Hearing Exhibit 390; IDFA Exhibit 56

Journal of Agricultural and Resource Economics 48(2):277–295 ISSN: 1068-5502 (Print); 2327-8285 (Online)
Copyright 2023 the authors
doi: 10.22004/ag.econ.320675

I Say Milk, You Say Mylk: Substitution Patterns and Separability in a Broadened Milk Category

Armen Ghazaryan, Alessandro Bonanno, and Andrea Carlson

This study tests the assumption of weak separability between demand for dairy and nondairy milk products by using food scanner data from 2012 to 2017 and estimating linear-approximate EASI demand systems. Our results show that the weak separability structures can be rejected. First, this finding shows that nondairy milk products compete with dairy milk for consumers' budget allocated to milk. Second, although milk demand studies often do not include nondairy milk, or assume weak separability, the exclusion of these products—or the separability assumptions—may lead to biased estimates.

Key words: dairy and nondairy milk, demand analysis, food scanner data, IRI InfoScan, LA-EASI, separability

Introduction

As US consumers have become more health and environmentally conscious, the market for plant-based alternative products (e.g., dairy-free cheeses and yogurts, plant-based meats, and nondairy beverages) has continued to grow (MÃd'kinen et al., 2016; O'Connor, 2019). According to the Plant Based Foods Association (Plant Based Foods Association, 2020), US sales of plant-based food products grew by 11. 4% in 2019, reaching a total market value of $5 billion. During the COVID-19 pandemic, growth in US retail sales of plant-based foods outpaced growth of total food sales .

Among the large number of plant-based products making waves in the food market landscape, nondairy milk products stand out due to their rapid increase in sales and popularity (Packaged Facts, 2020). Sales of nondairy milk products have grown rapidly, going from niche products sold mostly in health stores and the specialty products aisle of grocery stores to achieving mainstream status and becoming available in most coffee shops and grocery stores (Franklin-Wallis, 2019). The joint value of US sales of soy and almond milk rose from US $1.44 billion in 2010 to US $2.25 billion in 2018 and is expected to further grow to US $2.36 billion by 2024 (O'Connor, 2019).[1] In contrast, US dairy milk sales have been declining for decades, with the annual per capita consumption of dairy milk decreasing at increasing rates since 1995 (Haley, 2017). In recent years (2012–2017),

Armen Ghazaryan (corresponding author) is a PhD recipient and Alessandro Bonanno is an associate professor in the Department of Agricultural and Resource Economics at Colorado State University. Andrea Carlson is an economist at the Economic Research Service, US Department of Agriculture.
The findings and conclusions in this study are those of the authors and should not be construed to represent any oïňČcial USDA or US government determination or policy. This study was supported in part by the US 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).
This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.
Review coordinated by Dayton M. Lambert.

[1] Soy milk was the leader of the nondairy milk sector in terms of sales volume through 2014 and recently dropped to second, behind almond milk (O'Connor, 2019). This shift is likely due to almond milk's low caloric content, taste, absence of saturated fat, and high vitamin E content (Gulseven and Wohlgenant, 2014; Copeland, 2016; O'Connor, 2019).

volume sales of the dairy milk category fell 15% (Mintel Group, 2017). Although several factors are related to this decline, including competition from other product categories (e.g., new packaged smoothies and shakes, soft drinks, bottled tea, coffee, and water, Franklin-Wallis (2019) and market-related factors (e.g., declining cereal consumption, lack of innovation, and changes in the global milk market, Wiener-Bronner (2019), changes in consumer taste and the rising popularity of nondairy alternatives to dairy milk have contributed to the decline in dairy milk demand.[2]

Even though US nondairy milk sales have been increasing since the early 2010s, as of 2017 their market share was just 11.6% of the total milk sales value (Mintel Group, 2018). The increased consumption of nondairy milk products is due to an increase in the number of vegetarian or vegan consumers as well as consumers' beliefs regarding issues related to animal welfare and health (McCarthy et al., 2017), medical reasons (e.g., lactose intolerance), and sensory characteristics (e.g., taste, texture) (Ferreira, 2019). The nondairy sector's active promotion of its products as more nutritious and/or tastier alternatives to dairy milk also may have played a role in winning over consumers (Packaged Facts, 2018).

Nondairy milk varieties are suitable for the same uses as dairy milk (Ferreira, 2019; Plant Based Foods Association, 2019) and are likely substitute products for traditional dairy milk. However, most studies analyzing US milk demand abstract from the presence of nondairy milk (e.g., Davis et al., 2011, 2012; Choi, Wohlgenant, and Zheng, 2013; Chen, Saghaian, and Zheng, 2018; Li, Peterson, and Xia, 2018). Few studies include them (Dharmasena and Capps, 2014; Gulseven and Wohlgenant, 2014; Copeland and Dharmasena, 2015; Stewart et al., 2020), and some assume that demand for dairy milk is separable from demand for other emerging nondairy milk excluded from the demand system (e.g., Dharmasena and Capps, 2014; Gulseven and Wohlgenant, 2014; Copeland and Dharmasena, 2015; Stewart et al., 2020).

In this article we study the substitution patterns for the demand for dairy and nondairy milk to establish whether patterns of complementary or substitutability are more common between dairy and nondairy milk alternatives. Additionally, we test the assumption of weak separability between dairy and nondairy milk products demand along three dimensions: (i) dairy versus nondairy milk, (ii) dairy and soy milk together versus almond and other nondairy milk, and (iii) soy, almond, other nondairy, and dairy skim milk versus reduced-fat (1% and 2% fat) and whole-fat dairy milk. To achieve our goals, we use state-level weekly retail food scanner data of dairy and nondairy milk product sales from 2012 to 2017 to estimate linear-approximate Exact Affine Stone Index (EASI) demand systems while imposing specific restrictions that allow us to test for weak separability along the three dimensions defined above. To the best of our knowledge, this is the first study to implement a weak separability test using an EASI model.

Understanding whether the demand for dairy and nondairy milk can be treated as separable, and the dimensions along which this is possible,[3] can help decision makers operating in the dairy and nondairy milk sectors to better understand consumers' purchase decisions. The notion of demand separability assumes consumers' preferences for a specific group of goods to not depend upon the amount consumed of goods in other groups (Deaton and Muellbauer, 1980b). In the context of our analysis, demand for dairy milk would be separable from that for nondairy milk only if consumer preferences between two dairy milk products (i.e., skim and whole) are independent of the amounts (or types) of nondairy milk purchased. If that were the case, then dairy manufacturers should only be concerned about consumers switching between dairy products and not, say, whether consumers moving away from whole milk would choose a nondairy product instead of a dairy one.

[2] In spite of the decline of dairy milk's market share in the United States (Mintel Group, 2018), sales of several dairy milk categories have grown. Organic milk sales have increased since the mid-1990s (Alviola and Capps, 2010), reaching US $1.37 billion in sales in 2017 (Haddon and Parkin, 2018). Lactose-free milk has also become popular, with sales reaching an estimated US $881.1 million in 2017 (Copeland, 2016). Similar factors boosting the demand for nondairy milk might also be responsible for the increased sales of specialty dairy milk: For example, being lactose-free is a desirable attribute of both nondairy and some dairy milk products (McCarthy et al., 2017).

[3] Smith, Rossi, and Allenby (2019) find that category labels are inconsistent with separability structure of demand which may have implications for designing optimal marketing strategies.

The existing evidence on whether consumers perceive dairy and nondairy milk similarly is mixed. Most consumers are aware of the differences between dairy and nondairy milk: Survey results find that the majority (over 70%) of US consumers understand that nondairy milk does not contain cow's milk, while only 10% believe it does (International Food Information Council, 2018). In another survey, less than 32% of respondents associated nondairy milk brands with dairy milk after seeing images of dairy and nondairy milk products (Jackson and Newall, 2018). However, a survey commissioned by the Plant Based Foods Association (2019) found that the majority of both dairy (64%) and nondairy milk (71%) consumers believe that the "milk" term best identifies nondairy milk products as it sets correct expectations about the product and its use, suggesting that consumers see these products as similar.[4] However, as evidence supporting the beneficial properties of plant-based proteins continues to increase,[5] health-conscious consumers may see nondairy milk as a distinct, healthier (or at least perceived as such) alternative to dairy milk.

Our results show that, in most cases, dairy milk products are considered substitutes for nondairy milk, whereas nondairy milk products are seen as complements to one another. In contrast, dairy milk products are overall substitutes for both one another and for nondairy milk products. The results of the separability tests show that all three weak separability structures can be rejected, suggesting that consumers allocate their budget to all six milk types (dairy skim, dairy reduced-fat, dairy whole-fat, almond, soy, and other nondairy milk) when making a purchase decision. The implications of our findings are twofold. First, while nondairy milk competes with dairy milk for consumers' budget allocated to milk (in general), any price increase in one of the nondairy milk product categories will likely result in lower overall demand for products in this subcategory and more demand going to traditional dairy milk product categories. Second, studies of US milk demand should avoid assuming weak separability of dairy and nondairy milk demand and consider using a broadened milk category instead.

A Broadened Milk Category Demand System

Following the existing literature (Nayga and Capps Jr, 1994; Sellen and Goddard, 1997; Dhar, Chavas, and Gould, 2003), we specify a demand system for dairy and nondairy milk.[6] Specifically,

[4] The National Milk Producers Federation (NMPF) and other stakeholder groups have pushed for banning the use of dairy terminology for nondairy products. They argue that, when using dairy terminology, nondairy products benefit from the value some consumers place on dairy (National Milk Producers Federation, 2019). For example, 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. The PBFA claims that such policies would unfairly favor the dairy industry and would be unconstitutional (Plant Based Foods Association, 2019; Sibilla, 2019; Nilson, 2020). Several courts have so far dismissed lawsuits claiming that nondairy milk producers deceive consumers by using dairy terminology (Plant Based Foods Association, 2019). Despite that, a law proposed in January 2017 by Senator Baldwin of Wisconsin and supported by the NMPF—the Defending Against Imitations and Replacements of Yogurt, Milk, and Cheese to Promote Regular Intake of Dairy Everyday (DAIRY PRIDE) Act, promotes the enforcement of a stricter legal definition of milk in the United States—would prohibit nondairy milk producers from using the term "milk."

[5] A systematic review by Naghshi et al. (2020) found a positive association between the intake of plant protein and a lower risk of all-cause mortality and cardiovascular disease mortality.

[6] In our analysis we are implicitly assuming that the demand for dairy and nondairy milk is separable from that for all other goods. Under this assumption, our demand system constitutes a complete demand system. If the assumption of weak separability of milk demand from that of other goods does not hold, our demand system would be incomplete. In that case, failing to account for cross-price effects of the "outside" (to the products included in the unconditional demand system) products will lead to biased parameter and welfare estimates (LaFrance, 1993). We proceed positing the validity of our assumption for two reasons. First, at closer inspection, the severity of the issue limited. The biases presented by Table 3 of LaFrance (1993), which refer to unconditional and conditional incomplete specifications, and a conditional separable one, show overlapping 95% confidence intervals, and all include the true parameter values. Second, the data we use do not allow for using some of the approached proposed in the past, to account for the incomplete nature of our demand system, such as that by LaFrance and Hanemann (1989). Specifically, as we do not use household specific data, we cannot implement the method proposed by Zhen et al. (2014) and Ferrier and Zhen (2017) which use a numÃl'raire price index from the household income net of expenditure for the goods in the demand system and CPIs. Also, it should be noted that other studies which are focused on studying substitution patterns for different types of milk (i.e., Chen, Saghaian, and Zheng, 2018; Li, Peterson, and Xia, 2018) and not on welfare analysis, sidestep the issue.

we use the EASI demand system developed by Lewbel and Pendakur (2009). Besides sharing all the desirable properties of Deaton and Muellbauer's (1980a) widely used Almost Ideal Demand System (AIDS) and its variations (e.g., Bollino, 1987; Banks, Blundell, and Lewbel, 1997; Hovhannisyan and Gould, 2012), EASI provides two additional benefits. First, EASI is not limited by Gorman's (1981) rank-three restriction, thus allowing the shape of the Engel curve to be unrestricted and determined by the data (Lewbel and Pendakur, 2009). Second, EASI accounts directly for unobserved consumer heterogeneity, which is expressed in the error term (Zhen et al., 2014).

The empirical specification of the demand model is

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

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 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 state, week, and year fixed effects, respectively; α_{ij}, β_{il}, λ_{js}, η_{jr}, and ϕ_{jt} are parameters to be estimated; and ε_{jsrt} is the model's residual, which can be interpreted as unobserved consumer heterogeneity (in this case, the "consumers" are the state-level markets). The variable y_{srt} takes the following form:

$$
y_{srt} = \ln\left(x_{srt}\right) - \sum_{j=1}^{J} w_{jsrt} \ln\left(p_{jsrt}\right), \tag{2}
$$

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 (Lewbel and Pendakur, 2009; Zhen et al., 2014; Hovhannisyan, Mendis, and Bastian, 2019).

Price and Expenditure Elasticities

Following Zhen et al. (2014), we calculate LA-EASI expenditure elasticities as follows:

$$
\boldsymbol{E} = (diag(\boldsymbol{W}))^{-1}[(\boldsymbol{I}_J + \boldsymbol{B}\boldsymbol{P}')^{-1}\boldsymbol{B}] + \boldsymbol{1}_J, \tag{3}
$$

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

Hicksian and Marshallian elasticities are calculated as (Zhen et al., 2014):

$$
\epsilon_{ij}^{H} = \frac{\alpha_{ij}}{w_i} + w_j - \delta_{ij}, \text{ for all } i,j = 1,\ldots,J,; \ \epsilon_{ij}^{M} = \epsilon_{ij}^{H} - w_j \tau_i, \tag{4}
$$

where ϵ_{ij}^{H} (ϵ_{ij}^{M}) is the Hicksian (Marshallian) price elasticity of demand for product i with respect to the price of product j; τ_i is the expenditure elasticity of product i (i.e., the ith element of the vector $\boldsymbol{E}$), and δ_{ij} is the Kronecker delta, which equals 1 if $i = j$ and 0 otherwise.

A Test for Weak Separability Using LA-EASI

In this section, we construct a test for weak separability using estimated LA-EASI parameters following Moschini, Moro, and Green (1994) and Lakkakula, Schmitz, and Ripplinger (2016). These authors developed weak separability tests for nonlinear AIDS and quadratic AIDS models, respectively.

We follow Eales and Unnevehr (1988); Nayga and Capps Jr (1994); Sellen and Goddard (1997); and Lakkakula, Schmitz, and Ripplinger (2016) to characterize weak separability of the direct utility function. Let $\boldsymbol{q} = (q_1,\ldots,q_J)$ be a vector of consumption goods which can be ordered into Z separable groups and form Z subutility functions, such that the utility function, $U(\boldsymbol{q})$, can be represented as $U(\boldsymbol{q}) = U_0[U_1(q_1),U_2(q_2),\ldots,U_Z(q_Z)]$.

According to Goldman and Uzawa (1964), this 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 (G and H, respectively) is proportional to the product of the income effects (Goldman and Uzawa, 1964):

$$S_{ik} = \mu_{GH}(\boldsymbol{p},M)\frac{\partial q_i(\boldsymbol{p},M)}{\partial M}\frac{\partial q_k(\boldsymbol{p},M)}{\partial M} \text{ for all } i \in G,\ k \in H,\ G \neq H, \tag{5}$$

where $\boldsymbol{p} = (p_1,\ldots,p_n)$ is the vector of nominal prices, M denotes income, $\mu_{GH}(\boldsymbol{p},M)$ is the proportionality term that 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, Moro, and Green, 1994). If the direct utility function is weakly separable, then from equation (5) it follows that

$$\frac{S_{ik}}{\frac{\partial q_i(\boldsymbol{p},M)}{\partial M}} = \frac{S_{jk}}{\frac{\partial q_j(\boldsymbol{p},M)}{\partial M}} \text{ for all } i,j \in G,\ k \in H,\ G \neq H. \tag{6}$$

Weak separability can be expressed in terms of the elasticities of substitution between the goods in G and H, σ_{ik} and σ_{jk}, and the expenditure elasticities, τ_i and τ_j. 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):

$$\frac{\sigma_{ik}}{\sigma_{jk}} = \frac{\tau_i}{\tau_j} \text{ for all } i,j \in G,\ k \in H,\ G \neq H. \tag{7}$$

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

$$\sigma_{ik} = \frac{\epsilon^H_{ik}}{w_k} = \frac{\epsilon^M_{ik} + \tau_i w_k}{w_k} = \frac{\epsilon^M_{ik}}{w_k} + \tau_i. \tag{8}$$

For the LA-EASI demand model, for $i \neq l$, we have

$$\epsilon^H_{ik} = \frac{\alpha_{ik}}{w_i} + w_k - 1, \text{ for all } i,\ k = 1,\ \ldots,J;\ i \neq k. \tag{9}$$

Replacing ϵ^H_{ij} in the elasticity of substitution equation with (9) results in

$$\sigma_{ik} = \frac{\left(\frac{\alpha_{ik}}{w_i} + w_k - 1\right)}{w_k} = \frac{\alpha_{ik}}{w_i w_k} - \frac{1}{w_k} + 1. \tag{10}$$

To test for nonhomothetic weak separability, we impose the constraint in equation (7) and compare the results to those from a baseline model. Substituting the terms σ_{ik}, σ_{jk}, τ_i, and τ_j into equation (7) and further simplifying the equation gives

$$(11)\qquad \frac{\left[(\alpha_{ik} - w_i) / (w_i w_k) + 1\right]}{\left[\left(\alpha_{jk} - w_j\right) / \left(w_j w_k\right) + 1\right]} = \frac{\left[\left(\sum_{l=1}^{l=L} l\beta_{il} y^{l-1}\right) / \left(w_i + w_i \ln p_i \sum_{l=1}^{l=L} l\beta_{il} y^{l-1}\right) + 1\right]}{\left[\left(\sum_{l=1}^{l=L} l\beta_{jl} y^{l-1}\right) / \left(w_j + w_j \ln p_j \sum_{l=1}^{l=L} l\beta_{jl} y^{l-1}\right) + 1\right]}.$$

We follow existing studies that test for weak separability in demand and perform only tests of local separability at the mean. Global equivalents are too restrictive because 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 (Moschini, Moro, and Green, 1994; Sellen and Goddard, 1997; Lakkakula, Schmitz, and Ripplinger, 2016). Given that at the mean prices are normalized to be 1, $w_i \ln p_i \sum_{l=1}^{l=L} l\beta_{il} y^{l-1}$ drops out. Additionally, following Hovhannisyan, Mendis, and Bastian (2019), we interpret the intercept values of our LA-EASI demand model as predicted budget/expenditure shares and use them in place of expenditure shares in a given year, state, and week in the weak separability restrictions, which takes the following form:

$$(12)\qquad \frac{\left[(\alpha_{ik} - \alpha_{io}) / (\alpha_{io}\alpha_{ko}) + 1\right]}{\left[\left(\alpha_{jk} - \alpha_{jo}\right) / \left(\alpha_{jo}\alpha_{ko}\right) + 1\right]} = \frac{\left[\left(\sum_{l=1}^{l=L} l\beta_{il} \bar{y}^{l-1}\right) / (\bar{w}_i) + 1\right]}{\left[\left(\sum_{l=1}^{l=L} l\beta_{jl} \bar{y}^{l-1}\right) / \left(\bar{w}_j\right) + 1\right]},$$

where $\bar{y}$ is the average real expenditure.[7]

Data and Summary Statistics

We utilize weekly point-of-sale (PoS) scanner data from 2012 to 2017, originally supplied by Information Resource Incorporated (IRI) to the USDA Economic Research Service (ERS).[8] The sales data are collected through in-store scanners of affiliated retailers and are recorded at the Universal Product Code (UPC) level. Some affiliate chains provide data at the store level, others at a retail marketing area (RMA) level.[9] Given the scope of this research, we use the store-level data, which are then aggregated to the state level. As a result, the data we use do not include sales at retailers that only provide data at the RMA level.[10]

From the product dictionary, we identified 14,668 UPCs for dairy and nondairy milk sold by the retailers that provided store-level data for the years 2012–2017. The UPCs were aggregated into six products: dairy nonflavored skim milk, dairy nonflavored reduced-fat milk (e.g., 1% and 2%), dairy nonflavored whole milk, nonflavored almond milk, nonflavored soy milk, and nonflavored other nondairy milk. Examples of other nondairy milk include rice, cashew, oat, coconut, flax, hazelnut, walnut, grain, pecan, and other plant-based milk products.[11] We excluded the wide variety of flavored milk, to prevent arbitrarily combining different flavors and making additional assumptions about aggregability and separability that are counter to the goals of this study. By focusing on nonflavored

---

[7] Ideally, expenditure shares should be replaced by $\hat{w}_j = \alpha_{j0} + \sum_{l=1}^{l=L} \beta_{jl} \bar{y}_{srt}^{l} + \sum_{s=1}^{s=49} \lambda_{js} \bar{State}_S + \sum_{r=1}^{r=52} \eta_{jr} \bar{W}eek_r + \sum_{t=1}^{t=6} \phi_{jt} \bar{Y}ear^t$, where $\bar{S}tate$, $\bar{W}eek$, and $\bar{Y}ear$ 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.

[8] Access to data was granted via a third-party access agreement with IRI in co-operation with the USDA/ERS.

[9] 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.

[10] Note that store-level and RMA-level data combined cover about half of US retail food purchases as recorded by the October Economic Census (Levin et al., 2018). By focusing only on the store-level data, we retain about 26% of US retail milk purchases.

[11] It is worth noting that some of the products in our nondairy milk categories (e.g., almond, soy, and others) did not carry the term "milk" on their labels during the study period but were labeled as "beverages" or "drinks."

Table 1. Summary Statistics (N = 15,288)

Variable	Mean	SD	Min.	Max.	Mean (RMA and store level)
Weekly sales (USD/state), 2012–2017					
Skim milk	200,028	46,277	138,879	304,231	422,623
Reduced fat milk	668,955	60,064	566,949	806,391	1,441,956
Whole fat milk	399,617	33,663	338,779	511,615	834,444
Other nondairy milk	15,852	5,835	4,870	28,077	45,274
Soy milk	17,156	3,236	12,241	25,373	46,819
Almond milk	39,095	11,809	16,184	62,337	118,167
Average weekly expenditure shares					
Skim milk	0.141	0.024	0.104	0.186	0.145
Reduced fat milk	0.513	0.014	0.485	0.535	0.450
Whole fat milk	0.296	0.027	0.254	0.350	0.286
Other nondairy milk	0.011	0.004	0.003	0.020	0.016
Soy milk	0.011	0.001	0.009	0.015	0.016
Almond milk	0.026	0.008	0.010	0.041	0.041
Average weekly price (USD/64 oz)					
Skim milk	2.085	0.318	1.155	3.028	2.085
Reduced fat milk	1.990	0.262	1.169	2.813	1.963
Whole fat milk	2.060	0.248	1.274	2.683	2.052
Other nondairy milk	3.631	0.305	2.459	6.202	3.590
Soy milk	3.289	0.229	2.455	4.807	3.233
Almond milk	3.277	0.219	2.478	4.300	3.187

Notes: Average weekly prices are calculated by dividing the total expenditure on the product in the given state and week by the number of products sold in the same week-state pair, standardized to represent a 64 oz. (1 gallon) package.
Source: Authors' calculations using the 2012–2017 IRI InfoScan data for the United States.

milk sales, we still capture about 87.48% of dollar sales from the data. The sales data are further aggregated at the week and state level (contiguous United States), including the District of Columbia.

Aggregating the data by state and week yields 15,288 observations (6 years × 52 weeks × 49 states). 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 create a balanced panel. Data include the volume sold for each product as well as total expenditures, which are used to construct the variables of interest (discussed in the next section). Summary statistics are presented in Table 1, which also includes the mean values for the combined store- and RMA-level datasets, illustrating that the subset of store-level data used in this study is comparable to the full dataset of which it is a part.

Annual expenditure shares and sales for the six products over the years 2012–2017 are presented in Figures 1 and 2, respectively. For the period included in the analysis, the data show that the largest (although declining) expenditure share belongs to reduced-fat milk. Whole milk has the second-largest expenditure share, which appears to grow over time. Skim milk has the third-largest expenditure share, exhibiting the largest drop in budget shares among all milk types. For nondairy milk, almond milk's expenditure share increased the most, reaching almost 3.8% in 2017 from 1.4% in 2012. Soy milk had the fifth-largest expenditure share until 2014. Its value declined and was outpaced by other nondairy milk, which exhibited a sharp increase in its expenditure share.

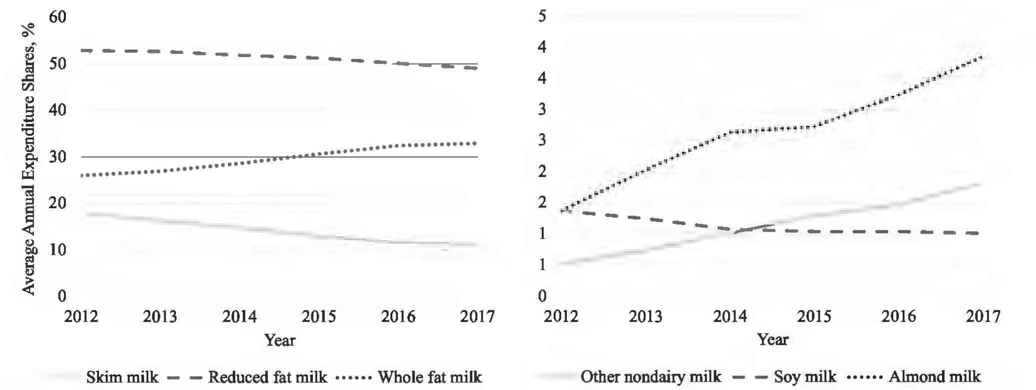

Figure 1. Average Annual Milk Expenditure Shares

Source: Authors' estimates using the 2012–2017 IRI InfoScan data for the United States.

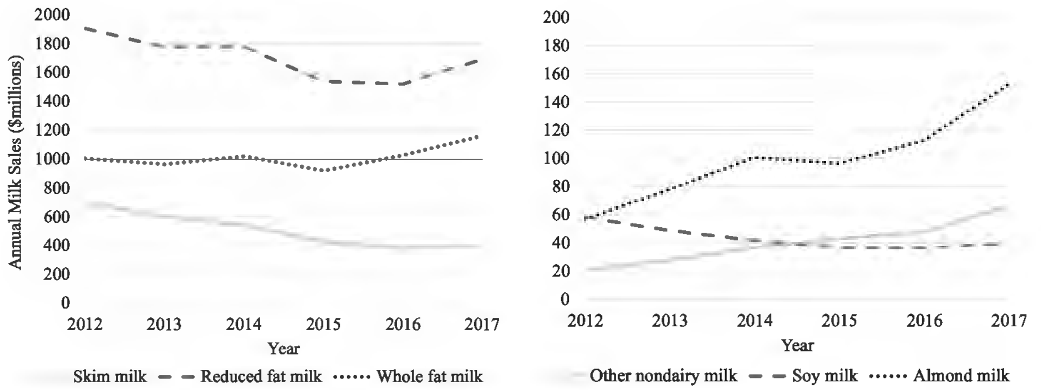

Figure 2. Annual Milk Sales

Notes: Authors' estimates using the 2012–2017 IRI InfoScan data for the United States.

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). The procedure allows error terms to be correlated across equations. We estimate a system of five equations; estimates of the sixth equation can be recovered through the theoretical restrictions listed above. The reduced-form expenditure equation is estimated with 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 up to $l = 5$. According to Pendakur (2009), for the demand system to converge, it is required that $L < J$. We tested the incremental change in the explanatory power of models with higher polynomial structures with a likelihood ratio (LR) test:

$$LR = 2\,(LL_{UR} - LL_{R})\,, \tag{13}$$

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

Expenditure Endogeneity

Since y_{srt} is constructed using expenditure shares, it is likely endogenous. To control for endogeneity of the Stone price-deflated real expenditure, we follow the approach of Dhar, Chavas, and Gould (2003) and Lakkakula, Schmitz, and Ripplinger (2016) and estimate a reduced-form equation for the real expenditure.

We follow Zhen et al. (2014) and construct the following instrumental variable:

$$\tilde{y}_{srt} \equiv \ln x_{srt} - \sum_{j=1}^{j=J} \bar{w}_j \ln \tilde{p}_{jsrt}, \tag{14}$$

where $\bar{s}$ is the average expenditure share of the jth good and $\tilde{p}_{jsrt}$ is the Hausman-type instrument (Hausman, 1996) for p_{jsrt}. To make our results comparable to those of previous studies, 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, Tobit, Davis et al. 2011, Davis et al. 2012, Chen, Saghaian, and Zheng, 2018; Li, Peterson, and Xia, 2018; or discrete choice, Choi, Wohlgenant, and Zheng, 2013) or data used (e.g., household scanner, Davis et al. 2011; Davis et al. 2012; Choi, Wohlgenant, and Zheng, 2013; Chen, Saghaian, and Zheng, 2018; or retail scanner, Li, Peterson, and Xia, 2018).[12] This instrument is the log of the average price of a given product sold in other states in the same week and year. The underlying assumption behind the validity of these instrumental variables 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. The reduced-form equation includes state, week, and 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. The statistic

$$DWH = \left(\vartheta_{\text{exog}} - \vartheta_{\text{endog}}\right)\left[VAR\left(\vartheta_{\text{exog}}\right) - VAR\left(\vartheta_{\text{endog}}\right)\right]^{-1}\left(\vartheta_{\text{exog}} - \vartheta_{\text{endog}}\right)', \tag{15}$$

where ϑ_{exog} is the vector of estimated coefficients without controlling for endogeneity and ϑ_{endog} is the vector of estimated coefficients after replacing real expenditures with the predicted values of the reduced-form equations. DWH is asymptotically distributed as a χ^2 statistic, with degrees of freedom equal to the number of positive diagonal elements of the matrix $\left[\text{VAR}\left(\vartheta_{\text{exog}}\right) - VAR\left(\vartheta_{\text{endog}}\right)\right]$ (Lakkakula, Schmitz, and Ripplinger, 2016).

Separability Test

Specifications of the LA-EASI demand systems where we impose the separability restrictions are tested against the unrestricted model using the size-corrected LR test. This test statistic is χ^2 distributed with degrees of freedom equal to the number of restrictions.

We apply the separability test to three product groupings presented in Table 2. In grouping 1, we hypothesize that the demand for dairy milk is weakly separable from the demand for nondairy milk. The logic behind this grouping is that most US milk demand studies have either explicitly or implicitly assumed separability along this dimension. In grouping 2, we assume that the demand for dairy milk and soy milk is jointly weakly separable from that for almond and other nondairy milk products. The logic for this grouping is that soy milk fortified with calcium and vitamins A and D is the only nondairy milk included by the US Department of Health and Human Services (DHHS) and the USDA as part of the dairy group in the *Dietary Guidelines for Americans, 2020–2025* (US Department of Agriculture and US Department of Health and Human Services, 2020). In grouping

[12] 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.

Table 2. Structure of Separable Demand Models

	Separable Groupings		
Product	**1**	**2**	**3**
Dairy: skim milk	A	A	A
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

Notes: In each grouping, all milk categories with the same letter are assumed to belong to the same group. Milk categories with different letters are assumed weakly separable.

Table 3. Model Specification Tests

Hypothesis:	Likelihood Ratio (LR)	Degrees of Freedom (df)	*p*-Value
(a) Linear EASI (i.e., linear Engel curve) vs. quadratic EASI	1,396.37	5	0.000
(b) Quadratic EASI vs. cubic EASI	101.93	5	0.000
(c) Cubic EASI vs. quartic EASI	223.77	5	0.000
(d) Quartic EASI vs. quintic EASI	485.41	5	0.000
DWH specification test	877.9	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 (tested for the quintic EASI specification) is rejected based on the Durbin–Wu–Hausman test statistic value.
Source: Authors' calculations using the 2012–2017 IRI InfoScan data for the United States.

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 milk products is lower than that of dairy milk (Vanga and Raghavan, 2018) and most nondairy milk products are comparable to skim milk in terms of calories (MÃď'kinen et al., 2016), which might lead consumers to believe that skim milk and nondairy milk are more similar categories of milk.

When formulating weak separability tests, it is helpful to determine the number of nonredundant weak separability restrictions, R, that can be calculated using the following formula (Moschini, Moro, and Green, 1994; Nayga and Capps Jr, 1994; Sellen and Goddard, 1997):

$$R = \left(\frac{N^2 + N - O^2 + O - \Sigma_o \left(n_o^2 + n_o \right)}{2} \right), \tag{16}$$

where N is the number of products in the separable groupings; O is the number of separable groups; and n_o is the number of products in group o. Grouping 1 has eight separability restrictions ($N = 6$, $O = 2$, $n_1 = 3$ for dairy milk products and $n_2 = 3$ for nondairy milk products). Groupings 2 and 3 have seven nonredundant weak separability restrictions.

Empirical Results and Discussion

The results of the tests based on equation (1) and presented in Table 3 indicate that the LA-EASI specification with a fifth polynomial in real expenditure (i.e., $L = 5$) is sufficient to capture the

Table 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	−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

Notes: Standard errors are in parenthesis. Single, double, and triple asterisks (*, **, ***) identify parameter estimates that are statistically different from 0 at the 10%, 5%, and 1% significance levels, respectively. The coefficients on state and week fixed effects are omitted for brevity.
Source: Authors' calculations using the 2012–2017 IRI InfoScan data for the United States.

curvature of the Engel curves. This is consistent with the results of Zhen et al. (2014), 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. The value of the DWH statistic, $DWH = 877$, and $k = 340$ leads us to reject the null of consistent parameter estimates of the model that does not control for endogeneity. Therefore, controlling for endogeneity of real expenditure is necessary to obtain consistent parameter estimates.[13]

[13] We also performed tests to detect serial autocorrelation of the errors in all the estimated equations. The Durbin–Watson test statistics obtained fell in a range of values consistent with failure to reject the null of no autocorrelation (1.72–1.98).

Table 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**	**Expenditure**
Skim	**−1.297**	0.864	−0.946	0.035	0.094	0.113	1.136
	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)
Reduced fat	0.219	**−1.666**	0.474	0.024	−0.018	−0.018	0.985
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Whole fat	−0.390	0.926	**−1.450**	−0.033	−0.010	0.016	0.941
	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Other nondairy	0.621	1.699	−1.413	**−1.634**	−0.112	−0.403	1.242
	(0.007)	(0.019)	(0.015)	(0.007)	(0.001)	(0.004)	(0.003)
Soy	1.178	−0.908	−0.261	−0.074	**−0.853**	0.008	0.910
	(0.004)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Almond	0.691	−0.537	0.162	−0.137	0.002	**−1.296**	1.114
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)

	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 the 1% significance level. Own-price elasticities are in bold.
Source: Authors' calculations using the 2012–2017 IRI InfoScan data for the United States.

LA-EASI parameter estimates are presented in Table 4. All intercept coefficients are statistically different from 0. Most of the week and state fixed-effect coefficients are also statistically significant but omitted for brevity. The coefficients on the year dummies, all of which are statistically significant, suggest that, compared to 2012, the expenditure shares on skim, reduced-fat, and soy milk (not shown in the table) decrease at an increasing rate every year, while those for whole-fat, almond, and other nondairy milk increase at an increasing rate.

Table 5 presents average Marshallian and Hicksian price elasticities as well as expenditure elasticities.[14] As expected, all own-price elasticities are negative and statistically different from 0 at the 1% probability level. Based on the Marshallian elasticities, reduced-fat milk has the highest (in

[14] An anonymous reviewer raised the point that concavity must be satisfied (or imposed) in order for our estimates to be consistent with an expenditure minimization problem. We used the estimated elasticities to verify that the estimated Slutsky matrix is negative semidefinite, which condition is—according to Lewbel and Pendakur (2009)—enough to ensure the regularity of the utility function. However, specific methods to impose the appropriate restrictions exist (see, e.g., in the context of a production problem the use of a Cholesky factorization proposed by Lau, 1978).

Table 6. Results of the Non-Nomothetic Weak Separability Tests

Separable Grouping	Number of Restrictions	Likelihood Ratio (LR) Test Statistic	Size-Corrected LR Test Statistic	Critical Value $\chi_{0.5}$
1	8	3,530	3,502	15.507
2	7	2,186	2,169	14.067
3	7	155	154	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.
Source: Authors' calculations using the 2012–2017 IRI InfoScan data for the United States.

absolute value) own-price elasticity (−1.67), followed by other nondairy (−1.63), whole-fat (−1.45), skim (−1.30), and almond (−1.30) milk. Soy milk is the only milk type with inelastic demand, showing an elasticity of −0.85. The elasticity magnitudes are consistent with those in previous studies. Davis et al. (2012) reported elasticities in the range of −3.82 to −1.07, with nonflavored skim milk demand being the most responsive to own-price changes among other nonflavored milk types. Dhar and Foltz (2005) found uncompensated own-price elasticities for rBST free, organic, and unlabeled milk 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.

Based on the cross-price elasticities, all milk types are substitutes for skim milk with the exception of whole milk (which is a complement), with the closest substitute being soy milk. For reduced-fat milk, the substitutes are skim, whole-fat, and other nondairy milk (closest substitute), while other milk types are found to be complements. Reduced-fat (closest substitute) and almond milk are substitutes for whole milk. For other nondairy milk, the only substitutes are skim and reduced-fat milk. Skim and almond milk are substitutes for soy milk, while dairy milk products are complements. For almond milk, the closest substitute is skim milk, followed by whole-fat and soy milk. Overall, the signs and magnitudes of cross-price elasticities suggest that when prices of nondairy beverages increase, there is some substitution between nondairy milk, 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 milk. Of the six cross-price elasticities among nondairy milk product categories, four suggest complementarity. However, only two cross-price elasticities suggest complementarity among dairy milk. These cross-price elasticity signs imply that in case of a price increase of one of the nondairy milk product categories, consumers are more likely to switch from the category of nondairy milk to dairy milk than they are to switch from the category of dairy milk to nondairy milk, in the case of a similar price increase of one of the dairy milk product categories.

Expenditure elasticities are the percentage change in the quantity demanded of a particular milk when the expenditures on each milk type increases by 1%. Expenditure elasticities are all positive and vary from 0.91 (soy milk) to 1.24 (other nondairy milk). Only the expenditure elasticities for reduced-fat, whole-fat, and soy milk are less than 1.

Table 6 reports the results of nonhomothetic weak separability tests. The unrestricted model (with imposed homogeneity and symmetry) is tested against each model in which we impose restrictions consistent with the separable groups, mentioned in Table 2, as well as the theoretical restrictions. Both the LR and the size-corrected LR test results suggest that the null of nonhomothetic weak separability is rejected for all separability structures tested. This implies that consumers consider all types of milk when making a milk purchase rather than allocating expenditures to specific subcategories before making a purchase. The implication of these results for researchers is that the common practice of excluding nondairy milk subcategories when estimating US milk demand may actually lead to biased results due to misspecification because the demand for dairy milk is not separable from that of nondairy milk.

Our results have two main implications. First, following Smith, Rossi, and Allenby (2019) and using our estimates and the results of our tests for the correct structure of the demand across dairy and nondairy milk subcategories, our results could help both sectors improve their allocation of marketing resources. From the perspective of the dairy industry, for example, our finding that dairy and nondairy milk do not belong to weakly separable demand groups—and the complex structures of substitutability and complementarity between different types of milk—indicates the necessity of developing marketing strategies to support the demand for dairy milk that account directly for the dynamics of nondairy milk demand. Because we find that when the price of one type of nondairy milk increases, consumers are more likely to switch to dairy milk compared to other nondairy options, a possible strategy would be to emphasize the (relative) costliness of the former compared to the latter. An indirect implication of our results is that some of the recent efforts by dairy producers' associations, focusing on less targeted strategies, such as lobbying for restricting the use of "milk" terminology to dairy products (discussed in footnote 4) may be less effective in counteracting the growth of nondairy alternatives.

Second, our results support the inclusion of a broader set of products when studying the demand for milk. As we briefly mentioned in the introduction, there are only a few instances of empirical analyses that include both dairy and nondairy products (Dharmasena and Capps, 2014; Gulseven and Wohlgenant, 2014; Copeland and Dharmasena, 2015; Stewart et al., 2020), and the inclusion of plant-based alternatives when analyzing the demand for dairy (or animal protein food categories in general) is still rather uncommon. Although the so-called "curse of dimensionality" may lead researchers to be parsimonious when deciding the number of products to include in their analysis when using demand systems, our results should act as a cautionary tale for researchers to at least include a nondairy aggregate in their demand systems, even if they are not directly part of the focus of the analysis.

Including nondairy products in the analysis of milk demand should be relatively easy for researchers using attribute-based demand models, which map consumer demand from a product space to an attribute space, circumventing the need to estimate a large number of own- and cross-price parameters. However, analyses using discrete choice models to study milk demand (e.g., Lopez and Lopez, 2009; Choi, Wohlgenant, and Zheng, 2013; Hirsch, Tiboldo, and Lopez, 2018; Liu et al., 2020) customarily exclude nondairy milk. In doing so, these studies implicitly assume that nondairy products either belong to the outside option (i.e., their mean utility is standardized to 0) or that they are not part of the consumers' choice set (i.e., they belong to a product category, for which consumers make a separate choice). Our results show that neither assumption is likely to hold and that, as a result, excluding nondairy alternatives from the analysis may lead to issues of misspecification, which may be particularly problematic in studies addressing welfare changes (e.g., Choi, Wohlgenant, and Zheng, 2013).

Discussion, Conclusions, and Limitations

Using weekly point-of-sale data from 2012 to 2017, we estimated the demand for dairy and nondairy milk products in the United States via the LA-EASI demand model. To our knowledge, this is the first study to extend weak separability restrictions for the LA-EASI model.

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 milk types when making a purchase decision. In other words, since the null hypotheses of weak separability are rejected, dairy and nondairy milk are not considered separate categories of products. Rather, consumers consider all six types of milk included in this study (skim, reduced-fat, whole-fat, soy, almond, and other nondairy milk) jointly when making a purchase decision.

Second, 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. We find that a price increase (decrease) among nondairy milk product categories results in higher (lower) sales of most dairy milk and lower (higher) sales of nondairy milk product categories since the latter are mostly complements to each other. Depending upon the product, when the price of one type of dairy milk increases, consumers mostly switch to other dairy milk products. In contrast, when the price of one type of nondairy milk increases, consumers are more likely to switch to dairy milk. However, the effects of a price change of a dairy milk are more complex since most dairy and nondairy milk are substitutes for dairy milk.

The results of our study are subject to several limitations. First, our analysis assumed that demand for dairy and nondairy milk is separable from the demand for other products. As discussed in footnote 6 and pointed out by an anonymous reviewer, estimated parameters can be biased if this assumption is violated. As our analysis does not focus on obtaining welfare measures, which would be the main source of concern if bias were present, and it is limited in scope, we believe in its usefulness for both dairy and nondairy milk sector operators as well as to provide some guidance to applied researchers studying markets that include plant-based products. That said, we encourage future research to use methods such as those developed by LaFrance and Hanemann (1989) and implemented in numerous other demand analyses (e.g., Zhen et al., 2014; Ferrier and Zhen, 2017).

Second, our analysis tested for demand separability by grouping products using predetermined dimensions. It is possible that other, more complex dimensions may be driving consumers to make decisions leading to demand separability. Instead of testing whether the demand for a group of products is separable, we could have used the approach suggested by Smith, Rossi, and Allenby (2019) to detect empirically the groups of separable products within/across the dairy and nondairy products in our data. Third, we do not control for the possible endogeneity of prices in our demand system. This decision was meant to make our results comparable to those of existing studies analyzing US milk demand, many of which do not control for price endogeneity. Additionally, results obtained in model specifications in which we controlled for price endogeneity as a robustness check were implausible (e.g., large and positive own-price elasticities). Fourth, to keep the analysis tractable, we excluded flavored milk (which Dharmasena and Capps, 2014, have found to compete with soymilk) as well as other products that may affect the substitutability between dairy and nondairy milk (e.g., goat milk, buttermilk, and bottled milkshakes). Future studies may either focus on those products or include them in addition to the six products included in this study. Finally, due to the data structure, we could not disaggregate the nondairy milk subcategory in products that are labeled as "milk" and those that are not. That is, this research does not directly answer the question of whether labeling nondairy products as "milk" makes them more or less substitutes to dairy products and whether they belong to a separable demand group relative to dairy milk.

[First submitted April 2021; accepted for publication March 2022.]

References

Alviola, P. A., and O. Capps. "Household Demand Analysis of Organic and Conventional Fluid Milk in the United States Based on the 2004 Nielsen Homescan Panel." *Agribusiness* 26(2010): 369–388. doi: 10.1002/agr.20227.

Banks, J., R. Blundell, and A. Lewbel. "Quadratic Engel Curves and Consumer Demand." *Review of Economics and Statistics* 79(1997):527–539. doi: 10.1162/003465397557015.

Bollino, C. A. "GAIDS: A Generalised Version of the Almost Ideal Demand System." *Economics Letters* 23(1987):199–202. doi: 10.1016/0165-1765(87)90039-5.

Chen, B., S. Saghaian, and Y. Zheng. "Organic Labelling, Private Label, and US Household Demand for Fluid Milk." *Applied Economics* 50(2018):3039–3050. doi: 10.1080/00036846.2017.1414936.

Choi, H.-J., M. K. Wohlgenant, and X. Zheng. "Household-Level Welfare Effects of Organic Milk Introduction." *American Journal of Agricultural Economics* 95(2013):1009–1028. doi: 10.1093/ajae/aat021.

Chouinard, H. H., D. E. Davis, J. T. LaFrance, and J. M. Perloff. "Milk Marketing Order Winners and Losers." *Applied Economic Perspectives and Policy* 32(2010):59–76. doi: 10.1093/aepp/ppp002.

Copeland, A., and S. Dharmasena. "Consumer Demand for Dairy Alternative Beverages in the United States and Its Implications to U.S. Dairy Industry." 2015. Paper presented at the annual meeting of the Agricultural and Applied Economics Association, July 26–28, San Francisco, California. doi: 10.22004/ag.econ.205334.

Copeland, A. M. *Consumer Demand for Conventional Fluid Milk and Selected Dairy Alternative Beverages in the United States*. Master's thesis, Texas A&M University, 2016.

Davis, C., S. Yen, D. Dong, and D. Blayney. "Assessing Economic and Demographic Factors that Influence United States Dairy Demand." *Journal of Dairy Science* 94(2011):3715–3723. doi: 10.3168/jds.2010-4062.

Davis, C. G., D. Dong, D. P. Blayney, S. T. Yen, and R. Stillman. "U.S. Fluid Milk Demand: A Disaggregated Approach." *International Food and Agribusiness Management Review* 15(2012): 25–50. doi: 10.22004/ag.econ.120856.

Deaton, A., and J. Muellbauer. "An Almost Ideal Demand System." *American Economic Review* 70(1980a):312–326.

———. *Economics and Consumer Behavior*. Cambridge, UK: Cambridge University Press, 1980b.

Dhar, T., J.-P. Chavas, and B. W. Gould. "An Empirical Assessment of Endogeneity Issues in Demand Analysis for Differentiated Products." *American Journal of Agricultural Economics* 85(2003):605–617. doi: 10.1111/1467-8276.00459.

Dhar, T., and J. D. Foltz. "Milk by Any Other Name: Consumer Benefits from Labeled Milk." *American Journal of Agricultural Economics* 87(2005):214–228. doi: 10.1111/j.0002-9092.2005.00713.x.

Dharmasena, S., and O. Capps. "Unraveling Demand for Dairy-Alternative Beverages in the United States: The Case of Soymilk." *Agricultural and Resource Economics Review* 43(2014): 140–157. doi: 10.22004/ag.econ.166028.

Eales, J. S., and L. J. Unnevehr. "Demand for Beef and Chicken Products: Separability and Structural Change." *American Journal of Agricultural Economics* 70(1988):521–532. doi: 10.2307/1241490.

Ferreira, S. "Going Nuts about Milk? Here's What You Need to Know about Plant-Based Milk Alternatives." 2019. Available online at https://nutrition.org/going-nuts-about-milk-heres-what-you-need-to-know-about-plant-based-milk-alternatives/.

Ferrier, P. M., and C. Zhen. "The Role of Income in Explaining the Shift from Preserved to Fresh Vegetable Purchases." *Journal of Agricultural and Resource Economics* 42(2017):329–349. doi: 10.22004/ag.econ.264065.

Franklin-Wallis, O. "White Gold: The Unstoppable Rise of Alternative Milks." *The Guardian* (2019). Available online at https://www.theguardian.com/news/2019/jan/29/white-gold-the-unstoppable-rise-of-alternative-milks-oat-soy-rice-coconut-plant.

Goldman, S. M., and H. Uzawa. "A Note on Separability in Demand Analysis." *Econometrica* 32(1964):387. doi: 10.2307/1913043.

Gorman, W. "Some Engel Curves." In A. Deaton, ed., *Essays in the Theory and Measurement of Consumer Behavior in Honor of Sir Richard Stone,* Cambridge, UK: Cambridge University Press, 1981, 7–30. doi: 10.1017/CBO9780511984082.003.

Gulseven, O., and M. Wohlgenant. "Demand for Functional and Nutritional Enhancements in Specialty Milk Products." *Appetite* 81(2014):284–294. doi: 10.1016/j.appet.2014.06.105.

Haddon, H., and B. Parkin. "Dairies Are Awash in Organic Milk as Consumers Jump to Alternatives." 2018. Available online at https://www.wsj.com/articles/dairy-producers-farmers-struggle-with-organic-milk-oversupply-1514889001.

Haley, M. "Livestock, Dairy, and Poultry Outlook." Situation and Outlook LDP-M-279, USDA Economic Research Service, Washington, DC, 2017. Available online at https://www.ers.usda.gov/webdocs/outlooks/85163/ldp-m-279.pdf [Accessed September 15, 2017].

Hausman, J. A. "Valuation of New Goods under Perfect and Imperfect Competition." In T. F. Bresnahan and R. J. Gordon, eds., *The Economics of New Goods,* Chicago, IL: University of Chicago Press, 1996, 207–248.

Hirsch, S., G. Tiboldo, and R. A. Lopez. "A Tale of Two Italian Cities: Brand-Level Milk Demand and Price Competition." *Applied Economics* 50(2018):5239–5252. doi: 10.1080/00036846.2018.1486016.

Hovhannisyan, V., and B. W. Gould. "A Structural Model of the Analysis of Retail Market Power: The Case of Fluid Milk." *American Journal of Agricultural Economics* 94(2012):67–79. doi: 10.1093/ajae/aar124.

Hovhannisyan, V., S. Mendis, and C. Bastian. "An Econometric Analysis of Demand for Food Quantity and Quality in Urban China." *Agricultural Economics* 50(2019):3–13. doi: 10.1111/agec.12461.

International Food Information Council. *Consumer Attitudes About Labeling Cow's Milk, Plant-Based and Non-Dairy Alternatives*. IFIC, 2018. Available online at https://www.foodinsight.org/wp-content/uploads/2018/10/Milk-Nomenclature_PDF_1.pdf.

Jackson, C., and M. Newall. *Americans Love Dairy Milk for Its Taste, Nutrition, and Affordability*. Washington, DC: IPSOS, 2018. Available online at https://www.ipsos.com/sites/default/files/ct/news/documents/2019-02/dmi_milk_press_release.pdf.

LaFrance, J. T. "Weak Separability in Applied Welfare Analysis." *American Journal of Agricultural Economics* 75(1993):770–775. doi: 10.2307/1243589.

LaFrance, J. T., and W. M. Hanemann. "The Dual Structure of Incomplete Demand Systems." *American Journal of Agricultural Economics* 71(1989):262–274. doi: 10.2307/1241583.

Lakkakula, P., A. Schmitz, and D. Ripplinger. "U.S. Sweetener Demand Analysis: A QUAIDS Model Application." *Journal of Agricultural and Resource Economics* 41(2016):533–548. doi: 10.22004/ag.econ.246253.

Lau, L. J. "Testing and Imposing Monotonicity, Convexity and Quasi-Convexity Constraints." In M. Fuss and D. McFadden, eds., *Production Economics: A Dual Approach to Theory and Applications, Volume I: The Theory of Production,* Amsterdam, Netherlands: North-Holland, 1978, 409–453.

Levin, D., D. Noriega, C. Dicken, A. Okrent, M. Harding, and M. Lovenheim. "Examining Food Store Scanner Data: A Comparison of the IRI InfoScan Data with Other Data Sets, 2008–2012." Technical Bulletin 1949, USDA Economic Research Service, Washington, DC, 2018.

Lewbel, A., and K. Pendakur. "Tricks with Hicks: The EASI Demand System." *American Economic Review* 99(2009):827–863. doi: 10.1257/aer.99.3.827.

Li, X., H. H. Peterson, and T. Xia. "Demand for Organic Fluid Milk across Marketing Channels." *Agricultural and Resource Economics Review* 47(2018):505–532. doi: 10.1017/age.2017.33.

Liu, Y., X. Chen, A. N. Rabinowitz, and B. Campbell. "Demand, Challenges, and Marketing Strategies in the Retail Promotion of Local Brand Milk." *Agricultural Economics* 51(2020): 655–668. doi: 10.1111/agec.12584.

Lopez, E., and R. A. Lopez. "Demand for Differentiated Milk Products: Implications for Price Competition." *Agribusiness* 25(2009):453–465. doi: 10.1002/agr.20219.

McCarthy, K., M. Parker, A. Ameerally, S. Drake, and M. Drake. "Drivers of Choice for Fluid Milk Versus Plant-Based Alternatives: What Are Consumer Perceptions of Fluid Milk?" *Journal of Dairy Science* 100(2017):6125–6138. doi: 10.3168/jds.2016-12519.

Mintel Group. "US Non-Dairy Milk Market Report." 2017.

———. "US Non-Dairy Milk Sales Grow 61% over the Last Five Years." 2018. Available online at https://www.mintel.com/press-centre/food-and-drink/us-non-dairy-milk-sales-grow-61-over-the-last-five-years.

Moschini, G., D. Moro, and R. D. Green. "Maintaining and Testing Separability in Demand Systems." *American Journal of Agricultural Economics* 76(1994):61–73. doi: 10.2307/1243921.

Muth, M. K., M. Sweitzer, D. Brown, K. Capogrossi, S. A. Karns, D. Levin, A. Okrent, P. Siegel, and C. Zhen. "Understanding IRI Household-Based and Store-Based Scanner Data." Technical Bulletin 1942, USDA Economic Research Service, Washington, DC, 2016.

MÃď'kinen, O. E., V. Wanhalinna, E. Zannini, and E. K. Arendt. "Foods for Special Dietary Needs: Non-Dairy Plant-Based Milk Substitutes and Fermented Dairy-Type Products." *Critical Reviews in Food Science and Nutrition* 56(2016):339–349. doi: 10.1080/10408398.2012.761950.

Naghshi, S., O. Sadeghi, W. C. Willett, and A. Esmaillzadeh. "Dietary Intake of Total, Animal, and Plant Proteins and Risk of All Cause, Cardiovascular, and Cancer Mortality: Systematic Review and Dose-Response Meta-Analysis of Prospective Cohort Studies." *BMJ* 370(2020):m2412. doi: 10.1136/bmj.m2412.

National Milk Producers Federation. "Citizen Petition Submitted on Behalf of The National Milk Producers Federation." 2019. Available online at https://www.nmpf.org/files/files/National Milk Producers Federation Citizen Petition and Attachments.pdf [Accessed March 1, 2021].

Nayga, R. M., and O. Capps Jr. "Tests of Weak Separability in Disaggregated Meat Products." *American Journal of Agricultural Economics* 76(1994):800–808. doi: 10.2307/1243741.

Nilson, P. "What's in a Name? The Fight over Milk." *Drinks Insight Network* (2020). Available online at https://www.drinks-insight-network.com/features/whats-in-a-name-the-fight-over-milk/.

O'Connor, C. *Soy and Almond Milk Production in the US*. IBISWorld, 2019. Available online at https://www.ibisworld.com/united-states/market-research-reports/soy-almond-milk-production-industry/.

Packaged Facts. *Dairy and Dairy Alternative Beverage Trends in the U.S.* Packaged Facts, 2018, 4th ed. Available online at https://bit.ly/3oGEf90.

———. "The Dairy & Dairy Alternatives Market." 2020. Available online at https://www.packagedfacts.com/Content/Featured-Markets/Dairy-and-Dairy-Alternatives.

Pendakur, K. "EASI Made Easier." In D. J. Slottje, ed., *Quantifying Consumer Preferences,* No. 288 in Contributions to Economic Analysis. Bingley, UK: Emerald Group Publishing, 2009, 179–206. doi: 10.1108/S0573-8555(2009)0000288010.

Plant Based Foods Association. *Re: Use of the Names of Dairy Foods in the Labeling of Plant-Based Products; Docket ID: FDA-2018-N-3522*. PBFA, 2019. Available online at https://www.plantbasedfoods.org/pbfa-comments-submitted-to-the-request-for-information-from-fda/.

———. *New Data Shows Plant-Based Food Outpacing Total Food Sales During COVID-19*. San Francisco, CA: PBFA, 2020. Available online at https://www.plantbasedfoods.org/plant-based-food-outpaces-total-food-sales-during-covid19/.

Sellen, D., and E. Goddard. "Weak Separability in Coffee Demand Systems." *European Review of Agricultural Economics* 24(1997):133–144. doi: 10.1093/erae/24.1.133.

Sibilla, N. "FDA Crackdown on Calling Almond Milk 'Milk' Could Violate the First Amendment." *Forbes* (2019). Available online at https://www.forbes.com/sites/nicksibilla/2019/01/31/fda-crackdown-on-calling-almond-milk-milk-could-violate-the-first-amendment/.

Smith, A. N., P. E. Rossi, and G. M. Allenby. "Inference for Product Competition and Separable Demand." *Marketing Science* 38(2019):690–710. doi: 10.1287/mksc.2019.1159.

Stewart, H., F. Kuchler, J. Cessna, and W. Hahn. "Are Plant-Based Analogues Replacing Cow's Milk in the American Diet?" *Journal of Agricultural and Applied Economics* 52(2020):562–579. doi: 10.1017/aae.2020.16.

US Department of Agriculture, and US Department of Health and Human Services. *Dietary Guidelines for Americans, 2020–2025*. Washington, DC: US Department of Agriculture, 2020, 9th ed.

Vanga, S. K., and V. Raghavan. "How Well Do Plant Based Alternatives Fare Nutritionally Compared to Cow's Milk?" *Journal of Food Science and Technology* 55(2018):10–20. doi: 10.1007/s13197-017-2915-y.

Wiener-Bronner, D. "America's Milk Industry Is Struggling. Don't Blame Oat Milk." *CNN* (2019). Available online at https://www.cnn.com/2019/11/21/business/milk-industry-dean-foods/.

Zellner, A. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57(1962):348–368. doi: 10.1080/01621459.1962.10480664.

Zhen, C., E. A. Finkelstein, J. M. Nonnemaker, S. A. Karns, and J. E. Todd. "Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System." *American Journal of Agricultural Economics* 96(2014):1–25. doi: 10.1093/ajae/aat049.