobservable product characteristics. Under this assumption, input prices allow product price changes due to variations in unobserved milk characteristics to be separated from exogenous changes in cost (Bonanno et al., 2015; Nevo, 2000).

The input prices we use as instruments are: average retail price of electricity (cents per kilowatt-hour) to commercial users, which varies by month and state (EIA, 2013); log of average weekly wages in retail trade (BLS, 2013), which varies by state and quarter, and its interaction with electricity price: the monthly milk "price received, parity, measured in $ / cwt" (NASS, 2019) is multiplied by an indicator for whole fat milk; additionally, we use the interactions of milk types with average monthly feed costs, veterinary and medicine costs, bedding and litter costs, and marketing costs from the "Monthly milk cost-of-production (COP) estimates" of the ERS; weekly national price of sugar averaged at the month level (Intercontinental Exchange, 2013) multiplied by the amount of added sugars in each product, which is included in the PPC data; and the three-month lagged monthly almond "price received, parity, measured in $ /lb" (NASS, 2019) multiplied by a continuous variable indicating the amount of nuts and seeds in a product.

The second set of instruments, BLP-type instruments, includes the sum of the content of added sugars and calcium (per oz) of products offered by other firms. The logic behind using these variables as instruments is that they will help disentangling endogenous changes in prices due to changes in unobserved product characteristics from exogenous changes in prices which occur because of changes in observed product characteristics, $\boldsymbol{x}_{jt}$ (Nevo, 2000).

To test for the presence of endogeneity we use a C-statistic under the null hypothesis that the suspected endogenous variable (price) is exogenous (Hayashi, 2000). We use a J-test (Hansen, 1982) to test the orthogonality of the over-identifying restrictions under the null hypothesis that the overidentifying instruments are uncorrelated with the errors. Using Staiger and Stock (1994)'s procedure, we assess instruments' strength and test whether the excluded instruments are only weakly correlated with the endogenous variables. To improve estimation efficiency (Berry et al., 1995; Reynaert & Verboven, 2014) and have estimates that are close to their true values (Vincent, 2015), we use Chamberlain's (1987) optimal instruments.

Results and Discussions

Estimates of the demand coefficients are presented in Table 3.2. The taste parameter for each product attribute with a statistically significant coefficient on the unobserved consumer characteristics can also be presented by the following equations:

(3.21) $$price = -1.751 + 0.159 v_i$$

(3.22) $$milk\ label = 1.008 + 0.280 v_i$$

(3.23) $$dairy\ aisle = -3.098 + 0.301 v_i$$

(3.24) $$almond\ milk = 1.039 + 0.386 v_i$$

(3.25) $$other\ nondairy\ milk = 0.920 + 0.287 v_i$$

Table 3.2: Estimated demand parameters and model performance

	Mean utility				Unobservables		
Variable	Coefficient		SE	Variable	Coefficient		SE
Price	-1.7513	***	(0.2246)	Price	0.1586	***	(0.0123)
Milk label	1.0080	***	(0.4017)	Milk label	0.2799	*	(0.1693)
Carton package	-1.9087	***	(0.3144)	Carton package	0.0000		(0.1163)
Dairy aisle	-3.0980	***	(0.5257)	Dairy aisle	0.3012	*	(0.1652)
Type: almond (vs soy)	1.0385	***	(0.1037)	Type: almond	0.3860	***	(0.1557)
Type: other nondairy	0.9198	***	(0.2337)	Type: other nondairy	0.2870	*	(0.1681)
Type: skim	3.2729	***	(0.2462)	Type: skim	0.0000		(0.2073)
Lactose free	2.4273	***	(0.3053)	Lactose free	0.6354	***	(0.1244)
Private label	-2.4914	***	(0.2225)	Private label	0.2235		(0.2272)
Type: 1% fat	3.3332	***	(0.1798)				
Type: 2% fat	3.8419	***	(0.2380)	Number of observations	22,958		
Type: whole fat	4.0362	***	(0.2526)	Number of markets	588		
Average unit size	-0.0402	***	(0.0088)	Number of Halton draws	50		
Flavor: vanilla (vs plain)	0.1062		(0.1092)				
Flavor: chocolate	0.4655	***	(0.1009)	Hansen J (p-val)[24] $\chi^2_{(17)}$ =	8.6790		(0.9498)
Organic	0.8306	**	(0.4062)	C stat (p-val)[25] $\chi^2_{(1)}$ =	30.4971		(0.0000)
Launch year	-0.0366	***	(0.0053)	Instrument power	Price		
(Log) av. number of products	-2.0391	***	(0.6158)	$F_{(18,22867)}$[26]	12.4175		
Constant	13.60836	***	(2.6243)	First-stage R^2	0.8711		

Note: *, **, and *** represent 10, 5 and 1% significance levels, respectively.
Month, state, and producer fixed effects' coefficients omitted for brevity.

[24] The p-value suggests that the null hypothesis of overidentifying instruments being uncorrelated with the errors cannot be rejected.
[25] The p-value suggests that the null hypothesis of price being exogenous can be rejected at the 1% significance level.
[26] Since the test of the joint significance of the instruments' parameters in the first-stage regressions produces an F-statistic value larger than 10 (Staiger and Stock (1994) "rule of thumb"), we can discard weak instruments as an issue.

$$\text{(3.26)} \qquad lactose\ free = 2.427 + 0.635 v_i$$

where v_i represents unobserved consumer characteristics. These equations suggest the existence of a varying degree of preference for these attributes among different consumers. The estimated mean utility parameters suggest that there is a negative relationship between prices and consumer preferences, as expected.

However, as suggested by the coefficient on the stochastic term of price (unobservables column in Table 3.2) there is some heterogeneity in consumers' responsiveness to milk prices. The estimated coefficients also suggest that there is a positive relationship between the presence of the "milk" label and consumer preferences, with some consumers valuing the label more than others, as indicated by the coefficient on the stochastic term of "milk" label. This finding is consistent with that of the PBFA (2019), which suggests that consumers prefer the term "milk" on nondairy beverages over other alternatives, such as "beverage" or "drink", as the latter are more closely associated with soft drinks and alcohol. Given that the labeling decision is made endogenously by the producers of nondairy milks, and we do not observe data on how these decisions are made, we believe that the effect of this decision on the dependent variable is mostly captured by the manufacturer fixed effects.

Unlike previous studies, which grouped different flavors into one category of "flavored" milk (Davis et al., 2012; Dharmasena et al., 2017), we allow for heterogeneity in preferences for specific flavors. Consumers prefer chocolate-flavored milk over non-flavored milk (dairy and nondairy combined), while there is no evidence of a preference for vanilla-flavored nondairy milk compared to non-flavored nondairy milk.

In terms of fat content, consumers show the highest preference for whole milk, followed by 2% fat, 1% fat, skim milk, almond milk, and other nondairy milk products, as compared to soy milk (base category). This is consistent with what we see in the market. As Figure 2.1 in Chapter 2 shows, even though reduced fat (1% and 2% combined) milks had the highest expenditure share, the share started decreasing in 2013, suggesting changing consumer preferences. In 2013, reduced fat milk is followed by whole fat milk (with increasing expenditure share), skim milk (with decreasing expenditure share), almond milk (increasing share), soy milk (decreasing share), and other nondairy milk (increasing share).

As expected, both the lactose-free and organic attributes are valued positively, even though the preference for lactose-free milk is more pronounced than that for organic. Other studies have found that the presence of organic label on milk increases purchase probability (Kiesel & Villas-Boas, 2007) and that consumers are willing to pay a premium for organic milk (Bernard & Bernard, 2009). McCarthy et al. (2017) also found that lactose-free is an important attribute for both dairy and nondairy milk consumers.

Consumers value carton packages negatively compared to all other packaging options combined (e.g. jug, glass, etc.). As expected, larger product size, which can serve as a proxy for package size, is slightly less desirable than smaller average product size. This may be due to the perishability of most of the products included in the dataset (both dairy and nondairy). Another finding that supports this explanation, is that the coefficient for products sold in the dairy aisle, where refrigerated dairy and nondairy milk products can be found, is negative. Given that we control for other product attributes (e.g. dairy vs nondairy, flavored vs non-flavored, organic vs non-organic, manufacturer fixed effects, etc.), this suggests that consumers prefer milk products with longer shelf life. Interestingly, in the 90s WhiteWave, the producer of Silk, found that after moving its product to the dairy aisle, more people bought it (Franklin-Wallis, 2019). In an interview to the Guardian, Blue Diamond's (known for Almond Breeze) director of marketing, Al Greenlee, told that in 2008 they followed a similar path and positioned their products in the dairy aisle to compete with Silk (Franklin-Wallis, 2019). Given the highly competitive nature of the refrigerated case, they did so by establishing "a partnership with the second largest dairy in the country" (Franklin-Wallis, 2019). According to the PBFA, the decision to place nondairy milks in the dairy aisle was originally made by the retailers to help consumers effortlessly find these products and boost sales, as consumers were looking for nondairy milks, as well as lactose-free or chocolate milk in the dairy aisle (PBFA, 2019).

The number of items available to consumers per market negatively impacts the demand for milk, as expected. Two possible explanations for this are that: (a) the higher the number of options available, the less the market share of each product; or as Ackerberg and Rysman (2002) suggest: "*… new products crowd out existing products in retail store or shelf space*" and (b) consumers are more likely to purchase a product when offered a limited number of choices rather than a wide range of options (Iyengar & Lepper, 2000). Additionally, the coefficient on the launch year is negative, suggesting that, on average, consumers prefer milk products that have been in the market for longer time.

Milk type-level average own-price elasticities (OPEs) of demand are presented in Table 3.3. The average OPE of all milk types combined (dairy and nondairy) is about -7.8, while the average OPE of dairy milk is -6.7 and that of nondairy milk is -11.3. Other studies, such as Gulseven and Wohlgenant (2015) and J. Li (2016), which estimated the demand for dairy and nondairy milks also found that nondairy milk had higher own-price demand elasticity than dairy milk. However, we find that the OPE of nondairy beverages with the "milk" term is -7.6 which is similar in magnitude to that of dairy milk products, and it is slightly more than half the magnitude than the OPE of nondairy beverages without the "milk" term (-14.2). This may suggest similar consumption patterns for nondairy beverages carrying the "milk" term on their label and dairy milk products.

Table 3.3: Average milk type-level own-price elasticities

Milk type	Avg. elasticity	Milk type	Avg. elasticity
Average (dairy and nondairy)	-7.8315		
Dairy	-6.6832	Nondairy	-11.276
Type: skim	-6.9698	Type: almond	-10.730
Type: 1% fat	-7.3867	Type: soy	-10.481
Type: 2% fat	-6.4430	Type: other nondairy	-12.052
Type: whole fat	-6.4831	Nondairy with "milk" label	-7.619
		Nondairy w/o "milk" label	-14.201
Non-flavored (dairy and nondairy)	-7.4202		
Non-flavored dairy	-6.4930	Non-flavored nondairy	-11.719
Flavored (dairy and nondairy)	-10.3810		
Flavored dairy	-9.9165	Flavored nondairy	-10.580

Note: Elasticities are averaged across consumers.

Among dairy milks, 1% fat milk demand is the most sensitive to price, with an average OPE of about -7.4, followed by skim milk with an average OPE of almost -7.0, whole fat milk, with -6.5 average OPE, and 2% fat milk, with -6.4 average OPE. Among nondairy milk types, soy milk demand is the least sensitive to changes in its own price, with an average OPE of -10.5, followed by almond milk (-10.7), and other nondairy milk products (-12.1). While the non-flavored dairy milk products' demand is less elastic (-6.5) than that of flavored dairy milk (-9.9), the opposite is true for nondairy milk products (non-flavored OPE: -11.7; flavored: -10.6).

Although the values of OPEs above may seem high, relatively greater elasticity values are expected when one works with a rather large number (72) of disaggregated products; in fact the higher the disaggregation level, the higher should the expected absolute values of elasticities be (Davis et al., 2012). For example, Hirsch et al. (2018) estimated the demand for dairy milk in two Italian regions (17 products in Turin and 19 products in Naples) using the BLP demand model and found OPEs ranging from about -13.7 to -4.3. Lopez and Lopez (2009) also used the same model to estimate the demand for 22 dairy milk products in the Boston area and found OPEs in the range of -8.5 and -1.9. The box plots of product-level OPEs for dairy and nondairy milk products is presented in Figure 3.1. The maximum value of cross price elasticities is 0.25, while the average is almost 0.03.

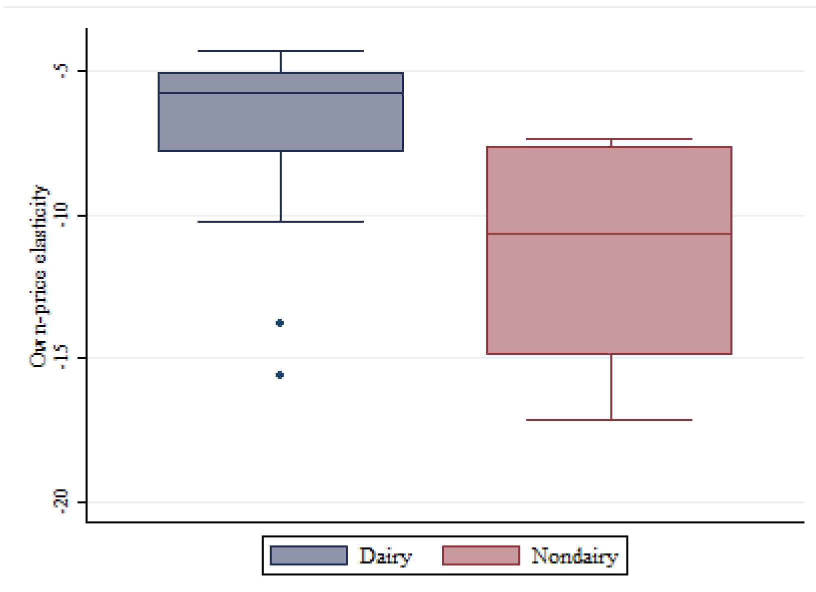

Figure 3.1: Product-level OPEs averaged across markets

The maximum value of cross price elasticities (which are omitted for brevity) is 0.25, while the average is almost 0.03. When the price of nondairy milk labeled as milk increases by 1%, the quantity demanded of dairy milk as an aggregate product category increases, on average, by 0.05%, and the quantity demanded of nondairy beverages not labeled as milk increases, on average, by 0.08%. However, a similar price increase for nondairy beverages not labeled as milk, leads to a small increase in the demand for both dairy milks (on average, by 0.001%) and nondairy milks with the “milk” label (0.002%). These cross-price elasticity magnitudes suggest that dairy milk is a closer substitute for nondairy milks labeled as milk, than it is for nondairy beverages not labeled as milk. At the same time, nondairy beverages not labeled as milk are closer substitutes for nondairy milks with the “milk” claim, than are the latter for the former. Interestingly, when the price of dairy milk increases by 1%, the quantity demanded of nondairy milks both with and without the “milk” label increases by 0.03%, suggesting that regardless of the dairy terminology use, both types of nondairy milks are perceived as equal substitutes for dairy milk.

Table 3.4 presents average prices (from the data), along with estimated marginal costs, PCMs, and percentage PCMs. The values for dairy milk manufacturers are aggregated by private label and manufacturer brands, while those for nondairy milk manufacturers are combined at the product type level (almond, soy, and other nondairy milk) and on whether or not they carry the milk label. On average, retailer managed brands attain the highest percent markups, followed by branded dairy, and nondairy milk products. This is in line with Lopez and Lopez (2009) who found that in the Boston milk market private label milk products had the highest percent markups. Both in the case of Lopez and Lopez (2009) and this study, the result is likely due to the low marginal costs of private label dairy milk products compared to other brands, allowing retailers to offer lower prices while still earning a higher markup. In non-relative terms, however, while private label dairy milk products show the highest PCMs, branded nondairy show the second highest, followed by branded dairy. This might partly explain why more shelf space is being devoted to nondairy milks as suggested by Gulseven and Wohlgenant (2014) and Haddon and Parkin (2018).

Table 3.4: Average prices (observed), and estimated marginal costs, PCMs, and percentage PCMs

Product aggregates	Price ($/64 oz.)	Marginal Cost	Price-marginal cost (PCM)	Percentage PCM
Private label vs branded				
Dairy: private label	2.5700	2.1345	0.4356	16.9482
Dairy: branded	2.7016	2.2984	0.4031	14.9227
Nondairy: branded	4.7187	4.2886	0.4301	09.1145
Nondairy type				
Type: almond	4.5717	4.1300	0.4417	9.6613
Type: soy	4.4491	4.0066	0.4425	9.9459
Type: other nondairy	4.9485	4.5332	0.4153	8.3921
Nondairy label type				
Nondairy with milk label	3.2782	2.8256	0.4526	13.8060
Nondairy w/o milk label	5.8712	5.4591	0.4121	7.0189

When comparing nondairy milk products' percentage PCMs based on the "milk" label presence we find substantially higher values for nondairy beverages labeled as milk (13.8060 vs 7.0189 for nondairy beverages not labeled as milk), which is close to the percent markup received from branded dairy products (14.9227). Even though nondairy beverages without the "milk" term are more than twice as expensive as dairy milk products and almost twice as expensive as nondairy beverages carrying the "milk" term, they show the lowest percent markups. Lopez and Lopez (2009) found a similar effect for specialty milks.

As shown in Table 3.4, nondairy products without the "milk" term have, on average, higher prices than those with the term. One explanation for this may be that nondairy products labeled as milk are more associated with dairy products, and thus, they compete in the market by offering prices closer to dairy milk, while nondairy products without the term "milk" might be perceived as different products. Thus, producers of these products can use higher prices to distinguish these products from the rest in the market and create an image of a higher-quality product. This is consistent the PBFA's statement, which suggests that "… the manner in which plant-based foods are labeled and marketed is often dependent on brand positioning", even though many brands choose to use the "milk" label together with clarifying terms, such as "dairy-free", "alternative", and others (PBFA, 2019). Another explanation is that all nondairy beverages not labeled as "milk" in our data are located in the non-refrigerated aisle[27], meaning that there might be additional costs of production, such as aseptic processing and tetra-pak packaging, making the prices higher. For example, Blue Diamond Growers states on its website that shelf-stable nondairy milks are produced using the aseptic process, which requires products to remain at a high temperature for a longer duration than the refrigerated milks, which are produced using a "dairy process". Additionally, the website states that: "*The packaging for the shelf-stable product is called tetra-pak and is designed for shelf stability of the unopened product for an extended period of time. The refrigerated product's packaging, on the other hand, is not constructed for shelf stability and must be refrigerated at all times.*" (Blue Diamond Growers, 2020).

Simulation Results

Consumers, on average, pay 57.6 cents per ounce of nondairy beverage with a "milk" claim ($\beta^{milklabel} / \alpha$ =1.008/1.751=0.576), or about 0.368 dollars per 64-ounce package. Given that the average prices of nondairy beverages carrying the "milk" term is \$3.278 per 64-ounce package, about 11.2% of their price can be attributed to the label itself. Had the nondairy beverages included in this study not carried the term "milk" on their packaging, consumers would have valued them less, and, as a result, may have showed a lower willingness to pay for

[27] According to Fleming (2018), shelf-stable nondairy milks can mostly be found in the middle aisle, often near the cereals.

them. This finding supports, although indirectly, one of the arguments advanced by the DAIRY PRIDE Act proponents that nondairy milk producers capitalize on the use of dairy terminology.

Table 3.5 presents the simulated welfare implications of the presence of the “milk” term on the labels of nondairy beverages for two scenarios. After estimating the price premium associated with the presence of the “milk” term on nondairy beverages, we used simulated prices for the nondairy milk products with the “milk” label and calculated the resulting changes in monthly consumer and producer surplus, as well as the total welfare. In scenario 1, we used the simulated prices for all nondairy beverages displaying the “milk” label; in scenario 2, we used the simulated prices for all nondairy beverages displaying the “milk” label, except for soy milk. The reason for this is that according to the 2015-2020 Dietary Guidelines for Americans, healthy eating patterns include: *“… fat-free and low-fat (1%) dairy, including milk, yogurt, cheese, or fortified soy beverages (commonly known as “soymilk”). Soy beverages fortified with calcium, vitamin A, and vitamin D, are included as part of the dairy group because of similarities to milk based on nutrient composition and in their use in meals”.* Note, that the simulated prices are not equilibrium prices and the resulting changes in welfare are for illustrative purposes only.

Table 3.5: Simulated welfare impact (in $ thousands) of the presence of “milk” claim on nondairy beverages

Welfare	Baseline in $ (a)	No Premium in $ (b)	Δ Welfare in $ (a)-(b)	% Δ Welfare
Scenario 1: All nondairy beverages with “milk” claim				
Consumer surplus	747,339,284	777,729,482	-30,390,198	-4.066
Producer surplus (PS)	73,958,077	66,904,659	7,053,418	9.537
Dairy PS	64,941,750	64,941,750	0	0

Nondairy PS	9,016,326	1,962,908	7,053,418	78.229
Almond PS	6,737,796	1,400,375	5,337,421	79.216
Soy PS	1,665,364	310,723	1,354,641	81.342
Other nondairy PS	613,167	251,811	361,356	58.933
Total welfare	821,297,361	844,634,141	-23,336,780	2.950
Scenario 2: All nondairy beverages with "milk" claim, except soy				
Consumer surplus	747,339,284	770,967,068	-23,627,784	-3.162
Producer surplus (PS)	73,958,077	68,259,299	5,598,777	7.705
Dairy PS	64,941,750	64,941,750	0	0
Nondairy PS	9,016,326	3,417,549	5,598,777	62.096
Almond PS	6,737,796	1,400,375	5,337,421	79.216
Soy PS	1,665,364	1,665,364	0	0
Other nondairy PS	613,167	251,811	361,356	58.933
Total welfare	821,297,361	839,326,368	-18,029,007	2.195

In the context of the DAIRY PRIDE Act, if the FDA recognizes the use of dairy terminology on nondairy milk products as deceitful/confusing, the results suggest that, in total, consumers overpaid about $30,390,198 (scenario 1)/ $23,627,784 (scenario 2) per month for the nondairy beverages labeled as milk. Had they not been charged this premium, their resulting surplus would have been higher by the same amount, or by about 29.85 cents (scenario 1)/23.21 cents (scenario 2) per consumer of nondairy milk (30,390,198 or 23,627,784 divided by the number of Americans that purchase nondairy milk: 316,128,829*0.322). However, only $7,053,418 (scenario 1)/$5,598,777 (scenario 2) was internalized by the manufacturers of nondairy beverages per month, which means that about $23,336,780 (scenario 1)/$18,029,007 (scenario 2) was a deadweight loss.

Under both scenarios, most of nondairy producers' surplus is attributable to the use of the "milk" term. In relative terms, soy milk producers benefit the most from the presence of the "milk" label, which is the source of about 81.2 percent of producer surplus. For almond milk producers, about 79.2 percent of the surplus is due to the use of the "milk" term, and for other nondairy milk producers—about 58.9 percent. Given that consumers do not receive anything "concrete/tangible" from the "milk" label on nondairy beverages except for the utility that comes with the label, one can say that producers of nondairy milk products capture an extra $7,053,418 in producer surplus under scenario 1, and $5,598,777 under scenario 2, for marketing their products as milk. This finding essentially supports the NMPF's claim that the producers of dairy milk alternatives use this terminology to benefit from dairy milk's favorable reputation.

Conclusions and Limitations

In this study, we used point-of-sale data on dairy and nondairy milk products in the U.S. and estimated the demand for these products via BLP demand model. One of our findings is that consumers value positively the presence of the "milk" term on nondairy beverages. Therefore, they overpay for these products while only a portion of that amount is internalized by the manufacturers and the rest is a deadweight loss. At the same time, we find that both nondairy beverages not labeled as milk and those labeled as such are equal substitutes for dairy milk.

The policy implication of our findings is that, if the FDA enforces manufacturers of nondairy beverages to stop using "dairy" terminology and manufacturers of these beverages lower the prices by the amount at which the "milk" term is valued by consumers, consumers' welfare will increase by more than the losses incurred by the manufacturers of nondairy beverages, resulting in an increase in total welfare.

We also find the highest percent markups in this market are associated with private label dairy milk products, suggesting that dairy milk operators may be working with very slim margins. In addition, we find that nondairy beverages labeled as milk have better performance in terms of percent markups than nondairy beverages without the "milk" term.

While this framework is helpful in analyzing the potential economic impacts of nondairy milk labeling, it comes with some limitations. Our analysis is based on several assumptions and the findings/conclusions may vary under different assumptions. One of the assumptions is that manufacturers play a Nash-Bertrand pricing game, however, it is possible that their market behavior can be represented better by a different game (e.g. Stackelberg). Another assumption is that consumers' preference heterogeneity can be captured by a normally distributed random coefficient on some of the product attributes, while it is possible that preference heterogeneity follows a different distribution. Third, we assume that nondairy beverages will be banned from using the "milk" term. However, it is possible that the enforcement might be more flexible and allow nondairy beverages to continue carrying the "milk" claim in conjunction with other clarifying terms, such as "milk substitute", "milk alternative", or other options. Thus, our calculations serve as upper bounds on potential welfare changes resulting from the DAIRY PRIDE Act suggested changes. Fourth, the simulated welfare changes do not consider strategic price adjustments following the ban, and / or other strategic responses (e.g. product withdrawals); the next chapter of this dissertation illustrates different outcomes of the ban under a series of strategic responses. Fifth, due to the lack of supply-side data, we attempt to capture product labeling decisions, which are endogenously made by producers of nondairy milks, by including producer fixed effects. Therefore, more refined data can help with the identification.

Chapter 4: Diversion Ratios and Counterfactual Analyses

Introduction

The analyses conducted in Chapters 2 and 3 of this dissertation illustrated different features of milk demand in the U.S., and the empirical results therein, were used to study the implications of the DAIRY PRIDE Act. In this chapter, we rely on the results and data from those two chapters, as well as additional analytical tools, to provide further analysis of the economic rationale behind the DAIRY PRIDE Act, and to simulate likely market outcomes of scenarios where the DAIRY PRIDE Act becomes a law.

In Chapter 2, we tested for separability of demand for dairy and nondairy milks. Also, we used cross-price elasticities of demand to analyze the degree of substitutability and complementarity among different types of milk. However, in markets where large disparities in sales values and volumes exist across different products, such as an expanded milk market where both dairy and nondairy milk coexist, using cross-price elasticities to identify closer substitutes (or complements) to a product may not be appropriate[28]. Using the results and data from Chapter 2, we calculate changes in the volume and dollar sales of each milk as a result of changes in the quantities and prices of other milks demanded. In other words, we use the concept of diversion

[28] Consider the following example. In a hypothetical market, assume that the cross-price elasticity between products A and B is 0.7, while the cross-price elasticity between products A and C is 3.0. Based on the standard interpretation of cross-price elasticities, products A and C are closer substitutes than are products A and B. Assume that all products are measured in the same unit, and the quantity demanded of product B is 500 units, while that of product C is 5 units. Based on the magnitude of the cross-price elasticities, if the price of product A were to increase 5%, product B's quantity demanded would increase by 3.5% or 17.5 units while product C's would increase 15% or by 0.75 units. Thus, when quantities are considered, product B benefits from product A's price increase more than does product C, even though product C is considered a closer substitute, if one only considers the gross elasticity measure.

ratios, first introduced by Shapiro (1996) as a tool to assess market definition in horizontal merger analysis, to evaluate whether strategic price changes by nondairy milk manufacturers can constitute a threat for dairy milk manufacturers. Particularly, by calculating the unit diversion ratios (UDR) and the dollar diversion ratios (DDR) proposed by Werden (1998), we can measure which milks might benefit (suffer) from potential price/sales changes by the other products in the market. In the context of the DAIRY PRIDE Act, these ratios can inform whether and by how much dairy (nondairy) milks are at risk of losing sales as a result of nondairy (dairy) milk producers' strategic pricing decisions.

In Chapter 3, we estimated the value attached to the "milk" label on nondairy milks and illustrated how much consumers were (over)paying for that label in 2013, what part of those payments were captured by the producers, and what instead consisted in a deadweight loss. However, such measures do not capture any market adjustment that would take place, were the DAIRY PRIDE Act to become a law. In the second part of the analysis included in this chapter, we use data and estimates from Chapter 3 to perform counterfactual simulations aimed at evaluating the consequences of the law according to different scenarios where nondairy milks stopped using the "milk" label, or if some of the existing nondairy milks exited the market. Specifically, we simulate two de-labeling and two product withdrawal scenarios where either all nondairy milks, or all nondairy milks except for soy milks are first banned from using the milk denomination on their products, and second, are withdrawn from the market. Using methods described in Bonanno et al. (2015), Chaudhuri et al. (2006), and Hausman (1996), we simulate new equilibrium market shares and prices, and calculate the resulting consumer and producer welfare changes from the status quo. These simulations will illustrate whether the de-labeling of nondairy milks will enhance or reduce consumer and producer welfare.

Background

Diversion Ratios

Shapiro (1996) provided two definitions of the diversion ratio[29]: (a) the fraction of consumers that switch to product B from product A as a result of an increase in the price of product A; and (b) the fraction of sales captured by product B that was lost by product A as a result of the latter's price increase. However, as illustrated by ten Kate and Niels (2014) the two definitions are not equivalent, because even if 100% of consumers switch from product A to product B, they may or may not purchase the same amount of product B (measured either in volume or monetary terms) as they did of product A. In this study, we use Shapiro's second definition of the diversion ratio.

Werden (1998) provided five measures of diversion to capture the substitutability of products. 1) Unit diversion (UD), which measures the absolute increase (decrease) in unit sales of substitute products when the price of a base product (in our example, product A) increases (decreases); the example provided in footnote 26 in the introduction is that of a UD. 2) Sales diversion (SD), which measures the absolute increase (decrease) in dollar sales of substitute products. In our example, assume products B and C sell at $2 and $3 per unit, respectively. Thus, the sales diversion is $35 for product B and $2.25 for product C. 3) Unit Diversion Ratio (UDR), which measures the change in unit sales of substitute products attributed to a change in the unit sales of the base product. Continuing with our example, assume that a 5% increase in the price of product A leads to a reduction of sales in the amount of 40 units. Therefore, the unit diversion ratio from product A to product B as a result of a 5% price increase is 43.75% (17.5/40) while

[29] According to Werden (1998), the term *diversion ratio* was first introduced by Shapiro (1996). However, the concept of diversion ratios was also discussed earlier by Willig et al. (1991).

the diversion ratio from product A to product C is only 1.87%. Based on this measure, product B is a closer substitute for product A than product C, even though cross-price elasticities would indicate the opposite. 4) Dollar Diversion Ratio (or Sales Diversion Ration - SDR), captures the change in dollar sales of substitute products attributed to a change in the dollar sales of the base product. 5) Relative Unit (dollar) Diversion ratio[30], measuring the change in unit (dollar) sales of substitute products relative to the change in unit (dollar) sales of the base product proportionate to their relative quantity or dollar-sales market shares, resulting from the base product's price change. In other words, the relative unit (dollar) diversion ratio is equivalent to the unit (dollar) diversion ratio multiplied by the market share of a substitute product relative to the market share of the base product.

Diversion ratios are used by the U.S. Department of Justice, the Federal Trade Commission (U.S.), the European Commission, and Canada's Competition Bureau to measure the impact of horizontal mergers in differentiated product markets on prices (Capps & Dharmasena, 2019)[31]. Different methods exist for measuring diversion ratios. One method for measuring diversion ratios is to use stated-preference consumer surveys (Reynolds & Walters, 2008), where consumers are asked which products or firms they would switch to following a small price increase. This is the most commonly used method in competition cases (Oxera, 2009). It is also possible to use an experimental revealed-preference method by removing a

[30] According to Werden (1998), the relative diversion ratio is the preferred method of measuring substitutability between products when one is concerned with geographically differentiated substitutes.

[31] In the antitrust and industrial organization literature, this phenomenon is referred to as "unilateral effects", which illustrates whether a merger is likely to create or enhance market power, thus allowing the firm to profitably increase prices above premerger levels (Capps & Dharmasena, 2019; Werden, 1998).

certain product from consumers' choice set and observing which products they switch to (Conlon & Mortimer, 2018). Lastly, a common approach is to calculate diversion ratios based on demand elasticity estimates, which is the approach taken in this study.

Several analyses used demand elasticity estimates to calculate diversion ratios: Abere et al. (2002) used elasticities from LA-AIDS and Rotterdam demand models, to calculate unit and dollar diversion ratios in the analysis of the Coca-Cola Company's acquisition of Cadbury Schweppes soda drinks in Canada. Their findings suggest that fruit juices and fruit drinks were the closest substitutes to Cadbury Schweppes soda drinks, and therefore, would be most affected in terms of lost sales volumes after the acquisition, if the Coca-Cola Company lowered the prices of Cadbury Schweppes soda drinks (Abere et al., 2002). Ivaldi and Verboven (2005) used the elasticities from a nested logit model to construct diversion ratios to analyze the effects of price increases for heavy trucks in Europe after a potential merger of Volvo and Scania. They found that, if both firms raised their product prices by 5%, their profits would increase in 12 out of the 16 European countries included in the study, while in four countries their joint operating profits would decrease slightly. Yuan et al. (2009) calculated diversion ratios based on elasticity estimates from a Barten synthetic demand model to analyze whether the introduction of Minute Maid Heart Wise (a functional orange juice) would cannibalize the sales of conventional Minute Maid products. Their findings suggest that the latter's sales would not be cannibalized, while the sales of the closest substitutes to Minute Maid Heart Wise would decrease. Unlike the studies mentioned above, which used brand-level data, Dharmasena and Capps (2012) used product category-level (e.g. regular soft drinks, diet soft drinks, fruit drinks, etc.) data and a Quadratic Almost Ideal Demand System model to calculate diversion ratios to assess which product categories the sales volumes of sugar sweetened beverages (SSBs) would be diverted to if a national tax on SSBs were to be introduced.

Product (De)labeling, Withdrawal, and Welfare Changes

Generally, the U.S. Government has pursued labeling policies to set fair competition rules for producers, improve consumer safety and health, and to reduce information asymmetries between consumers and producers (Hadden, 1986). A closely related literature to this chapter includes studies that have analyzed the welfare effects of different labeling regulations. For example, Zago and Pick (2004) used a conceptual framework of vertical differentiation to analyze the welfare effects of the European Union's (EU) regulation on the protection of products with Geographical Indicators and Designations of Origin. One of the goals of the regulation was to help farmers increasing income by offering higher quality products (Zago & Pick, 2004). However, the study found that, depending on the market power dynamics and production cost differences, the regulation can either: (a) improve consumers' and high-quality product producers' welfare, while lowering that of low-quality producers, or (b) can benefit high-quality producers with market power while hurting consumers, or (c) can even have an overall welfare-reducing effect (Zago & Pick, 2004).

Loureiro and Hine (2004) found that mandatory labeling of genetically modified organisms in the U.S. would come with higher costs than benefits for consumers. Similarly, Lusk et al. (2005) suggested that such a labeling would, on average, reduce American consumers' welfare, even though it has increased European consumers' welfare. Fulton and Giannakas (2004) found instead that the welfare impacts of such labels can be different for consumers, producers, and life science companies, resulting in different labeling preferences between these market participants. In a review of the literature on food process labeling, Messer et al. (2017)

concluded that while appropriate labeling oversight can narrow the information gap between producers and consumers, create added value for both groups, and meet consumer demand for higher quality standards, process labeling can also confuse consumers and stigmatize certain products which are not scientifically proven to be inferior.

To our knowledge, Bonanno et al. (2015) is the only study analyzing the welfare effects of de-labeling of a product, which is one of the simulation scenarios presented in this chapter. Particularly, using the Italian yogurt market as a case study, they evaluated the impact of the removal of health claims from yogurt packaging in the context of the European Union's regulation on nutrition and health claims (Reg (EC) No. 1924/2006). They found that, if truthful claims were to be denied, both consumers' and producers' welfare would decrease (Bonanno et al., 2015).

Other studies have assessed the welfare effects of introducing new products to the market or withdrawing existing ones. Using U.S. cereal market data, Hausman (1996) estimated the effect of not accounting for new product introduction on the Consumer Price Index (CPI), finding that the CPI can be overstated by about 20-25 percent, depending on the assumption regarding the industry's competitive structure. Hausman and Leonard (2002) divided the impact of new product introduction on consumer welfare into a price and a variety effect. The former represents the effects of price changes on consumer welfare due to product introduction (likely to result in a price decrease if competition increases), whereas the latter captures the effect of an increase in the number of products available (Hausman & Leonard, 2002). Hausman and Leonard (2002) method was adapted by Chaudhuri et al. (2006) to estimate welfare changes from the withdrawal of products from the market. Specifically, Chaudhuri et al. (2006) simulated a scenario where, as a result of patent enforcement, Indian manufacturers of fluoroquinolone withdraw their products from the local market, finding that a sizeable amount of consumer surplus would be lost. Using the same approach, Bonanno et al. (2015) estimated that, after a potential withdrawal of functional yogurts from the Italian market, both consumer and producer welfare would decrease, with consumers incurring most of the losses.

Methods

Diversion Ratios

To illustrate how diversion ratios can be obtained from demand elasticity estimates, we follow Capps and Dharmasena (2019). Consider we want to determine how much the quantity demanded of product *j* changes as a result of a change in the quantity of product *i* (unit diversion ratio). Assume that the two products are measured in the same units. This relationship can be presented as follows:

$$UDR_{ji} = \frac{\partial q_j}{\partial q_i}, \tag{4.1}$$

where UDR_{ji} is the unit diversion ratio from product *i* to product *j*, while ∂q_j and ∂q_i are the changes in the quantities of goods *j* and *i,* respectively. Assume that both products' quantities are affected by a change in the price of product *i* (∂p_i). Thus, to measure this effect, equation (4.1) can be rewritten as:

$$UDR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}}{\frac{\partial q_i}{\partial p_i}}. \tag{4.2}$$

After multiplying both the numerator and denominator by p_i / q_j and rearranging, we obtain:

(4.3) $$UDR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}\frac{p_i}{q_j}}{\frac{\partial q_i}{\partial pi}\frac{p_i}{q_j}} = \frac{e_{ji}}{e_{ii}}\frac{q_j}{q_i},$$

where e_{ji} is product *j*'s uncompensated cross-price elasticity of demand with respect to a change in product *i*'s price; and e_{ii} is the uncompensated own-price elasticity of demand.

Similarly, the dollar diversion ratio, which measures how much dollar sales are diverted from product *i* to product *j*, as a result of product *i*'s price increase, takes the following form:

(4.4) $$DDR_{ji} = \frac{e_{ji}}{e_{ii}}\frac{q_j}{q_i}\frac{p_j}{p_i} = UDR_{ji} * \frac{p_j}{p_i}.$$

For the calculation of UDR and DDR, we use the average price and quantity values presented in Chapter 2, as well as the average own- and cross-price demand elasticities derived from the LA-EASI demand model. Particularly, we measure the unit and dollar diversion ratios averaged across years (2012-2017), in addition to measuring the unit diversion ratios separately for the years 2012 and 2017 (first and last years observed in the data) to capture any changes in respective magnitudes. This will illustrate whether some products have become closer substitutes (complements) over time, given that the sales of whole fat dairy, almond, and other nondairy milks have been increasing in the study period, while the sales of skim, reduced fat, and soy milks have been decreasing.

Simulating the Welfare Effects of Nondairy Milks De-labeling and Withdrawal

Following the same assumptions used in Chapter 3, we assume that U.S. milk manufacturers are oligopolistic firms selling differentiated products, and that prices are the outcome of a multi-product Nash-Bertrand equilibrium. These assumptions are widely used in the industrial organization literature studying differentiated product markets (Berry et al., 1995; Bonanno et al., 2015; Di Giacomo, 2008; Hirsch et al., 2018; Lopez & Lopez, 2009; Nevo, 2001; Petrin, 2002). We simulate four counterfactual scenarios—first, all nondairy milk products are banned from using milk terminology; second, the ban applies to all nondairy milks except for soy drinks, given that this is the only nondairy milk category that DHHS and USDA currently include in the dairy group (DHHS & USDA, 2015); third, all nondairy milks using the "milk" label are withdrawn from the market; and fourth, all nondairy milks using the "milk" label, except for soy milks are withdrawn from the market.

We follow the approach developed by Bonanno et al. (2015) to evaluate the welfare effects of product de-labeling. For the nondairy milk with a "milk" claim, we can set the binary variable indicating whether product *j* is labeled as milk, $X_j^{milklabel} = 0$, to simulate the scenario when consumers do not see the "milk" term on nondairy milks. After setting $X_j^{milklabel} = 0$, we obtain the new market shares by solving equation (3.9).

Let "*scen0*" be either one of the two de-labeling scenarios considered (milk terminology removed from all nondairy milks; or except for soy milks). Then, the simulated effect of the removal of the "milk" claim from nondairy milks on producer surplus is:

$$\Delta\Pi_n^{scen0} = \sum_{j \in \mathcal{G}_n} (p_j^0 - mc_j) M \left(s_j^{scen0}(p^0) - s_j^0(p^0) \right) , \tag{4.5}$$

where p_j^0 and s_j^0 are product *j*'s price observed in the data and predicted share, respectively. Marginal costs (mc_j) are assumed to be unaffected by the labeling change. Consumer welfare changes can be calculated using the following equation:

(4.6) $$EV_i = \sum_{j=1}^{j=J} \ln\left(\sum_{i=1}^{i=I}\left(\exp\left(u_{ij}^{scen0}\right)\right)\right) - \sum_{j=1}^{j=J} \ln\left(\sum_{i=1}^{i=I}\left(\exp\left(u_{ij}^{0}\right)\right)\right),$$

where $u_{ij}^{scen0} = \alpha_i + \delta_j(\mathbf{x}_j^{scen0}, p_j^0, \xi_j; \theta_1) + \mu_{ij}(\mathbf{x}_j^{scen0}, p_j^0, \boldsymbol{v}_i, \mathbf{D_i}; \theta_2) + \varepsilon_{ij}$, and $u_{ij}^0 = \alpha_i + \delta_j(\mathbf{x_j}, p_j^0, \xi_j; \theta_1) + \mu_{ij}(\mathbf{x_j}, p_j^0, \boldsymbol{v}_i, \mathbf{D_i}; \theta_2) + \varepsilon_{ij}$ is the baseline/status quo scenario, where products are not de-labeled.

Multiplying equation (4.6) by the market size, *M*, gives the total change in consumer welfare. Note, that these welfare changes do not consider any price adjustments, instead they represent a transitionary period, before the market reaches a new equilibrium. To calculate the new equilibrium vectors of shares and prices (s_j^{scen1} and p_j^{scen1}, respectively), we simultaneously solve equation (3.9) for shares and (3.11) for prices (from the previous chapter) after setting $X_j^{milklabel} = 0$. The resulting changes in producer welfare are:

(4.7) $$\Delta\Pi_n^{scen1} = M \sum_{j \in \vartheta_n} \left(s_j^{scen1}(p_j^{scen1} - mc_j) - s_j^0(p_j^0 - mc_j) \right) .$$

Given that consumers value the "milk" label positively (based on the findings from Chapter 3), we can expect lower consumer welfare in case producers of nondairy milks do not lower the prices. However, given that producers price their products strategically, *a priori*, it is hard to predict the consumer and producer welfare effects of de-labeling.

In the next scenarios we consider the withdrawal of the nondairy milks from the market. In principle, these scenarios consider what would happen if, once milk labels can no longer be used, the estimated sales decline push manufacturers to withdraw the product form the market entirely. Following Bonanno et al. (2015), Chaudhuri et al. (2006), and Hausman and Leonard (2002), we decompose the sources of welfare changes into two components: a variety effect, which captures the impact of fewer milk options available to consumers; and a competition effect, measuring the impact of price changes as a result of less competition. Mathematically, the variety effect is captured by the difference in the original EV and that calculated at prices that set the demand for the market-exiting products to zero, called virtual prices, without changing the other products' prices. To measure the competition effect, we calculate the EV based on simultaneously estimated new equilibrium prices and shares for the remaining products and subtracting it from the EV calculated at the virtual prices[32]. New equilibrium shares and prices are calculated using equations (3.9) and (3.11), respectively once de-labeled products are removed. The resulting producer welfare changes can be calculated using the following equation:

$$(4.8)\ \Delta\Pi_n^{withdrawal} = M\sum_{j\in\vartheta_n}\left(s_j^{withdrawal}(p_j^{withdrawal}-mc_j)-s_j^0(p_j^0-mc_j)\right)=\sum_{-j\in(\vartheta_n-\vartheta'_n)} s_{-j}^0\left(p_{-j}^0-mc_{-j}\right),$$

where ϑ'_n is the number of products remaining in the market produced by producer *n*, with $\vartheta'_n \le \vartheta_n$; $-j$ represents the nondairy milk withdrawn from the market; $s_j^{withdrawal}$ and $p_j^{withdrawal}$ are the new equilibrium market shares and prices of the remaining products, respectively. Examples of studies that have used a similar approach for analyzing the welfare effects of product introduction include Di Giacomo (2008), Petrin (2002), and Pofahl and Richards (2009).

Results

Diversion Ratios

The UDRs calculated using IRI PoS data and LA-EASI demand elasticities, as discussed in Chapter 2, are presented in Table 4.1. For all types of milk, one unit is equal to 64 oz. A

[32] In practice, if the goal is to use the virtual prices for welfare calculations, one can either estimate the virtual prices or fix them at high values, which is the approach we took. The resulting welfare estimates are the same under both options.

negative sign on the UDR suggests that the quantity demanded of the product in that row will increase (decrease) due to a decrease (increase) in the quantity demanded of the product in the respective column. Therefore, the two products are substitutes. Similarly, a positive sign[33] indicates the quantity demanded of the product in a given row will decrease (increase) after the quantity demanded of the product in the respective column decreases (increases). Thus, the two products are complements. Larger negative (positive) magnitudes suggest that the two products are closer substitutes (complements).

The results suggest that for dairy milks, the closest substitutes are other dairy milks. For example, for skim milk, reduced fat milk is by far the closest substitute, followed by almond, soy, and other nondairy milks, while whole fat milk is a complement. Particularly, a unit (64 oz.) decrease in the quantity of skim milk demanded leads to 0.74 units of increase in the quantity of reduced fat milk demanded, and to only 0.05 units of increase in the quantity of almond milk demanded. For reduced fat milk, the closest substitute is whole fat milk, followed by skim and other nondairy milks, while soy and almond milks are complements. That is, about 0.28 and 0.11 units of sales are captured by whole fat and skim milks, respectively, after a unit is diverted from reduced fat milk. In comparison, less than 0.01 units are captured by other nondairy milks. Reduced fat milk is the closest substitute for whole fat milk, followed by almond milk, while all other milks are complements for whole fat milk. As a result of a unit decrease in the quantity of whole fat milk demanded, the quantities of reduced fat and almond milks demanded increase by about 0.63 and less than 0.01 units, respectively.

[33] Note, that the interpretation of signs is different from that of cross-price elasticities.

Table 4.1: Unit diversion ratios calculated based on the LA-EASI demand model

	Skim	Reduced fat	Whole fat	Other nondairy	Soy	Almond
Skim	1.000	-0.114	0.283	-0.575	**-2.317**	**-0.804**
	(0.000)	(0.001)	(0.014)	(0.000)	(0.000)	(0.000)
Reduced fat	**-0.738**	1.000	**-0.634**	**-1.740**	1.973	0.567
	(0.002)	(0.000)	(0.001)	(0.007)	(0.011)	(0.002)
Whole fat	0.676	**-0.281**	1.000	1.200	0.552	-0.248
	(0.002)	(0.000)	(0.000)	(0.005)	(0.003)	(0.001)
Other nondairy	-0.015	-0.007	0.013	1.000	0.086	0.090
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Soy	-0.046	0.006	0.004	0.061	1.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Almond	-0.055	0.007	-0.005	0.226	-0.006	1.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Sum	0.822	0.612	0.661	0.172	1.288	0.603

Notes: Diversion ratios in bold indicate the closest substitute for the product in that column. All estimates are statistically significant at the 0.01 level. Standard errors are shown in parentheses. The measurement unit for all milks is 64 oz.

Interestingly, dairy milks are the closest substitutes for nondairy milks. Particularly, for other nondairy milk, the closest substitutes are reduced fat and skim milks, while all other milks are complements. When the quantity of other nondairy milk demanded decreases by one unit, that of reduced fat and skim milks increases by about 1.74 and 0.57 units, respectively. For both soy milk and almond milk, the closest substitute is skim milk. A unit decrease in the sales of soy milk leads to 2.32 units increase in the sales of skim milk, while a similar decrease in the sales of almond milk, leads to an increase of 0.80 units in sales of skim milk. For soy milk, the only other substitute is almond milk, with a UDR of less than 0.01. However, for almond milk, the other substitutes are whole fat milk, with a UDR of 0.25, and soy milk, with a UDR of less than 0.01.

The comparison of UDRs from 2012 and 2017 is presented in Table 4.2. The values in the table suggest that reduced fat, other nondairy, soy, and almond milks became closer substitutes for skim milk, while whole fat milk became a closer complement. During the same period, skim, whole fat, and other nondairy milks became closer substitutes for reduced fat milk. For whole milk, reduced fat milk became a farther substitute, while skim, other nondairy, and soy milks became a farther/ "weaker" complement. Among nondairy milks, only soy milk "acquired" closer substitutes (skim and almond milks). For other nondairy and almond milks, the magnitudes of substitutability towards other milks has decreased.

The calculated DDRs presented in Table 4.3 suggest that for every dollar diverted from skim milk, consumers would spend a total of \$0.04 on other dairy milks (reduced fat: +\$0.70, whole fat: -\$0.66) and a total of \$0.18 on nondairy milks. Similarly, every dollar decrease in the sales of reduced fat milk would increase the sales of other dairy milks by \$0.41 and decrease the sales of nondairy milks by a total of \$0.01. Every dollar diverted from whole fat milk would increase the sales of other dairy milk by \$0.33 and decrease the sales of nondairy milks by \$0.02. As a result of a dollar decrease in the sales of other nondairy milks, consumers would spend about a total of \$0.59 more on dairy milks and \$0.26 less on soy and almond milks combined. A dollar decrease in the sales of soy milk would lead to a decrease of both dairy and nondairy (almond and other nondairy) milk sales of about \$0.09. Lastly, after a dollar decrease in the sales of almond milk, \$0.31 would be diverted to dairy milk sales, while nondairy milks sales (soy and other nondairy) would decrease by about \$0.10. These results show that, on average, dairy milks as an aggregate product category would benefit more from the lower sales of nondairy milks

Table 4.2: Comparison of UDRs from 2012 and 2017

	Skim		Reduced fat		Whole fat		Other nondairy		Soy		Almond	
	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017	2012	2017
Skim			-0.112	**-0.118**	0.314	0.256	-0.943	-0.347	-1.957	**-2.313**	-1.314	-0.495
			(0.000)	(0.000)	(0.002)	(0.001)	(0.007)	(0.002)	(0.028)	(0.017)	(0.010)	(0.003)
Reduced fat	-0.589	**-0.841**			-0.702	-0.572	-2.782	-1.094	1.653	1.977	0.919	0.351
	(0.003)	(0.005)			(0.004)	(0.003)	(0.018)	(0.006)	(0.022)	(0.014)	(0.007)	(0.002)
Whole fat	0.526	0.785	-0.274	**-0.291**			1.915	0.753	0.449	0.564	-0.382	-0.167
	(0.003)	(0.005)	(0.001)	(0.001)			(0.012)	(0.005)	(0.006)	(0.004)	(0.002)	(0.001)
Other nondairy	-0.011	**-0.017**	-0.007	**-0.008**	0.014	0.012			0.067	0.086	0.135	0.057
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			(0.001)	(0.001)	(0.001)	(0.000)
Soy	-0.036	**-0.052**	0.006	0.006	0.005	0.004	0.096	0.038			-0.004	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)			(0.000)	(0.000)
Almond	-0.040	**-0.064**	0.007	0.008	-0.005	-0.005	0.341	0.149	-0.004	**-0.006**		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)		
Sum	0.850	0.810	0.621	0.598	0.625	0.696	-0.373	0.499	1.209	1.308	0.353	0.745

Notes: Diversion ratios in bold indicate that from 2012 to 2017 the product in the row has become a closer substitute to the product in the column. Standard errors are shown in parentheses.

Table 4.3: Dollar diversion ratios calculated based on the LA-EASI demand model

	Skim	Reduced fat	Whole fat	Other nondairy	Soy	Almond
Skim	1.000	-0.119	0.281	-0.322	**-1.425**	**-0.493**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.008)	(0.002)
Reduced fat	**-0.703**	1.000	**-0.606**	**-0.939**	1.173	0.336
	(0.002)	(0.000)	(0.001)	(0.004)	(0.007)	(0.001)
Whole fat	0.663	**-0.290**	1.000	0.674	0.342	-0.153
	(0.002)	(0.000)	(0.000)	(0.003)	(0.002)	(0.001)
Other nondairy	-0.026	-0.013	0.024	1.000	0.094	0.099
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Soy	-0.072	0.010	0.007	0.055	1.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Almond	-0.086	0.012	-0.008	0.205	-0.006	1.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Sum	0.776	0.600	0.696	0.674	1.179	0.785

Notes: Diversion ratios in bold indicate the closest substitute for the product in that column. All estimates are statistically significant at the 0.01 level. Standard errors are shown in parentheses. The measurement unit for all milks is 64 oz.

than do nondairy milks from lower sales of dairy milks. Moreover, when reduced fat and whole fat milk dollar sales decrease, so do the sales of nondairy milks as an aggregate product category.

De-labeling and Withdrawal

For all simulations, the data and demand estimates presented in Chapter 3 are used as a baseline. The simulated percentage changes in prices, price-cost margins (PCMs), market shares, and profits for all four scenarios (scenario 1: all nondairy milks are de-labeled; scenario 2: all nondairy milks except for soy milk are de-labeled; scenario 3: all nondairy milks carrying the "milk" label are withdrawn from the market; and scenario 4: all nondairy milks labeled as milk, except for soy milk, are withdrawn from the market) are presented in Table 4.4. Additionally, we report in the "No price adjustment" columns estimated changes in share for an intermediate scenario, where products are de-labeled, but prices are not adjusted. All values are percentage changes relative to the baseline scenario.

The results indicate that under scenarios 1 and 2, when there is no price adjustment, the profits of milk manufacturers, and manufacturers of nondairy milks not labeled as milk increase, while those of nondairy milks carrying the "milk" label decrease (columns 2 and 7). Particularly, under scenario 1 with no price adjustment, almond, soy, and other nondairy milk sales would need to increase by about 38, 44, and 13 percent, respectively, for the producers of these products to be indifferent to the change in labels. Under scenario 2, these values are 39 and 14 percent for almond and other nondairy milks, respectively, while soy milk manufacturers' profits increase by about 9 percent. In aggregate, nondairy milks previously labeled as milk would lose about 73 and 53 percent market shares due to de-labeling, under scenarios 1 and 2 with no price adjustment, respectively.

The percent changes in profits after price adjustments (new equilibrium prices) under both scenarios are in the same direction as those obtained without price adjustment, albeit in most cases showing larger magnitudes for dairy milks and smaller magnitudes for nondairy milks. Under scenario 1, soy milk product profits are the most negatively affected, with decreased profits of about 44 percent, followed by almond milk with almost 38 percent lower profits, and other nondairy milks, with profits lower by about 12 percent. Under scenario 2, profits from soy milk products increase by about 10 percent, while almond milk products' profits are the most negatively affected, with profits lower by about 39 percent, followed by other nondairy milks with—14 percent lower profits. Profit losses occur even though the simulations

Table 4.4: Simulated effects of DAIRY PRIDE Act: de-labelling and withdrawal of nondairy milks carrying the “milk” label

	De-labeling: all nondairy milks					De-labeling: all nondairy milks except soy				
	No p. adj.	After price adjustment				No p. adj.	After price adjustment			
Milk type	%ΔΠ	%Δp	%ΔPCM	%Δshare	%ΔΠ	%ΔΠ	%Δp	%ΔPCM	%Δshare	%ΔΠ
Diary: private label	4.527	0.236	1.352	3.137	4.530	3.652	0.189	1.086	2.527	3.639
Dairy: branded	5.139	0.085	0.488	4.779	5.284	4.153	0.072	0.429	3.808	4.251
Type: almond	-37.973	-0.438	-2.871	-37.347	-37.832	-39.047	-0.395	-2.615	-38.498	-38.947
Type: soy	-43.900	-0.541	-3.721	-42.995	-43.755	9.451	-0.187	-1.185	10.949	9.632
Type: other nondairy	-12.573	-0.115	-0.632	-12.678	-12.428	-13.720	-0.113	-0.657	-13.791	-13.622
Nondairy with milk label	-73.236	-0.774	-5.584	-71.524	-73.116	-53.259	-0.590	-4.256	-51.488	-53.131
Nondairy w/o milk label	8.780	0.058	0.836	8.036	8.942	7.134	0.048	0.692	6.494	7.233

	Withdrawal: all nondairy milks with milk label				Withdrawal: all nondairy milks with milk label except soy			
Milk type	%Δp	%ΔPCM	%Δshare	%ΔΠ	%Δp	%ΔPCM	%Δshare	%ΔΠ
Diary: private label	0.779	4.365	42.532	48.195	0.614	3.448	30.567	34.616
Dairy: branded	0.044	0.204	40.485	41.550	0.056	0.292	29.698	30.659
Type: almond	0.025[a]	0.378[a]	-99.625	-99.662	0.034[a]	0.516[a]	-99.653	-99.687
Type: soy	0.042[a]	0.676[a]	-99.256	-99.290	-0.415	-2.869	-46.420	-48.916
Type: other nondairy	0.012[a]	0.195[a]	-53.532	-56.577	0.024[a]	0.337[a]	-57.627	-60.343
Nondairy with milk label	-	-	-100	-100	-0.647	-4.701	-89.791	-90.472
Nondairy w/o milk label	0.019	0.298	48.293	48.468	0.029	0.436	35.463	35.839

Source: Authors’ simulations from estimated parameters.

Notes: Δ, p, PCM, and Π denote change, price, price-cost margin, and profits, respectively. “a” indicates that the value is relative to the baseline prices and PCMs of the respective nondairy milk types not labeled as “milk” even before a policy implementation.

suggest that after de-labeling, manufacturers of nondairy milks will lower the prices of products previously labeled as milk, on average, by about 0.8 percent (scenario 1) and 0.6 percent (scenario 2). These results are as expected, given that consumers were found to positively value the “milk” label on nondairy milks, as shown in Chapter 3.

The simulation results also suggest that under both scenarios, both branded and private label dairy milk prices increase by about 0.07-0.2 percent, while market shares increase by about 2.5-4.8 percent, resulting in higher profits for their producers in the range of 3.6-5.3 percent. At the same time, according to our results, manufacturers of nondairy milks which were not carrying the “milk” label even before de-labeling, will increase the prices by about 0.05-0.06 percent, and yet experience increased market shares (6-8 percent), and increased profits (7-9 percent).

Based on the simulation results of product withdrawal scenarios, all dairy milk manufacturers increase their products' prices compared to the baseline scenario. However, the price increase is higher for private label dairy milks under scenarios 3 and 4, compared to scenarios 1 and 2, while the opposite is true for branded dairy milk prices. Under the withdrawal scenarios, dairy milk manufacturers’ profits increase, on average, by 30.7-48.2 percent. Under scenario 3, where all nondairy milks labeled as milk are withdrawn from the market due to profit losses as a result of de-labeling, the average prices of the remining nondairy milks (those, that were not labeled as milk even before de-labeling) are also higher than their prices under the baseline scenario. However, the price increases of nondairy milks previously not labeled as milk is lower than in the case of de-labeling. Specifically, almond, soy, and other nondairy milk prices are, on average, about 0.02, 0.04, and 0.01 percent higher, respectively, than in the baseline scenario. As a result of market reorganization, profits of the remaining nondairy milk manufacturers increase by about 48.5 percent. Under scenario 4, however, while all other milk prices increase, soy milk prices decrease by about 0.4 percent, compared to the baseline scenario. The simulated welfare changes obtained under the withdrawal scenarios are likely to be the upper bounds, since it is unlikely that all the products assumed to disappear from the market in this study, will actually exit once DAIRY PRIDE Act is enacted. Welfare changes for the de-labeling and withdrawal scenarios are presented in Table 4.5.

Consumer welfare decreases under all scenarios, with the smallest losses (about 2 percent or $15.9 million per month) taking place when all nondairy milks except for soy milks are de-labeled, and the largest loss (about 19 percent or $142.1 million per month) taking place when all nondairy milks labeled as milk are withdrawn from the market. In the latter case, a small part of consumer welfare loss (almost $27.8 million per month) is due to the variety effect, showing that consumers positively value the availability of the withdrawn products in the market; while the competition effect is almost $114.4 (142.16-27.79) million per month, showing that consumers' welfare would further decrease as a result of the remaining products' price increases occurring after product withdrawal.

Nondairy milk manufacturers' welfare also decreases under all scenarios, again, with the smallest loss under scenario 2 (about 57 percent or more than $5.2 million per month) and the largest loss under scenario 3 (96.6 percent or almost $8.7 million per month). As expected, dairy milk manufacturers' welfare increases in all cases, ranging between $2.2-28.8 million per month, which is only a fraction of the losses incurred by consumers and/or nondairy milk manufacturers. In other words, under all scenarios, only a small percentage of consumer welfare losses are captured by producers of dairy milks, while the majority is a deadweight loss. The total welfare

Table 4.5: Simulated welfare effects of DAIRY PRIDE Act implementation

		De-labeling						Withdrawal					
		No price adjustment			Price adjustment			Variety effect			Total effect		
		Consumer surplus (CS)											
Scenario	Baseline	New CS	ΔCS	%ΔCS	New CS	ΔCS	%ΔCS	New CS	ΔCS	%ΔCS	New CS	ΔCS	%ΔCS
All milk labels	747.34	730.23	-17.10	-2.29	726.96	-20.38	-2.73	719.55	-27.79	-3.72	605.18	-142.16	-19.02
All except soy	747.34	734.05	-13.29	-1.78	731.48	-15.86	-2.12	725.99	-21.35	-2.86	649.01	-98.32	-13.16
		Producer surplus (PS)											
Scenario	Baseline	New PS	ΔPS	%ΔPS	New PS	ΔPS	%ΔPS				New PS	ΔPS	%ΔPS
All milk labels													
Nondairy PS	9.02	2.54	-6.47	-71.78	2.56	-6.46	-71.64				0.30	-8.72	-96.66
Dairy PS	64.94	67.58	2.64	4.06	67.63	2.69	4.15				93.78	28.84	44.41
All except soy													
Nondairy PS	9.02	3.85	-5.16	-57.26	3.87	-5.15	-57.13				1.12	-7.90	-87.63
Dairy PS	64.94	67.06	2.12	3.27	67.10	2.16	3.33				85.96	21.02	32.36
		Total welfare (TW)											
Scenario	Baseline	New TW	ΔTW	%ΔTW	New TW	ΔTW	%ΔTW				New TW	ΔTW	%ΔTW
All milk labels	821.30	800.36	-20.94	-2.55	797.15	-24.14	-2.94				699.27	-122.03	-14.86
All except soy	821.30	804.97	-16.33	-1.99	802.45	-18.85	-2.29				736.09	-85.21	-10.37

Source: Authors' simulations from estimated parameters;
Notes: All numbers (except for %) are in million USD. Competition effects' results are omitted for brevity. Δ denotes change.

loss under scenarios 1, 2, 3, and 4 are almost $24.1, $18.8, $122.0, and $85.2 million per month, respectively.

Discussion and Policy Implications

In this section we discuss the policy implications of these findings. Assume that the DAIRY PRIDE Act becomes a law and that the law negatively affects the sales of nondairy milks (which is consistent with de-labeling resulting in lower shares of nondairy milks). The diversion ratios analysis suggests that, ceteris paribus, from every unit decrease in the sales of other nondairy and almond milks, about 1.12 and 0.48 units, respectively, will be diverted to dairy milk sales. However, a unit decrease in the sales of soy milk will lead to about 0.21 units lower sales of dairy milks.

In monetary terms, a dollar decrease in the sales of other nondairy milks leads to an increase of dairy milk sales by about $0.59. Similarly, a dollar decrease in the sales of almond milk increases the sales of dairy milks, on average, by about $0.31, while such a decrease in the sales of soy milk decreases the sales of dairy milks by $0.09. The comparison of the UDRs between 2012 and 2017 also suggest that most of nondairy milks that were substitutes to dairy milks in 2012 have become closer substitutes in 2017. At the same time, most of dairy milks that were substitutes to nondairy milks in 2012 have become lesser substitutes in 2017. From a policy perspective, this indicates that if de-labeling leads to lower sales of nondairy milks, an even smaller share of those sales will be diverted to dairy milks.

Also, any policy (e.g. the DAIRY PRIDE Act) that might affect the prices or the quantities of any of these milks demanded will not be a zero-sum game, since the UDR values do not sum to zero in any of the columns in Table 4.1. The only time when nondairy milks (soy, almond, and other nondairy milks combined) benefit (lose) from a reduction (increase) in the quantity of any milk (dairy or nondairy) demanded, is when skim milk's sales decrease (increase). In this case, about 0.12 units of each "unsold" skim milk unit will be diverted to nondairy milks. In all other cases, nondairy milks as a combined product category, will experience decreased (increased) sales due to a decrease (increase) in the sales of any milk. In contrast, dairy milks as a combined product category benefit (lose) from decreased (increased) sales of other nondairy and almond milks, but not from decreased (increased) sales of soy milk.

The counterfactual simulation results of de-labeling and withdrawal suggest that the most likely effect of the DAIRY PRIDE Act, assuming it would result in de-labeling of nondairy milk products, would be to increase dairy milk producers' welfare. Such an increase in profitability for milk manufacturers would be even larger if some of the nondairy milks exit the market as a result of de-labeling. However, if the goal is to improve consumer welfare or the total welfare (consumers' welfare and that of dairy and nondairy milks manufacturers), product de-labeling would have the opposite effect. In other words, nondairy milk de-labeling would be a consumer- and overall welfare-reducing policy, and the effect would be even larger, if some nondairy milks disappear from the market. This is explained by two factors: (a) consumers value the availability of nondairy milks labeled as "milk" and (b) as a result of decreased competition after product withdrawal, the prices of remaining milks will likely increase, further lowering consumer welfare.

Contextualizing the results of the simulation performed in this chapter with the results from the first two chapters, one may draw more nuanced policy implications. The results of Chapter 2 indicated that dairy and nondairy milk demands are not separable. Also, the cross-price elasticities estimated in Chapter 2 indicate that nondairy milk are close substitute to dairy milk, whereas we obtain different patterns using UDR. Specifically, while based on the cross-price elasticities the closest substitute for skim milk is soy milk, using UDR, we find it to be reduced fat milk. Similarly, for reduced fat milk, cross-price elasticities suggest that other nondairy milk are the closest substitutes, however based on the UDR, the closest substitute appears to be whole fat milk. Finally, for other nondairy milk, the cross-price elasticities suggest that the closest substitute is skim milk, while the UDR suggests that it is reduced fat milk. The UDR results illustrate that dairy milk sales benefit substantially more from decreases in the quantities of other dairy milks demanded than from similar decreases in the quantities of nondairy milks demanded, which may suggest that the DAIRY PRIDE Act alone may not be enough to revitalize the dairy milk industry.

Additionally, the policy implications of the de-labeling and withdrawal simulations are based on the assumption that using “milk” labeling for nondairy milks is not a deceitful practice. Assume, instead, that the FDA recognizes the labeling of nondairy milks as “milk” deceitful. Thus, consumers would, benefit from a de-labeling policy, because in the presence of untruthful labels consumers overpay about $30.4 million per month for nondairy milks (see Table 3.5 in Chapter 3), which is almost $10 million higher than what they would pay if all nondairy milks carrying the “milk” term were de-labeled (see Table 4.5). However, if all those milks or all except for soy milks were withdrawn from the market, consumer welfare would be substantially lower than in the case when all untruthful milk claims remained on nondairy milk labels. The additional consumer welfare losses in this case of lower availability would be in the range of 67.9-111.8 million per month.

Conclusions

Using the data and estimates described in Chapters 2 and 3, in this chapter we applied two different approaches to understand the potential effects of a potential law banning the use of the "milk" term on nondairy milks. The first approach, mostly used in antitrust analysis, relies on the use of unit and dollar diversion ratios to show where the sales of different types of milk will be diverted to in the case of expected price or demand changes when label revisions are required. This method also allows one to understand whether strategic price changes by nondairy milk producers can constitute a threat for dairy milk producers and vice versa. The second approach, based on the industrial organization literature, allowed us to simulate four scenarios, where either all nondairy milks labeled as milk or all except for soy milk are de-labeled or withdrawn from the market as a result of de-labeling. These simulations illustrated the potential effects of such a law on milk prices, market shares, profits, as well as consumer and producer welfare.

Results based on the UDRs and DDRs suggest that dairy milks are closer substitutes for both dairy and nondairy milks than are nondairy milks. However, dairy milks have become weaker substitutes for nondairy milks over the years, while nondairy milks have become closer substitutes for dairy milks. The diversion ratios also indicate that any policy negatively affecting the demand of different types of milk will not be a zero-sum game. That is, ceteris paribus, a unit or dollar decrease in the sales of any of the milks will mostly be diverted away and only a small portion will be captured by other milks, resulting in an overall decrease in aggregate milk sales.

The simulation results suggest that nondairy milk de-labeling will lead to lower prices of these products and higher prices of milks not affected by the policy. As a result, dairy milk manufacturers will sell more and increase profits by about 3.3-44.4 percent. At the same time, the profits associated with the production of nondairy milks previously labeled as milk will decrease in the range of 53.1-71.6 percent, depending on the scenario considered. Due to these large profit losses, manufacturers of nondairy milks previously using the "milk" label may decide to withdraw those products from the market. In this case, the prices of the remaining products in the market will increase even further, resulting in larger profits for dairy milk manufacturers. Under all four scenarios, the policy reduces the welfare of consumers and nondairy milk manufacturers, while increasing the welfare of dairy milk manufacturers. However, the losses are substantially larger than the gains, resulting in net deadweight losses.

Given that these analyses are based on the data and demand estimates described in Chapters 2 and 3, any of the limitations previously discussed also apply to this study. Additionally, while we illustrate how the prices and sales of different milks might be affected by the implementation of the DAIRY PRIDE Act, and how those changes might affect consumers' and producers' welfare, we do not estimate how these changes may affect the intake of different nutrients and, as a result, consumers' diets and health. Thus, future studies can implement simulations of how nondairy milk de-labeling might change consumers' nutrient intake. Given the considerable heterogeneity in the nutritional profile of different types of dairy and nondairy milks, policymakers should also consider this aspect of consumer welfare.

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