THE HUMANE LEAGUE Labs

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MILKING IT

Exploring the impact of plant-based milk in the US

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EXECUTIVE SUMMARY

This project aims to evaluate the impact of the increasing availability of plant-based milk alternatives on demand for fluid dairy milk in the United States. We investigate this question by conducting three analyses: (1) gathering and comparing different sources of plant-based sales data to investigate data variability and to determine whether plant-based milk sales are sufficient to replace declining dairy sales, (2) summarizing research on the relationship between plant-based and dairy milks to determine whether the products are price substitutes for each other, and (3) estimating demand for whole and 2% dairy milk in separate periods between 2001–2019 and comparing one period's responsiveness to price fluctuations against the other period to determine whether dairy milk demand has undergone major changes that could have been caused by the expansion of plant-based milk products. Our results confirm that the volume of plant-based milk consumed has increased over time, but not enough to fully explain the observed decline in dairy milk consumption. We find that dairy sales are relatively insensitive to changes in prices of plant-based milks while plant-based milk sales respond to changes in prices of lower-fat dairy milks more than higher-fat dairy milks. Unusual data patterns and estimation results suggest that the dairy demand model needs refinement before drawing confident conclusions, but our tentative findings indicate that whole and 2% dairy milk consumption is decreasing despite decreases in price and that consumer responsiveness may have changed in recent years. That said, the overall results suggest that we cannot confidently attribute all of this potential change in dairy milk demand to consumption of plant-based milk products.

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1. INTRODUCTION

Plant-based alternatives to animal food products are making headlines, and dairy alternatives in particular have expanded in variety and market presence in the past decade. Some animal advocates and plant-based product manufacturers hypothesize that the increasing abundance of plant-based versions of fluid milk, butter, cheese, and yogurt has offset demand for dairy products by providing competitive alternatives, while some in the dairy industry suggest otherwise. However, empirical evidence about the impact of growth in availability of and demand for plant-based alternatives on demand for animal products is limited.

This project aims to evaluate the impact of plant-based milk alternatives, specifically their increasing availability, on demand for fluid dairy milk products in the United States (US). Informed by historical data, previous research, and economic theory, we examine three relationships to investigate the impact of plant-based milks by evaluating: (1) whether quantity sales of plant-based alternatives are sufficient to replace declining dairy sales, (2) whether cross-price elasticities indicate a price substitute relationship, and (3) whether the own-price elasticity of dairy products has increased over time, suggesting an increase in the presence of substitute products.

Our work expands on the literature around milk consumption and substitution patterns, which has recently begun to include plant-based alternatives. Most closely related to our first line of evidence is Stewart et al. [1], which examines household panel data on plant-based and dairy milk sales and finds that fluid volume of plant-based milk purchases can account for only about 1/5th of the decrease in volume of dairy milk purchases [1, p13]. A vector autoregressive (VAR) time-series model is used to simulate counterfactuals in which plant-based sales grow at a much slower rate, a phenomenon that the authors suggest might have occurred if the government had enacted a policy preventing companies from selling plant-based alternative products with the word "milk" on their labels. As expected, the research design does not provide causal identification but does find correlational evidence suggesting that sales of plant-based milks are associated with some decline in dairy milk sales. To expand on these results, we collect data on plant-based milk prices, quantity sales, and dollar sales from public sources. We use these public data to validate the IRI data used in Stewart et al.'s analysis and verify overall trends in the plant-based milk market.

A small but growing body of literature investigates the relationships between plant-based and dairy milks by estimating cross-price elasticity, or how the quantity demanded of one product responds to changes in price of another. Dhar and Foltz [2] shows that early commercial soy milk products were substitutes only for flavored dairy milks. Using more current data, Dharmasena and Capps [3] shows that soy milk is a substitute for plain dairy milk averaged across all types. Copeland and Dharmasena [4] finds a similar relationship for soy and dairy milk, although the estimates of cross-price elasticities between almond and dairy milks suggest a complement relationship. Li [5] finds that coconut, almond, and soy milks are complements for plain dairy milk. Ghazaryan [6] finds that soy, almond, and "all other" nondairy milks are substitutes for skim dairy milk; almond and soy milks are complements for 2% and 1% dairy milk combined; and almond milk is a substitute for whole dairy milk while soy milk is a complement. We qualitatively synthesize these results to compile and clarify these relationships.

These studies provide a complicated picture of the price relationships between plant-based and dairy milk, but relative prices may not be the only influence that plant-based milks have on the demand for dairy milk. Economic theory suggests that demand for plain dairy milk should be determined by several factors, including dairy milk prices; the prices and availability of substitute products like nondairy

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milk and other ready-to-drink beverages; consumer incomes; expectations about future prices; and tastes and preferences. Theory also suggests that the own-price elasticity of demand for any product, a measure of the responsiveness of demand to price changes that is calculated from the underlying demand structure, will increase in the long run when there are more substitute products available. We therefore look for evidence of changes to the structure of dairy milk demand that could have been caused by the increase in the number and variety of plant-based milks; to do so, we estimate and compare short-run plain dairy milk price elasticities across different time periods. This method is employed in the energy economics literature to investigate potential structural changes in demand for fuel [7; 8]. While the available data do not allow us to isolate the different reasons for substitution, evidence of an increase in the own-price elasticity of dairy milk over time would provide support for the existence of a substitution relationship between plant-based and dairy milk through a mechanism other than price.

Our results suggest that plant-based milk proliferation may not be the most important factor in the decline of dairy milk. The validation of plant-based data in Section 2 suggests that consumption of plant-based milk has increased but not enough to substitute for the concomitant decrease in dairy milk consumption. Our investigation into the relationships between products in Section 3 shows that changes in plant-based milk prices do little to affect demand for dairy milk, on average. Thus, any offsetting of dairy milks by plant-based milks may be for reasons other than relative price changes. The analysis of dairy demand in Section 4 illuminates unusual data patterns and provides unexpected estimation results. The data show that dairy consumption has decreased alongside decreasing dairy prices, to the point that our tentative elasticity estimates are *positive* in the later period. Future work to uncover the underlying factors of the substitution relationship and to understand the puzzle of positive dairy demand elasticities may interest researchers looking explore these relationships in more depth, as we discuss in Section 5, but those working to refine the dairy elasticity estimation procedure may wish to investigate a different demand model.

2. VALIDATING GROCERY DATA

2.1. Methodology

To better understand variability in estimates of plant-based milk market characteristics and to validate the data used in Stewart et al. [1], we compare other available data on plant-based milk sales with the data extracted from Stewart et al. First, we search government and industry publications for annual country-level US data on three measures of the plant-based milk alternative market: average unit prices, quantity sales, and dollar sales (where dollar sales = average unit price × quantity sales). Second, we extract the data, which are available in the file `data/raw/public-plant-revenues.csv` in the Open Science Framework (OSF) repository for this project at https://osf.io/E95DP/. All subsequent references to a data repository or directories refer to this location. Third, the data are coded by source (for example: IRI, Nielsen, or SPINS), and any details about the data collection methods are extracted. Documentation of each published data point is provided in `data/raw/source-records`. Fourth, we use the data extraction software `WebPlotDigitizer` [9] to obtain weekly data on the number of gallons of plant-based milk consumed per household published in Figure 2 of Stewart et al. These data are located in the file `data/raw/stewart-plant-quantity.csv`. We convert this to weekly dollar sales by multiplying the price per gallon of plant-based milk (provided in Stewart et al. and linearly interpolated) and the annual number of households in the United States (from the United States Census Bureau's Current Population Survey historical tables [10]). We calculate the annual sales of plant-based milks with 52-week rolling sums.

Fifth, in a minor deviation from our preregistration [11, p. 3], we convert all dollar sales estimates to percentages of total grocery spending in the corresponding time periods using data from the USDA [12]. For example, rather than report that $13 billion dollars of plant-based milk were sold in a given year, we report that 0.2% of dollars spent on groceries were spent on plant-based milks that year. This change to the analysis does not effect the validation since all estimates were scaled by comparable factors, but presents a more accurate view of the plant-based milk market by eliminating trends in population growth, inflation and changes in overall grocery purchasing behavior. The final analysis data, including the preregistered outcome of dollar sales (named `plant_spend`), are located in the file `data/final/plant-based-milk-sales-grocery-share.csv`. Finally, we compare the various estimates of plant-based milks prices and sales to look for consistency between sources.

2.2. Results

Our search generates a validation data set with 19 estimates of dollar sales of plant-based milks from nine publications and no estimates of average unit price or quantity sales. The validation data represent the plant-based milk market from 2015 to 2019, with most data points after 2016. Therefore, half of the Stewart et al. data can not be validated. Data sources for the validation data are Nielsen (9), SPINS (2), or SPINS and IRI jointly (8). The majority of the validation data are published by two non-profits promoting plant-based milks: The Good Food Institute and the Plant-Based Foods Association. The remaining data were published in a government report, in an industry conference proceedings, and by Nielsen itself. All the validation data are based on grocery scanner data, where sales data are collected at the point of purchase, rather than the consumer panel surveys from IRI used in Stewart et al.

Figure 1 displays 17 of the 19 validation data points alongside the Stewart et al. data. The data reflect sales of plant-based milks as a percentage of total grocery sales in a 52-week period. Two outliers around 0.58%, which come from the same source, are excluded from the figure for readability. The remaining data form two clusters, around 0.205% and 0.24%, where data points representing similar time periods show substantial discrepancies. This corresponds to a difference of about $150 million dollars in one example pair of data points. These clusters do not correlate with source, publisher of the data or any other obvious factor in the reported data collection methods. Where Stewart et al. data does overlap the validation data, it matches the lower cluster relatively closely. Taken as a whole, the data suggest an upward trend of approximately 0.015 percentage points per year.

2.3. Conclusions

The results of our validation are mixed. We find discrepancies within the validation data which were not explained by any reported differences in data collection methods. We speculate that these discrepancies may be explained by differences in the definition or construction of the plant-based milk category across publications. For example, perhaps the complex of coconut-based beverages (coconut juice, milk, water, cream) may be difficult to reliably classify into plant-based milks (that is, dairy analogs) and other beverages. Better reporting on the details of the data collection methods might allow further investigation of these discrepancies and make the resulting data more credible.

The close overlap between the Stewart et al. data and some of the validation data is notable, especially given differences in data collection methods (grocery scanner vs. consumer panel surveys). However, other parts of the validation data do not correspond with the Stewart et al data. While the overall trend of the Sewart et al. data is reproduced in the validation data, some minor trends are not, like the decline during 2015 and subsequent increase in 2016.

In addressing our research question of whether quantity sales of plant-based alternatives are sufficient to replace declining dairy sales, our validation of the Stewart et al. data corroborates their conclusions. The fluid volume of plant-based milk sold is insufficient to replace the volume of dairy milk Americans used to consumed, at least over their study period from 2013 to 2017. The volume of plant-based milk purchased during each of those years accounts for only 1/5th of the decline in dairy volume [1, p13]. Due to a lack of data beyond these dates, we are unable to extend the conclusions to present day.

3. SYNTHESIS OF ELASTICITIES

3.1. Methodology

Our qualitative synthesis of the price relationships between dairy and plant-based milks, or the cross-price elasticities, follows the synthesis without meta-analysis (SWiM) reporting guidelines [13; 14]. SWiM guidelines ensure transparent and systematic reporting of synthesis methods when meta-analysis is not applied. Our methodology uses a consolidated version of the guidelines provided in Campbell et al. [13] as a framework.

Study selection and grouping criteria Our main criterion for selecting studies is the presence of an empirically estimated cross-price elasticity of demand between plant-based and dairy milks. We conduct a literature search using the key words "estimated," "cross-price elasticity," "milk demand," "dairy," "nondairy," "soy milk," "almond milk," "oat milk," and "plant-based milk," which identifies six studies that estimated cross-price elasticities of dairy and plant-based milks [2; 3; 5; 6; 15; 16]. Okrent et al. [16] is excluded from the synthesis because it provides elasticity estimates only for the aggregation of soy, almond, and rice milk, which would not have been comparable to any other estimates.

These studies report elasticity estimates for several pairs of products, and we group the results accordingly in our

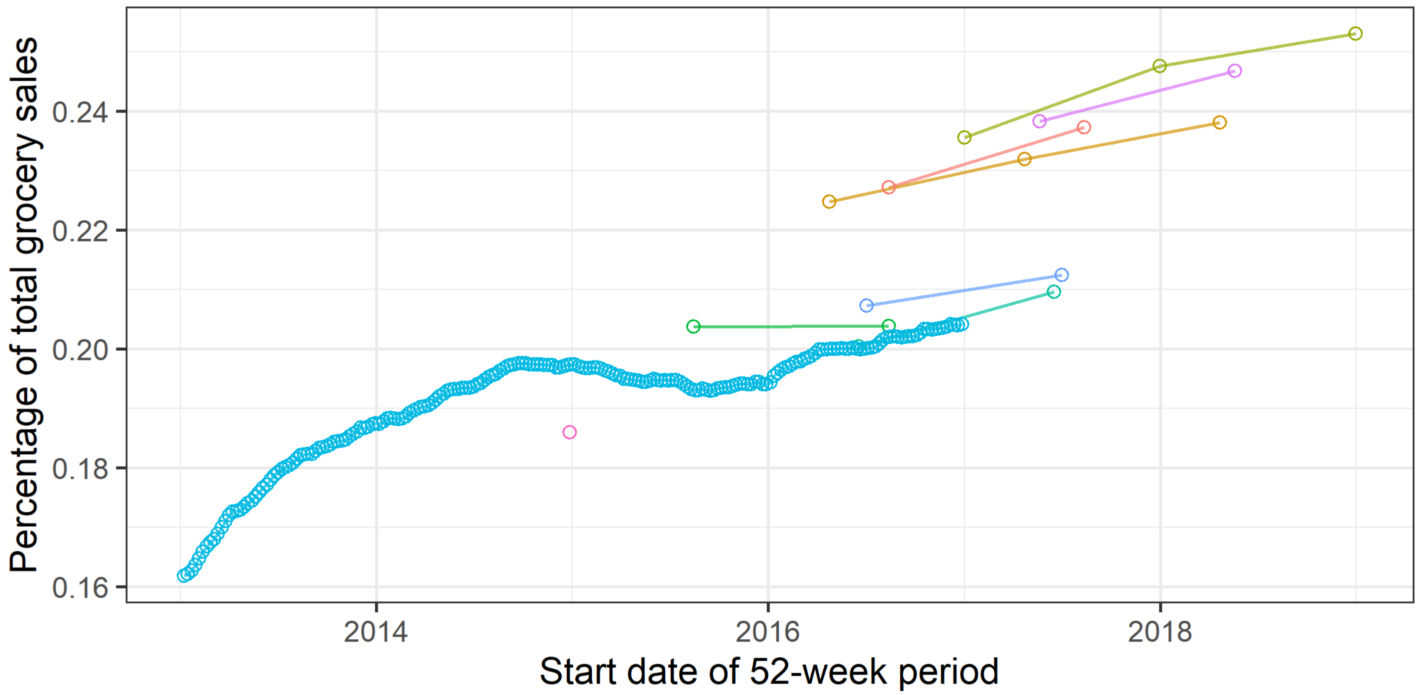

Figure 1 Plant-based milk sales as a percentage of total grocery sales
About 0.2% of all dollars spent on groceries in the United States are spent on plant-based milks each year. Each data point represents the percentage of grocery dollars spent on plant-based milks during a 52-week period starting on the given date. Solid lines connect estimates of the plant-based milk market provided in the same publication and thus most directly comparable. Supporting data and code are available in the repository https://osf.io/E95DP/.

analysis. For example, we group estimates of the elasticity of soy milk demand with respect to a change in whole dairy milk price distinctly from estimates of elasticities of whole dairy demand with respect to almond milk price.

Standardized metric Elasticity of demand is, by definition, constructed to be a unit-free measurement of the percentage change in quantity demanded of one good that is associated with a one percent increase in either that good's own price ("own-price elasticity") or the price of another good ("cross-price elasticity"). Therefore, elasticities are already standardized across studies. We use elasticity magnitude and sign as our standardized metric for synthesis. The sign of a cross-price elasticity estimate has economic significance, indicating whether a pair of products behave as substitutes (positive sign) or complements (negative); similarly, the magnitude of the elasticity indicates the strength of the relationship. Own-price elasticities are almost always negative, but the magnitude of the estimate indicates whether demand for a good is "elastic" (more negative than -1) or "inelastic" (between -1 and 0). We focus on mostly on cross-price elasticities in this section and discuss own-price elasticities in Section 4.

Synthesis method From each study and for each estimate of elasticity within the study, we extract the data source, sample size, sample period, estimation strategy, point estimate, and whether the estimate was statistically significant (where available, and either as reported or calculated from reported standard errors.).[1] These data are located in the file `data/raw/synthesis-crossprice-elasticities.csv`. We calculate the mean of the elasticity point estimates and number of results that contribute to the calculation, and we tally the number of positive and negative estimates. We plot all results for each elasticity using point estimates and their statistical significance on a plot centered around zero,[2] and we discuss the implications of the elasticity means in the section below.

Briefly, we qualitatively discuss below differences in the reported effects between studies in the context of data sources, sample size, empirical setting (sample period and

[1] Three of the five studies only provide qualitative statistical significance of the elasticity estimates.

[2] We choose zero as midpoint of our plot since our economic conclusions about the elasticity relationship change on either side of this threshold.

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geographic aggregation level), estimation strategy, and statistical significance of results. Finally, we briefly and qualitatively discuss below our certainty of our synthesis conclusions by considering the residual risk of bias for each study.

3.2. Results

Selection, grouping, and metric We extract 74 out of 135 total own- and cross-price elasticity estimates for nine plain milk types as defined by the study authors: soy, almond, coconut, other nondairy (which includes rice, cashew, coconut, flax, hazelnut, walnut, grain, pecan, and "other" milks), dairy (which includes plain fluid milk of all fat content), whole, reduced/ low fat (which includes 2% and 1% milkfat milk), skim, and skim/low fat (which includes skim and 1% milkfat milk). Flavored milk, lactose-free milk, and milkshakes are not included.

The most commonly studied milk type is soy (included in all five studies), followed by almond and the aggregated dairy category. All studies report both the compensated and uncompensated elasticities, which provide an estimate of the pure substitution effect (compensated) and both the price substitution effect and the income effect together (uncompensated) [17, p. 82]. Our synthesis focuses on the uncompensated elasticities as they provide a more complicated but potentially more realistic look at consumer behavior under a price change because they account for the impact that a price change has on a consumer's overall budget. The interested reader can find the compensated elasticity results in the data set.[3]

Synthesis Uncompensated cross-price and own-price elasticities for plant-based milk demand are shown in Figure 2, while elasticities for dairy milk demand are given in Figure 3. Estimates of the same product pairs are grouped together in individual plots, and these plots are arranged in columns by product demanded and in rows by price-change product. For example, the first column of Figure 2 shows estimates of the change in soy milk demand associated with changes in prices of soy, almond, coconut, other nondairy, dairy, whole, reduced/low fat, skim dairy, and skim/low fat milk. Contributing studies of each estimate are listed on the right of the figure. Solid points indicate statistical significance. Note that positive cross-price elasticities indicate substitute goods; negative cross-price elasticities indicate complementary goods, or goods purchased together; and zero cross-price elasticities indicate no relationship.[4]

Figures 2 and 3 show that all estimates of own-price elasticities are negative, as expected from the economic theory of normal goods like milk. We observe that estimates of more narrowly defined product types generally have larger own-price elasticity magnitudes. This pattern also aligns with economic theory, which suggests that product categories defined with lower levels of aggregation (for example, "whole milk" as opposed to "dairy") will have more close substitutes to switch to in the event of a price change.

On the other hand, few strong patterns emerge when examining cross-price elasticities. For example, the first column of Figure 2 suggests that soy milk demand increases when the price of lower fat dairy milks rises but decreases when the prices of higher fat dairy milks rise. Almond milk is a weak substitute for most of the different aggregation levels of dairy milk when prices of these products increase, except reduced/low fat milk for which it is a complement. Notably, the dairy milk elasticities shown in Figure 3 suggest that changes to plant-based milk prices have very little effect on demand for disaggregated dairy milk products.

The mean elasticities and counts of negative and positive results shown in Table 1 provide a very broad summary of results across studies. We confirm that the average of own-price elasticities are negative as expected, and the averages follow the expected descriptive behavior of own-price elasticities (e.g., broader categories like "dairy" have smaller elasticities than narrow categories like "coconut."). Soy milk has the most estimates and the most mixed results. On average, demand for soy milk decreases when the prices of alternate goods increase with the exception of the "dairy" type and lower fat dairy milks. However, the counts of negative and positive results support the trend observed in the first column of Figure 2: that the elasticity estimates with respect to changes in dairy milk prices vary widely but the balance of the estimates leans slightly toward complementarity.

[3] The compensated elasticities extracted from these studies are generally smaller in magnitude (closer to zero) than the uncompensated elasticities, which reflects the result from economic theory of normal goods that the substitution effect alone should be smaller than the substitution and income effects combined [17, p. 83].

[4] The two different cross-price elasticities for pairs of products are not necessarily symmetric, especially in the case of uncompensated elasticities, which account for both the income and substitution effects. Theory suggests that compensated elasticities, those that only account for the substitution effect of a relative price change in the two products, is more likely to be symmetric, but our synthesis data shows that estimated results do not strictly follow this symmetry.

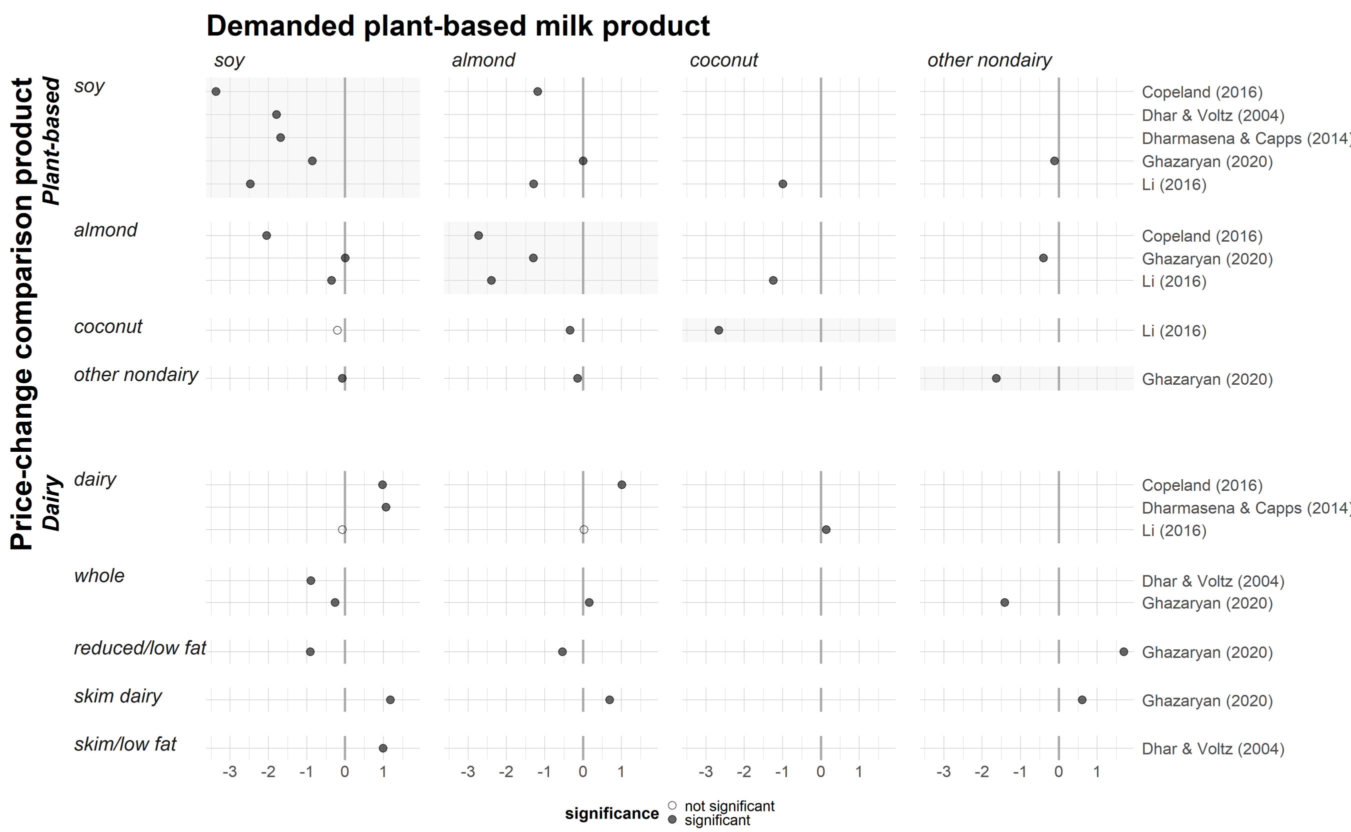

Figure 2 Uncompensated elasticity estimates for plant-based milk demand
Compensated elasticity estimates and elasticity estimates for product types not included in this synthesis are located in the final data file `data/final/synthesis-crossprice-elasticities.csv` in the repository https://osf.io/E95DP/. Panels with shaded backgrounds contain estimates of own-price elasticities. For cross-price elasticities, positive estimates indicate substitute goods, negative indicate complementary goods, and zero estimates indicate no relationship. Significance is determined by a level of $p \leq 0.05$.

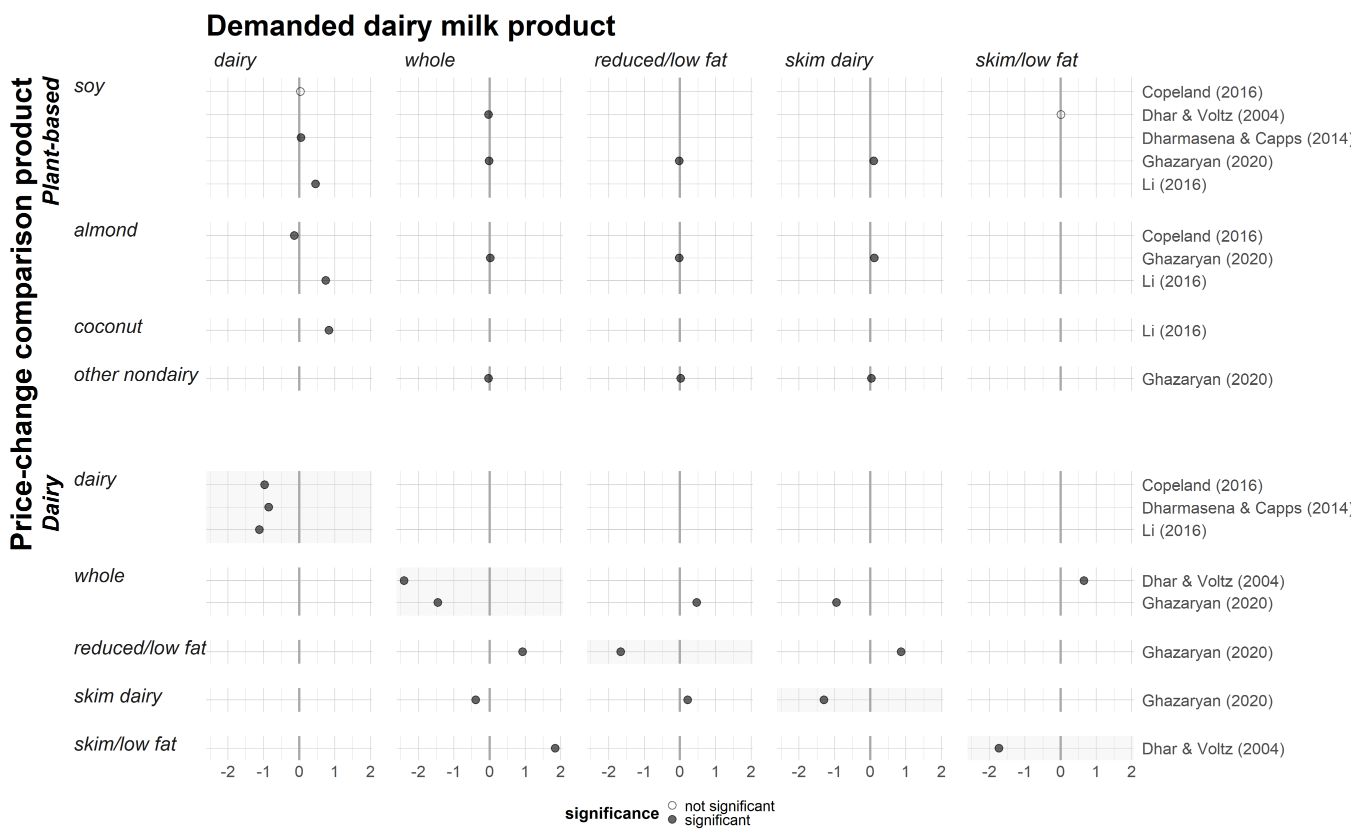

Figure 3 Uncompensated elasticity estimates for dairy milk demand
Compensated elasticity estimates and elasticity estimates for product types not included in this synthesis are located in the final data file `data/final/synthesis-crossprice-elasticities.csv` in the repository https://osf.io/E95DP/. Panels with shaded backgrounds contain estimates of own-price elasticities. For cross-price elasticities, positive estimates indicate substitute goods, negative indicate complementary goods, and zero estimates indicate no relationship. Significance is determined by a level of $p \leq 0.05$.

Table 1 Mean and negative/positive counts of uncompensated elasticities estimates

price of	demand for almond	coconut	dairy	other nondairy	reduced/ low fat	skim dairy	skim/ low fat	soy	whole
mean of almond results	-2.14	-1.24	0.30	-0.40	-0.02	0.11		-0.80	0.02
number of (-,+) results	(3,0)	(1,0)	(1,1)	(1,0)	(1,0)	(0,1)		(2,1)	(0,1)
coconut	-0.34	-2.66	0.83					-0.20	
	(1,0)	(1,0)	(0,1)					(1,0)	
dairy	0.52	0.14	-0.98					0.66	
	(0,2)	(0,1)	(3,0)					(1,2)	
other nondairy	-0.14			-1.63	0.02	0.04		-0.07	-0.03
	(1,0)			(1,0)	(0,1)	(0,1)		(1,0)	(1,0)
reduced/low fat	-0.54			1.70	-1.67	0.86		-0.91	0.93
	(1,0)			(0,1)	(1,0)	(0,1)		(1,0)	(0,1)
skim dairy	0.69			0.61	0.22	-1.30		1.18	-0.39
	(0,1)			(0,1)	(0,1)	(1,0)		(0,1)	(1,0)
skim/low fat							-1.73	0.99	1.84
							(1,0)	(0,1)	(0,1)
soy	-0.82	-0.99	0.18	-0.11	-0.02	0.09	0.01	-2.03	-0.02
	(2,1)	(1,0)	(0,3)	(1,0)	(1,0)	(0,1)	(0,1)	(5,0)	(2,0)
whole	0.16			-1.41	0.47	-0.95	0.66	-0.58	-1.92
	(0,1)			(1,0)	(0,1)	(1,0)	(0,1)	(2,0)	(2,0)

Heterogeneity in results Previous syntheses of elasticities have found that the differences in empirical setting and modeling decisions may contribute to the differences in estimates of milk elasticities, and when few results are available, caution should be exercised in forming conclusions about the influence of research design on results [18, p. 220]. Our discussion focuses on high-level observations about the studies in our sample.

Three of the included studies [3; 5; 15] use a censored regression procedure to estimate quantity demand functions, while the other two papers [2; 6] employ variations on the almost ideal demand system (AIDS) model to estimate expenditure functions. These procedures have important differences: while censored regression provides independent elasticity estimates for each pair of milks, the expenditure functions in the AIDS model estimate elasticities while accounting for correlation between the error terms in each equation. That is, AIDS models account for the unobserved impact that one product might have on another product. As such, the AIDS-estimated elasticities are generally closer to zero than those estimated with censored regression.

Censored regressions are commonly used with household choice data like the Nielsen HomeScan data, and thus data source is correlated with choice of estimation model in our synthesis. Data source influences sample size: household choice data sets generally have larger sample sizes than the city- or state-level data sets commonly used to estimate AIDS estimation models. Larger samples reduce standard errors and sampling variance. However, we do not observe any systematic differences in statistical significance between studies using different data sources or estimation methods. All studies report statistical significance for the majority of their results. In rare cases, a very small sample could bias the magnitude of the estimates; however, none of the included studies have such small samples (the smallest, Dhar et al. [2], uses weekly observations of 12 cities over 260 weeks). We find no qualitative evidence that data source plays a role in the differences between study estimates other than through its correlation with estimation model.

The collection date of the data does not create any discernible patterns in product pairs with multiple results. For example, the elasticity of soy with respect to dairy price changes is positive (indicating substituting toward soy) before 2012 [3; 15] but slightly negative in 2014 [5]. Alternately, earlier estimated dairy elasticities with respect to changes in almond milk price are negative, while later estimates are near zero. Overall, no strong temporal trends are observed. Due to the inconsistent definition of products across studies, the dairy elasticity estimates from earlier studies are not comparable to estimates from later studies and we are unable to test our hypothesis of increasing dairy demand elasticities over time. Similarly, we are unable to confirm our dairy demand estimation results because none of the studies in the synthesis analyze data after 2017 and none estimate results for whole and 2% milk combined.

3.3. Conclusions

Our synthesis results are fairly uncertain, due to the very small number of estimates for each product type's own- and cross-price elasticities as well as inconsistencies in reporting of standard errors across studies. Future research on plant-based milk demand should report standard errors to allow for quantitative meta-analysis methods. Additionally, observational studies generally suffer from residual risk of bias due to unobserved variables that affect both explanatory and outcome variables. In this context, we may be concerned about quality characteristics such as ethical reputation. The authors of each study in our sample take care to reduce the estimation bias that emerges from their specific empirical setting, but measures of quality are rarely available.[5] This potential residual risk of bias combined with the small number of estimates leads us to rate the certainty of each result as moderate and the certainty of our overall conclusions, discussed below, to be moderate-low.

Broadly, our synthesis leads us to conclude that demand for dairy milk is fairly unresponsive to changes in plant-based prices, although individual dairy milk products seem to respond to changes in prices of other dairy products. For example, price increases of middle fat content dairy milks like 1% and 2% milks seem to increase demand for both whole and skim milks, implying substitutes, while increases in price of whole and skim milks seem to decrease demand for the other respective product, indicating complements. This conclusion supports the findings of Andreyeva et al. [18]. On the other hand, demand for most plant-based milks exhibit some kind of response to increases in dairy milk prices, although the overall response is mixed across both sign and magnitude. Purchases of plant-based milks increase when the price of skim milk increases, while price increases of higher fat dairy milks are associated with a slight fall in demand for plant-based milks. The point estimates of these elasticities vary in magnitude more than those of dairy milks with respect to plant-based price changes, but the variation does not appear to be connected to any study characteristic in particular.

Overall, we find evidence to suggest a price relationship between different dairy milk types, confirming some of Ghazaryan's [6, p. 46] conclusions. However, our synthesis of estimates conflict with the author's other conclusion that plant-based milk consumers switch to dairy in light of a plant-based price change. We do not find strong evidence on average of an association between plant-based milk prices and demand for dairy milk, and the response of plant-based demand with respect to dairy prices is mixed. We discuss the implications of these conclusions alongside the results of our other analyses in Section 5 below.

4. DAIRY ELASTICITY ESTIMATION

Our final analysis looks for evidence of an increase in the own-price elasticity of plain dairy milk demand over time. Theory leads us to hypothesize that, if plant-based milks are substitutes for dairy milks, demand for dairy milk will become more responsive to changes in its own price as the number and availability of plant-based products increase over time.

4.1. Methodology

To test whether own-price elasticity of plain dairy milk has changed over time, we recover and compare price elasticities estimated for separate time blocks using monthly data from 2001-2019. We use an almost ideal demand system (AIDS) model, which has desirable theoretical and statistical properties that make it a common choice in the extensive body of research on dairy milk demand [19].

Model Our analysis estimates the parameters in a system of three demand equations: demand for plain dairy milk, for other nonalcoholic beverages, and for all *other* foods and beverages excluding products in the former two categories. We initially defined plain dairy milk to include unflavored whole, 2%, 1%, and skim dairy milks; however, due to a lack of retail price data (discussed immediately below), our final plain dairy milk category includes only whole and 2% milk. The other nonalcoholic beverages category includes

[5] We may be concerned that the unobserved ethical reputation of a brand or product might bias the demand estimates by influencing both demand as well as price. Consumer preferences for ethical characteristics influence the observed quantity purchased, but their influence only enters the statistical demand estimation through the error term. These preferences may also affect prices, one of the main explanatory variables in the estimation model, because suppliers recognize that they can increase the price of goods with strong ethical reputations.

bottled water, juice, and other beverages except plant-based milks.[6] The demand estimation procedure estimates the expenditure function of product i in month t, given in simplified form as

$$w_{it} = \alpha_i + \sum_j \gamma_{ij} \ln p_{jt} + \beta_i \ln\left(\frac{x_t}{P_t}\right) + u_{it} \qquad (1)$$

where

- w_{it} is expenditure share of product i in month t,
- p_{jt} is the price of each product j in month t,
- x_t is total expenditure in month t,
- P_t is a constructed price index such that $\ln P_t = \sum_i w_{it-1} \ln p_{it}$,
- u_{it} is the product-time specific error term, and
- $\alpha_i, \gamma_{ij}, \beta_i$ are model parameters.

We initially preregistered [11, p. 5] a plan to control for overall income and time trends in the demand model to further improve comparability across time periods. However, when we include these variables using a scaling function procedure following Gould et al. [20], diagnostics indicate that the estimation results are heavily biased and the estimated model does not satisfy the properties required for theoretically consistent demand function.[7] The AIDS model includes expenditure shares and total expenditures, so it accounts for an important part of the variation in consumption across different household incomes. While there may be remaining variation in our results due to different levels of disposable income and other factors captured by a time trend, we suspect that correcting the error may not substantially change the results discussed in Section 4.2, given that the baseline model accounts for a large amount of potential bias. Even if a model including overall income and time trends did support our hypothesis that dairy demand has become more elastic over time, the results in Sections 2.2 and 3.2 lead us to suspect that increased availability of plant-based milks may explain only a small part of that change. Therefore we conclude that the information benefit from debugging the procedure to include trends is outweighed by the estimated time cost of diagnosing the cause of the error and correcting it, and we proceed with the baseline AIDS model without trend variables as our preferred specification.

Historically, the AIDS model equations were derived to simplify the translog demand model, which is complicated to estimate and suffers from biased estimates when product prices are collinear (that is, when a linear relationship exists between the prices). The linear approximation AIDS (LA-AIDS) model replaces the nonlinear translog price index with a linear one and provides precise linearization of the underlying model when the prices of the categories are moderately collinear [21]. We check for price collinearity by examining variance inflation factors (VIF) of each explanatory variable, where a VIF value of 1 means that there is no correlation between the variable in question and the other explanatory variables. Since the VIFs of the price variables are higher than our preregistered threshold of 1.5 [11, p. 5], we proceed with the linear approximation.[8] We implement the LA-AIDS model and the seemingly unrelated regression method for estimating parameters for systems of equations using the `micEconAids` package [23; 24; 25] for the statistical programming language `R` [26].

Analysis strategy To understand changes in elasticities over time, we estimate and compare elasticities across separate time blocks of similar length chosen to: (1) exclude major US recessions, (2) exclude the 2007–2008 global food crises, and (3) place several years between blocks to ensure a substantial difference in the number and availability of plant-based milk products in each block. Our main analysis compares elasticities from January 2002–December 2006 against elasticities from January 2015–December 2019. We calculate both the compensated and uncompen-

[6] Given our interest in the relationship between plant-based and dairy milks, ideally we would include a separate demand equation for plant-based milks so that we could provide our own estimates of cross-price elasticities to incorporate into our conclusions in Section 3.2. However, we were not able to obtain data on monthly sales and prices of plant-based milks similar in scope to our dairy milk data. In our demand estimation, expenditures on plant-based milks are accounted for in the other food and beverages category.

[7] Specifically, the expenditure functions fail to satisfy the condition that they are monotonically increasing in prices in the 2015-2019 period, and residual plots indicate a strong systematic pattern that does not appear in the residual plots of the baseline model.

[8] The particular VIF threshold value of 1.5 is somewhat arbitrary. There are many rough and sometimes conflicting guidelines as to what constitutes "high" levels of collinearity that are applied when using VIF for diagnostics; in reality, the other factors in the research design should be examined alongside VIF for guidance [22]. In our context, the LA-AIDS model is constructed to handle collinearity that the fully nonlinear AIDS cannot, so we only need to determine whether *some* collinearity exists in the data.

sated elasticities[9] from the estimated demand parameters using the `aidsElast` function for the LA-AIDS model. We compare the differences in calculated elasticities using a Student's *t*-test (with a preregistered significance threshold of $\alpha = 0.10$ [11, p. 5]) on the null hypothesis that the estimates are the same in the two time blocks [7]. We conduct robustness checks of our results with two additional analyses using different choices of time blocks: one following the US Federal Reserve's definition of recessions to control for the impact of recessions on our estimates (comparing October 2001–February 2007 against July 2009–December 2019), and one with similar price trends to account for the potential impact of consumer expectations of prices on elasticity estimates (comparing January 2002–December 2006 against January 2012–December 2016).[10]

Prices The monthly price indices for the other nonalcoholic beverages category and the total food and beverage category are collected from the BLS Consumer Price Index (CPI) Urban Consumers database [27]. Following Gould et al. [20], the total food and beverage price index serves as the price index for the "other foods and beverages category."

To the best of our knowledge, there are no publicly available monthly data between 2001–2019 that report the average retail price over all plain dairy milk varieties and only dairy milk products. The USDA's Agricultural Marketing Service (AMS) produces the monthly *Retail Milk Prices* report that covers only whole and 2% milk varieties starting in 2001 [28], and there is a CPI series covering all fluid milk prices between 1946–2020 [29], which has been confirmed by personal communication with BLS researchers to include plant-based beverage milks alongside their dairy counterparts. To accommodate this data deficiency, we planned to predict average retail prices for whole, 2%, 1%, and skim plain dairy milk between 2001–2019 using wholesale "all-milk" prices[11] between 2001–2019 from the National Agricultural Statistics Service's (NASS) *Agricultural Prices* report [30] and retail price data between 1996–1998 from Mittal et al. [31], and then confirm the accuracy of the prediction using diagnostic tests. However, the results of the tests fail to meet the preregistered criteria for accuracy [11, p. 6], so we choose to follow our contingency plan to estimate the overall demand system with "plain dairy milk" defined as only whole and 2% milks in order to use the AMS retail price data [28]. We discuss the prediction and diagnostic process in more detail below.

Our ex-post prediction method begins with collecting the retail price data for whole, 2%, 1%, and skim milk products published in Appendix V of Mittal et al. [31]. These data cover the 26-month period starting in January 1996, and they were collected by Mittal et al. from Nielsen and various US state milk marketing agencies. We conduct preliminary diagnostic tests to determine the time series properties of these data. The results of the diagnostic tests show that the Mittal et al. price data are autocorrelated and level but not trend stationary: we fail to reject the null hypothesis of the ADF test ($p = 0.5431$), we fail to reject the null of the KPSS test for level stationarity ($p \geq 0.1$), we reject the null of the KPSS test for trend stationary ($p = 0.05379$), and we reject the null of no autocorrelation for the Ljung-Box tests, indicating the presence of up to four lags (all $p \leq 1.058 \times 10^{-5}$).[12]

These diagnostics indicated that an ARIMA model is more appropriate than an ordinary least squares model to predict prices from these data. We apply the `auto.arima` routine in `R`, which chooses the most appropriate ARIMA model by estimating several different specifications and reporting the results for the most appropriate model according to repeated KPSS tests (to determine the number of lag differences) and the lowest Akaike information criterion (AICc) value of iterated fitted models (to determine the autoregressive and moving average order). The routine identifies a model with a first-order difference and no mov-

[9] Uncompensated elasticities consider the price and income effects of a price change on consumer behavior, but compensated elasticities provide a clearer picture of the pure price substitution effect. Both are important for policy considerations, although uncompensated elasticities provide a more realistic circumstance. The preregistration of this project contained a typo [11, p. 5], stating incorrectly that we would calculate the "unconditional" and "conditional" elasticities for the demand equations, rather than "uncompensated" and "compensated" elasticities, respectively.

[10] Elasticities are constructed to measure the change in demand associated with a change in observed prices. However, this calculation does not capture the demand changes that might occur due consumer perception of these observed price changes. For example, a sharp change in price might lead consumers to believe that the price change is temporary; however, if prices remain high for a longer period of time, consumers may adjust by switching to lower-priced substitutes. Choosing time blocks with similar trends may alleviate differences in consumer expectations of future prices between the separate time blocks.

[11] "All-milk" price is the gross price (before deductions related to transportation, marketing, and fees) received by dairy milk producers for fluid milk with a standard fat content.

[12] All tests used a significance level of $p \leq 0.10$.

ing average or autoregressive terms as the model with the lowest AICc value. We include all-milk price as a covariate in the `auto.arima` routine. Using the results of the estimated ARIMA model, we then predict the values of average retail plain milk prices between 2001-2019 from all-milk price data between 2001-2019 using the `forecast` function in the `auto.arima` package.

We test the accuracy of the prediction by conducting the entire model selection, estimation, and prediction procedure for a subset of plain dairy milk products where actual price data are available. We predict the retail price of whole and 2% dairy milk and compare those predictions with the observed retail price data from the AMS [28]. We measure the difference between our model's fitted values and actual 2001-2019 data and determine the prediction was not a sufficiently accurate prediction of retail prices. Both the mean absolute error (MAE $=$ \$0.841 $\geq$ \$0.30) and the mean absolute scaled error (MASE $= 24.181 \geq 1$) significantly exceeded our preregistered accuracy thresholds [11, p. 6].[13] Following the contingency plan specified in the preregistration, we proceed with estimating the overall demand system using only whole and 2% milks in the plain dairy milk category, allowing 1% and skim milk to fall into the other food and beverages category; thus, the Mittal et al. price data are not used in the elasticity analysis. While this decision limits the scope of our analysis and narrows the research question that we can answer, this subset of products still accounts for a significant portion of the market, at around 75% of volume sales of the plain dairy milk category [32].

Expenditure shares Along with overall income data, expenditure data for the other nonalcoholic beverage category and total food and beverages are collected from the Bureau of Labor Statistics' (BLS) Consumer Expenditure (CE) survey public-use micro-data files on monthly expenditure between 2001 and 2019 [33]. Data are reported for individual households, and we take the average over each month's reported income and expenditures for each category.

Average household expenditures for the plain dairy milk category are constructed as the product of average retail prices (for the whole and 2% subset) and total quantity sales, divided by the number of households in the US reported by the US Census Bureau [34]. Monthly total quantity sales of dairy milk are reported by the AMS and include sales of consumer-packaged dairy milk products to consumer-facing outlets like retail stores, schools, and other institutions that sell packaged products directly [32]. The data account for all dairy milk products separately, so we aggregate the quantity sales of whole and 2% dairy milk into total plain dairy milk quantity sales. The units of these quantity figures are millions of pounds of packaged milk products, which we convert to gallons using the factor 1 gallon $=$ 8.62 pounds, following the USDA Economic Research Service's guidelines for agricultural commodity unit conversion [35].

Total food and beverage expenditures are used to calculate expenditure shares for each demand category as well as to estimate the expenditures for the all other food and beverages category. We calculated the all other food and beverages category by subtracting the expenditures of plain dairy milk and other nonalcoholic beverages from total food and beverage expenditures [20]. Expenditure shares are calculated as expenditures in that category divided by total food and beverage expenditures.

The final data set used for demand elasticity analysis is available in comma separated value format or `R` data format in the files `data/final/dairy-elast-analysis-data.csv` and `data/final/dairy-elast-analysis-data.R` in the OSF repository. All input files used in the construction of this data set are located in the directory `data/raw`. Table 2 presents summary statistics for the main variables in the estimation model.

Endogeneity Endogeneity, or bias introduced when estimating models in which explanatory and outcome variables are determined simultaneously, can affect the estimates of demand functions that include price. This issue can be solved using instrumental variable (IV) methods in conjunction with the main estimation procedure. We check for endogeneity using the `ivreg` package and routine: we estimate individual expenditure functions, then perform the Hausman test for endogeneity, and finally calculate an F-statistic to test for joint significance of the price instruments. The results of the Hausman test ($p = 0.10$) indicate that we can not reject the null that dairy price is uncorrelated with the error term, so we conclude that prices are not subject to endogeneity bias in this setting.

[13] We choose the threshold MAE $\leq$ \$0.30 to allow for roughly 10% error, according to the range of observed average prices for whole and 2% milk products. MASE is constructed as a unit-free measure of error such that MASE ≥ 1 indicates that a random walk prediction would be better than the predicting model in question. We calculate MAE and MASE using the `Metrics` package in `R`.

Table 2 Summary statistics

statistic	mean	st. dev.	median	min	max	n
dairy expenditure share	0.01	0.002	0.01	0.01	0.01	227
dairy quantity (gallon)	0.95	0.15	0.97	0.58	1.29	227
dairy price ($ per gallon)	3.33	0.29	3.29	2.74	3.88	227
all foodbev expenditure	357.61	22.26	358.62	306.86	399.88	227
other foodbev expenditure share	0.96	0.005	0.96	0.95	0.97	227
all foodbev price index ($ per unit)	2.19	0.28	2.20	1.71	2.59	227
nonalcoholic expenditure share	0.03	0.005	0.03	0.02	0.04	227
nonalcoholic price index ($ per unit)	1.58	0.12	1.63	1.38	1.72	227
income ($)	5, 346.82	745.47	5, 372.41	3, 643.33	6, 939.57	227

This table shows the summary statistics of the main variables in the dairy demand estimation model. Income and expenditure variables as per household. Units of each variable are shown in the parentheses.

Therefore, we proceed with the baseline LA-AIDS model, without using IVs.[14]

We avoid inducing endogeneity by employing the lagged Stone price index. This index corrects for the standard Stone price index commonly used in the LA-AIDS model, which has been shown to induce bias since contemporaneous expenditure shares appear simultaneously in both sides of the estimation equation [23]. The lagged Stone price index uses previous period expenditures in its construction and therefore bypasses this issue.

4.2. Results

We discuss the results of our preferred demand specification, which, to recap Section 4.1, estimates demand for whole and 2% dairy milk using the LA-AIDS model with the lagged Stone price index for the estimation periods January 2002 to December 2006 and January 2015 to December 2019. This specification includes prices, but not income or time trends, as explanatory variables. We choose this as our preferred specification after examining the pre-estimation diagnostics discussed in Section 4.1 and post-estimation diagnostics and checks for consistency with economic theory, discussed below.

Figure 4 illustrates some unusual patterns in the dairy data that foreshadow the unexpected results of our estimation. Dairy milk sales show a steady decrease over the sample period. On the other hand, dairy prices are highly variable, although in the later of our two estimation periods they follow a somewhat stable decreasing trend. These two trends align with the observations of Stewart et al. [1]. These trends may be the basis for the counterintuitive elasticity results we discuss below, since during this later period prices decrease alongside consumption. Further, the plot of dairy expenditure share suggests that it may be more heavily influenced by price during the later period than during the earlier period, which may contribute to the statistically significant and sizable positive elasticity of dairy demand that we find.

Demand model Table 3 reports the estimated LA-AIDS model, with the parameters of expenditure equation 1 for each of the three products and two estimation periods in the table columns. While the dairy expenditure equation in the early period (column 1) contains more statistically significant point estimates than all other expenditure equations, the overall fit of this equation is worse than that of the later period (column 4), as indicated by the R^2 values. The R^2 values also indicate that the model fits the later period data better than the early period. Examination of residual plots supports this conclusion, as we discuss more below. The R^2 of the expenditure functions for nonalcoholic beverages (columns 2 and 5) and other food and beverages (columns 3 and 6) suggest that the estimation model explains less of the variance for these products than for dairy milk products.

The results of the robustness check specifications (available in the file `supplementary/robustness-results.ods`) are generally qualitatively similar to the results of the main

[14] Before testing for endogeneity, we determined that lagged prices are strong instruments for contemporaneous prices, as indicated by the F-test ($p < 2 \times 10^{-16}$) for joint significance. However, we do not use these instruments in the final estimation procedure.

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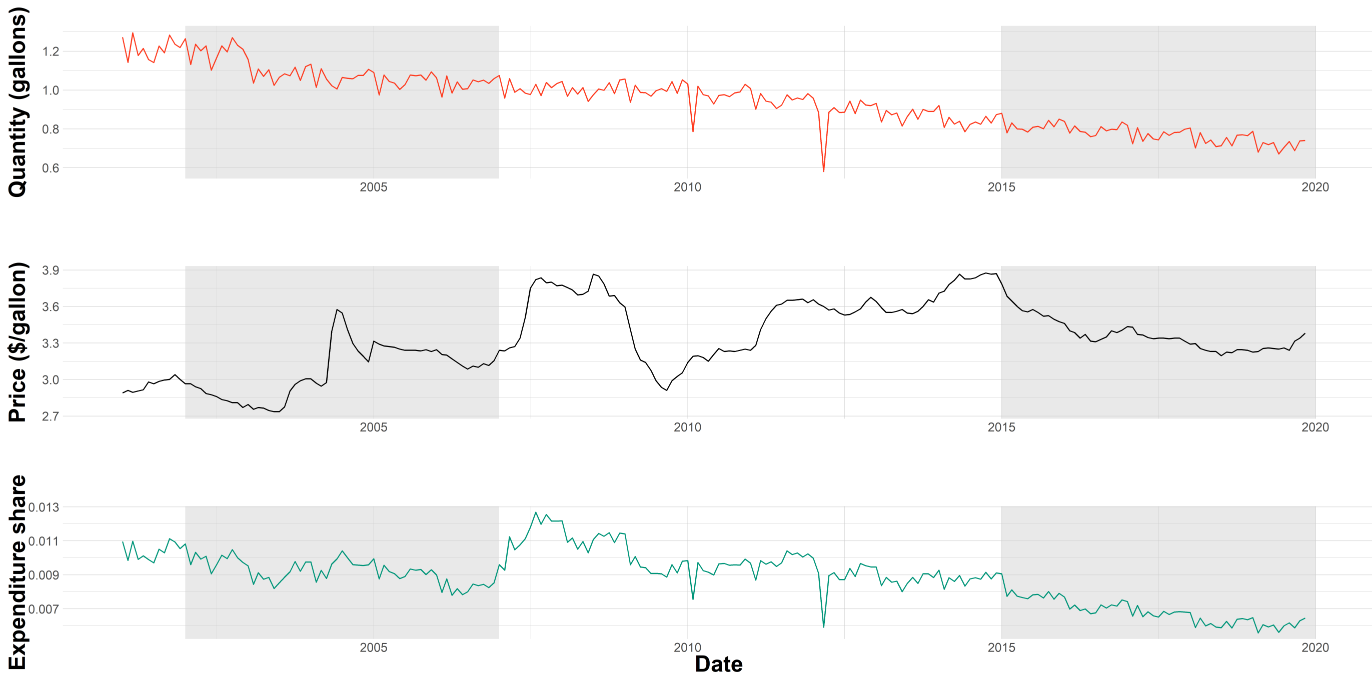

Figure 4 Dairy quantities, prices, and expenditure shares over the full sample period
The top panel displays gallons of whole and 2% dairy purchased each month per household. The middle panel shows prices in dollars per gallon. The bottom panel displays expenditure shares, which are the ratio of dairy expenditures (calculated as retail dairy price times quantity sales) to total food expenditures. The estimation periods January 2002–December 2006 and January 2015–December 2019 are shaded in grey. Supporting data and code are located in the repository https://osf.io/E95DP/.

Table 3 Parameter estimates

	2002–2006			2015–2019		
	(1)	(2)	(3)	(4)	(5)	(6)
expenditure on	dairy	nonalcoholic	other food/bev	dairy	nonalcoholic	other food/bev
constant (α_i)	0.0618 * **	−0.0959	1.0341 * **	−0.0073	0.0476	0.9597 * **
	(0.018)	(0.072)	(0.071)	(0.025)	(0.145)	(0.148)
price index (β_i)	−0.0101 * *	0.0186	−0.0085	0.0009	−0.0109	0.0100
	(0.003)	(0.013)	(0.013)	(0.004)	(0.029)	(0.029)
dairy price (γ_{i1})	0.0084 * **	0.0126 * *	−0.0210 * **	0.0159 * **	−0.0121.	−0.0038
	(0.001)	(0.003)	(0.004)	(0.001)	(0.006)	(0.005)
nonalcoholic	0.0126 * *	−0.0515 * *	0.0389*	−0.0121.	−0.1028 * *	0.1150 * **
price (γ_{i2})	(0.003)	(0.016)	(0.017)	(0.006)	(0.034)	(0.030)
other food/bev	−0.0210 * **	0.0389*	−0.0179	−0.00385	0.1150 * **	−0.1111 * **
price (γ_{i3})	(0.004)	(0.017)	(0.019)	(0.005)	(0.030)	(0.028)
R^2	0.5942	0.2208	0.1596	0.8469	0.3610	0.1611

Significance levels: $p < 0.001$ '***'; $p < 0.01$ '**'; $p < 0.05$ '*'; $p < 0.1$ '.'. This table shows the results of the LA-AIDS model with lagged Stone price index. Standard errors are shown in parentheses below each estimate.

model. We cannot unequivocally determine whether the main model better fits the data: comparing the R^2 of each equation among the different models, we find that the main model explains the late period data better than either alternative model, but the early period data are best explained by the robustness check using the Federal Reserve's defined recession periods. Since the time periods for the main model were chosen to account for unobserved bias better than arbitrarily chosen periods, we interpret these mixed results to imply that some residual bias still impacts the main model in the early period. As discussed in Section 4.1, we believe the cost of correcting for this remaining bias is greater than the benefit at this time.

Similar to many demand systems, the AIDS model parameters do not have intuitive interpretations [23]. We turn to the elasticity results before discussing the economic implications of our estimates, since elasticities are constructed specifically to provide a unit-free and straightforward interpretation of demand models.

Elasticities Table 4 provides the elasticity estimates for both estimation periods. As with the parameter estimates from which these elasticities are calculated, we observe that the statistical significance of the different estimates is mixed. Our main parameters of interest, the dairy demand elasticities, exhibit unexpected results: the own-price elasticity estimate from the early period is very small, negative, and not statistically significant, while the corresponding late period elasticity is large, positive, and statistically significant. We interpret these results very cautiously, as finding unbiased empirical evidence for positive own-price elasticities is very rare and has only been shown to affect subsistence consumption in communities experiencing extreme poverty [36].[15] However, taking the results at face value, the early period estimate suggests that there is a 0.013% decrease in the quantity demanded of dairy milk when the price increases by 1%. This effect is economically very small and indicates that the early period demand is highly inelastic. On the other hand, the later period estimate indicates that a 1% increase in dairy milk price is associated with a 1.35% increase in the quantity demanded. Thus, later period demand is elastic (in a positive direction).

The other own-price elasticities largely align with economic theory and are statistically significant. The estimates are negative, and the more narrowly defined product (nonalcoholic beverages) is much more elastic than the more broadly defined product category (all other foods and beverages). On the other hand, the cross-price elasticities between dairy milk and other nonalcoholic beverages suggest that these products are substitutes in the early period but complements in the later period. Although we find our elasticity estimates tenuous, we proceed with the preregistered hypothesis test [11, p. 6]. We reject the null hypothesis of no difference between the 2002–2006 uncompensated dairy demand elasticity of -0.013 and the 2015–2019 elasticity of 1.34 ($p = 0.0002$).

Estimation diagnostics We examine different types of residual plots to provide more insight into the unexpected dairy demand results. Figure 5 plots fitted and actual dairy expenditure shares along with the residuals for each point for an overview of the goodness-of-fit of the estimation procedure. Comparing residual plots of separately estimated time periods against the residual plot from the estimated full sample model shows slightly smaller residuals for the full model; this indicates, unsurprisingly, that more data improves the model fit and implies that we may need longer time periods or more frequently collected data to be more confident in our interpretation of results.

Comparing the residual plots over time for each sample period in Figure 6 suggests unaccounted-for trends, perhaps income and time trends, may cause the residuals to be more concentrated in 2015–2019 compared to 2002–2006. Further, the plots suggest that the 2002–2006 data may not have constant variance over the period. Ljung-Box tests and autocorrelation function plots also indicate that the price and expenditure variables are autocorrelated up to at least four lags.

Similar to residuals plotted over time, comparing the residuals against fitted expenditure shares in Figure 7 indicates differences in variance across fitted levels of expenditure. In the 2002–2006 plot, the residuals in the mid range of expenditure share levels are larger compared to the lower and upper levels. The residuals in the 2015–2019

[15] While economic theory does not *entirely* rule out the possibility of upward-sloping demand curves, researchers face a number of empirical difficulties in isolating a direct and causal positive relationship between price and quantity. Jensen and Miller [36] overcome these difficulties by conducting a randomized controlled trial in which they provide subsidies on rice purchases to Chinese households. The authors find evidence of an inverted-U shaped demand function, and they confirm the basic conditions in which these consumer behavioral patterns are expected to exist. Namely, they confirm that these behaviors arise when the product in question has very few substitutes and when the households have limited budgets but are not so poor that they only purchase staple products.

Table 4 Elasticity estimates

		2002-2006			2015-2019		
	demand for	dairy	nonalcoholic	other food/bev	dairy	nonalcoholic	other food/bev
compensated	dairy price	−0.0137	0.5225 **	−0.0120*	1.3506 ***	−0.3961.	0.0028
		(0.190)	(0.172)	(0.004)	(0.289)	(0.228)	(0.005)
	nonalcoholic	1.2839 **	−3.1761 ***	0.0620 ***	−1.7548.	−4.3516 ***	0.1491 ***
		(0.424)	(0.741)	(0.018)	(1.011)	(1.114)	(0.031)
	other food/bev	−1.2701*	2.6535 **	−0.0499*	0.4042	4.7477 ***	−0.1519 ***
		(0.510)	(0.776)	(0.020)	(0.800)	(0.992)	(0.029)
uncompensated	dairy	−0.0128	0.5057 **	−0.0212 ***	1.3428 ***	−0.4004.	−0.0040
		(0.191)	(0.174)	(0.004)	(0.287)	(0.226)	(0.005)
	nonalcoholic	1.2861 **	−3.2174 ***	0.0395*	−1.7892.	−4.3709 ***	0.1185 ***
		(0.422)	(0.737)	(0.018)	(1.014)	(1.112)	(0.031)
	other food/bev	−1.1728.	0.8860	−1.0095 ***	−0.6895	4.1333 **	−1.1249 ***
		(0.656)	(1.094)	(0.026)	(1.042)	(1.452)	(0.045)

Significance levels: $p < 0.001$ ‘***’; $p < 0.01$ ‘**’; $p < 0.05$ ‘*’; $p < 0.1$ ‘.’. This table shows elasticities for the LA-AIDS model with lagged Stone price index. Positive cross-price elasticities indicate substitutes, and negative indicate complements. Standard errors are shown in parentheses below each estimate.

appear more concentrated at higher levels of expenditure shares. These plots confirm the presence of remaining bias but suggest that this bias may not have a large effect on the estimates.

4.3. Conclusions

Our elasticity estimates for whole and 2% dairy milk reflect the unusual patterns observed in the underlying data: while economic theory suggests that demand for a good falls when its price rises and therefore own-price elasticities are always negative, we see the opposite relationship in the later period of our dairy data. However, the methodology does not fully isolate the effect of price on consumption. The observed patterns could be explained by demand for dairy milk falling for reasons other than prices (own or competing product prices). For example, changes to consumer perception of dairy milk nutritional quality, environmental impact, and ethical status may cause demand for dairy milk to fall over time regardless of the price especially as more members of younger generations begin to make the purchasing decisions for their households [37].

Omitting these factors may create residual bias in our dairy elasticity estimation, and more work would be needed to include these variables. To include variables of consumer perception, careful modeling and data sourcing will be needed, since measuring such factors of demand is notoriously difficult in quantitative analysis. We might include survey data on consumer reasons for purchasing plant-based milks, should we be able to find such survey data measured consistently during our estimation periods. In the case of income and time trends discussed in Section 4.1, we have concluded that the cost of debugging the estimation procedure to include these variables outweighs the benefit we may gain. Similarly, we may be able to account for some of the variation in variance that may occur because of unobserved trends using a statistical correction known as robust standard errors. However, since robust standard errors are not included in the `MicEconAids` package, finding an alternate computational package or manually constructing an estimation routine would not be worth the time cost.

5. DISCUSSION AND CONCLUSIONS

We have investigated the hypothesis that plant-based milks have contributed to the decline in consumption of dairy milk by examining changes in the volume of plant-based and dairy milk consumption over time; checking whether plant-based milks are price substitutes for dairy milks; and estimating changes in dairy milk own-price elasticity over time (which might increase due to the increasing presence of close substitutes). We find that consumption of

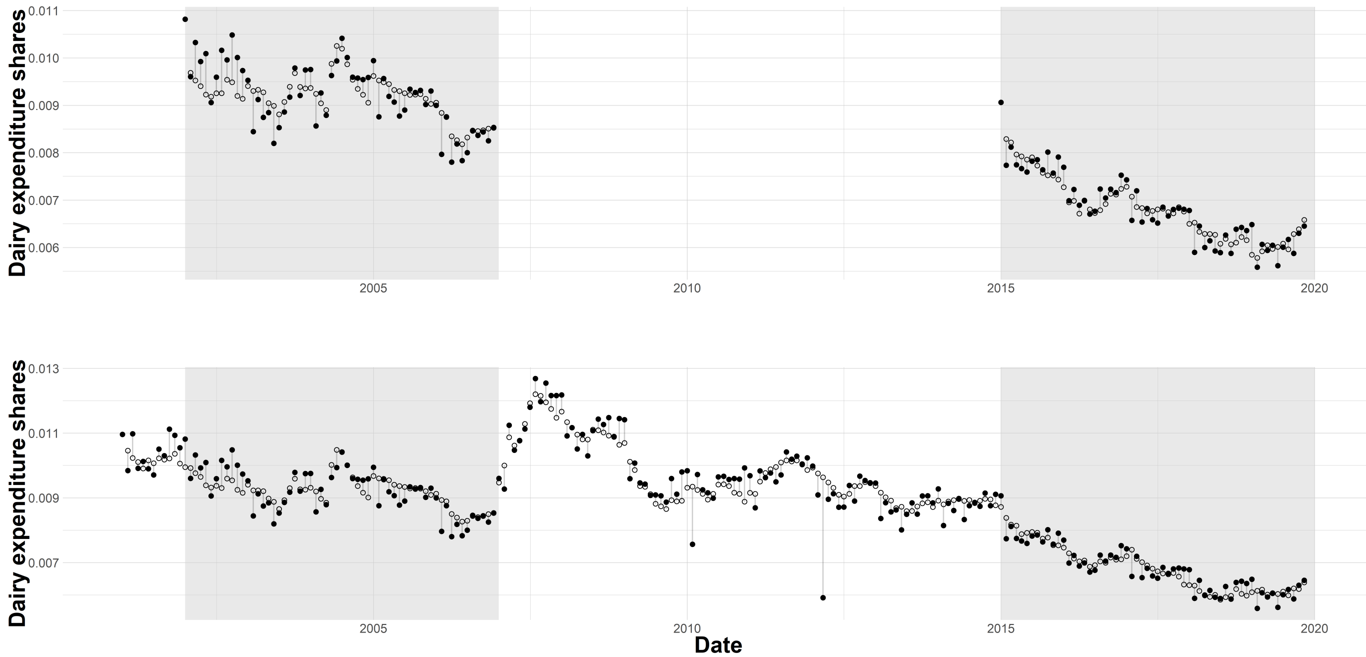

Figure 5 Fitted and actual dairy expenditure shares over time
Data and residuals from time periods estimated separately (top panel) vs. full sample (bottom panel). Actual values are indicated with hollow points, fitted values with solid points, residuals by the vertical lines connecting actual and fitted points. The main estimation periods are shaded in grey. Supporting data and code are located in the repository https://osf.io/E95DP/.

plant-based milk has increased but not nearly enough to substitute for the concomitant decline in dairy milk consumption; that dairy milk sales do not respond strongly to changes in prices of plant-based milk, indicating that on average the products are not price substitutes; and that tentative estimates suggest dairy milk elasticities have gone from very inelastic to positive, implying that dairy milk demand *increases* as prices increase. Given these findings, our conclusion is that recent declines in dairy milk consumption do not appear to be primarily caused by substitution toward plant-based milk and that any offset in dairy consumption that does occur because of plant-based consumption is more likely driven by factors other than relative prices. Further work would be needed to identify these other factors of dairy demand.

Our findings are importantly limited by data availability. Recent data on average unit prices and prices per unit of fluid volume of plant-based milks are unavailable. This limits our comparison of the volume of plant- and dairy-based milk consumption to 2013–2017. Future work to compile these data, for example by scraping data from national grocery chain websites and advertisements, would be valuable. Our certainty in the results of the cross-price elasticity synthesis are limited by the few available estimates and the lack of consistent reporting standards across studies. We tentatively find that dairy sales on average are not especially sensitive to changes in price of plant-based milks, although some estimates suggest plant-based milk sales respond to changes in dairy prices. Future work may increase the certainty of these qualitative conclusions as more estimates of plant-based milk elasticities are published.[16] However, this synthesis would also benefit from quantitative meta-analysis, which is not currently possible as standard errors of the cross-price elasticities are not regularly published and raw data are unavailable to calculate them.

Our initial dairy demand results, while tentative, raise questions that may be interesting outside of this study's overall hypothesis. For example: if not price, what factors drive consumers to switch to plant-based milks away from dairy? Can we more confidently estimate how dairy elas-

[16] The literature on plant-based milk demand continues to grow. Immediately before publication of the working draft of this study, we identified two newly published studies estimating demand elasticities for plant-based milks alongside dairy milks [38; 39].

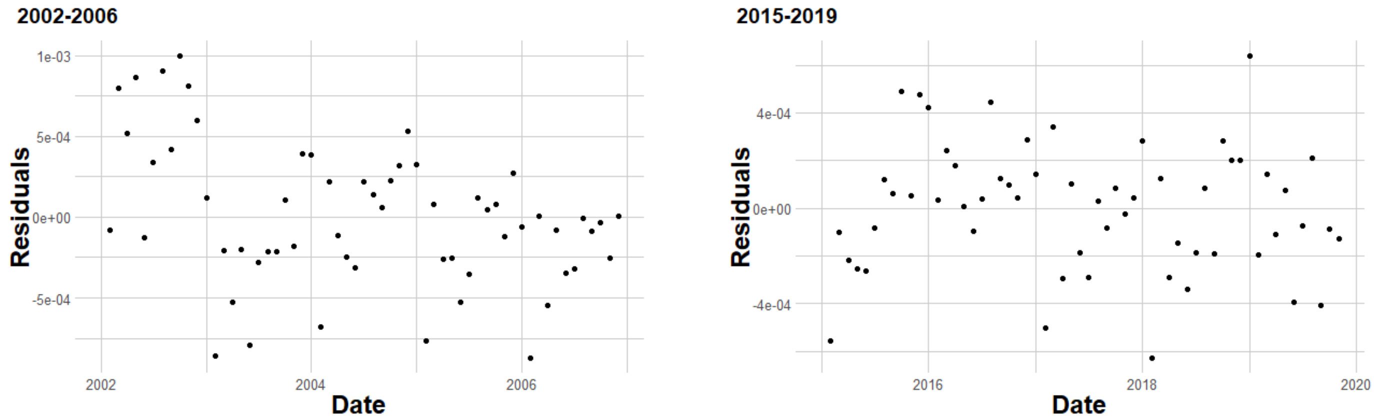

Figure 6 Dairy expenditure share residuals vs. time for each time period
Supporting data and code are located in the repository https://osf.io/E95DP/.

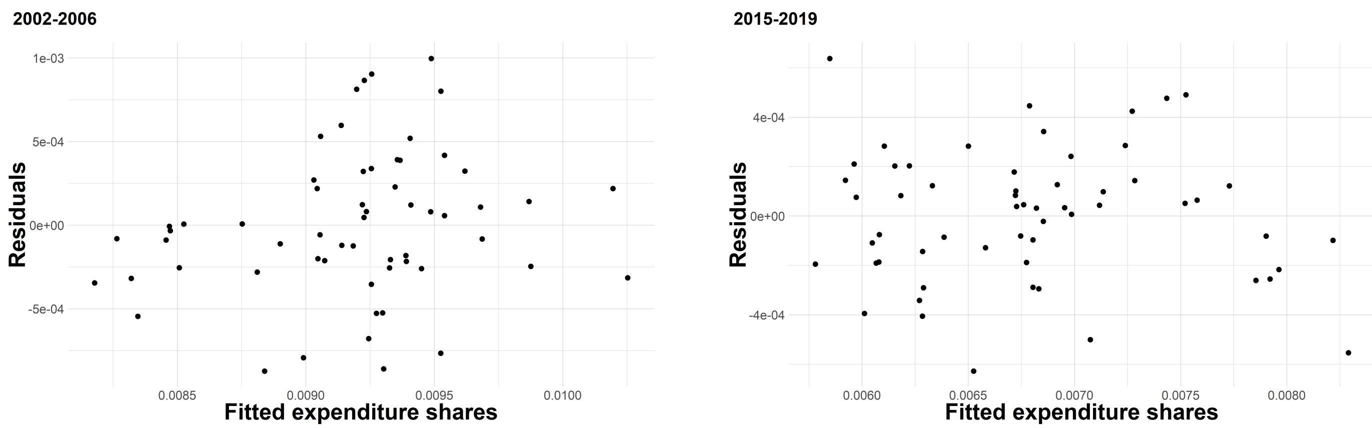

Figure 7 Dairy expenditure share residuals vs. fitted expenditures for each time period
Supporting data and code are located in the repository https://osf.io/E95DP/.

ticities have changed over time? What factors of dairy milk demand can explain the positive elasticities we find here?

Animal advocates might prioritize research to understand substitution patterns with more depth and granularity, although we advise these researchers to consider a different demand model than the LA-AIDS model. For example, future work might investigate the central question (do consumers substitute plant-based milks for dairy milks?) directly using a lesser-known substitution elasticity of demand system model [40]. Alternately, a discrete choice model of demand based on product characteristics could identify important underlying factors in the substitution decision. Both of these methods rely on the availability of grocery scanner or household panel data for both dairy and plant-based milks, and therefore may be cost prohibitive. However, especially in the case of the discrete choice demand system, researchers may be able to answer multiple important questions. They could provide an updated and comprehensive estimation of plant and dairy milk cross-price elasticities which could be used in conversations with food manufacturers or in future meta-analysis studies. They could also analyze the dairy demand elasticities in more recent years to confirm or disconfirm our unusual positive elasticity results.

Advocates may also consider applying the methods of this study to a broader range of products with plant-based alternatives. Within dairy, studies of butter and ice cream, both of which have numerous plant-based alternatives available, might be especially useful. However, studies of plant-based meats, plant-based egg substitutes or even alternatives to non-edible animal products, like leather, would all be beneficial. By studying a broad range of plant-based alternatives to animal products, advocates might develop a general notion of the impact of plant-based alternatives in reducing animal product consumption.

While perhaps less useful to advocates, our positive dairy demand elasticities present an interesting academic puzzle. Future work to confirm these results might synthesize previous estimates of dairy milk elasticities to understand how dairy milk demand elasticities have changed over time. The literature on dairy milk demand is extensive and may allow researchers to conduct a meta-analysis that accounts for time. Should these positive elasticities be confirmed, other work could investigate whether dairy milk has become a Giffen good. As the main hypothesized cause of Giffen consumption behavior is the interaction between the income effect and the substitution effect of a price change, future work to investigate the differences between uncompensated and compensated dairy elasticities might shed light on the question. Alternately, Jensen and Miller's [36] analysis establishes a specific experimental setting to test the Giffen good hypothesis. While recreating the authors' randomized controlled trial may not be feasible, future work could use quasi-experimental methods to approximate the experiment and estimate a demand function that includes a variety of income measures, which may provide insight into the Giffen behavior of dairy milk consumers.

6. DECLARATIONS

6.1. Funding

This project is funded in part by a grant from the Food Systems Research Fund (https://www.fsrfund.org/about).

6.2. Conflicts of interest

Samara Mendez and Jacob Peacock are affiliated with The Humane League Labs (THLL). THLL performs scientific research to inform animal advocacy strategy. THLL is a program of The Humane League (THL), a 501(c)(3) nonprofit organization that "exists to end the abuse of animals raised for food." THLL is editorially independent from THL, and any other funders, in reporting research results. The design, execution, analysis, interpretation, and reporting of THLL research is performed entirely by THLL staff, without oversight by other THL staff or leadership. To further mitigate potential conflicts of interest, THLL demonstrates commitment to transparency by adhering to open science practices, including public preregistration of studies and analysis plans as well as publication of supporting data, computer code, and materials for all THLL research.

6.3. Authors' contributions

Jacob Peacock and Samara Mendez conceptualized the project. All authors developed the methodology. Samara Mendez led manuscript writing. All authors reviewed and approved the final manuscript.

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