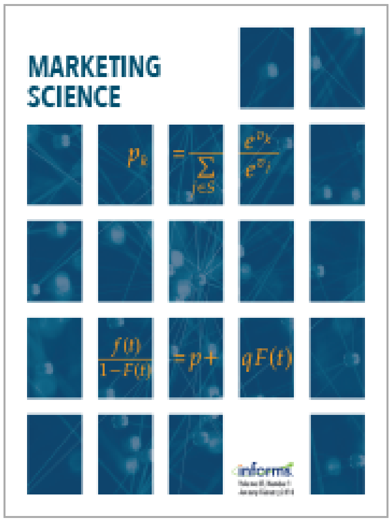


Marketing Science

Will a Fat Tax Work?

Romana Khan, Kanishka Misra, Vishal Singh

MARKETING SCIENCE
Vol. 35, No. 1, January–February 2016, pp. 10–26
ISSN 0732-2399 (print) | ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2015.0917

Will a Fat Tax Work?

Romana Khan
Graduate School of Business, Özyegin University, 34794 Cekmeköy/Istanbul, Turkey, romana.khan@ozyegin.edu.tr

Kanishka Misra
Ross Business School, University of Michigan, Ann Arbor, Michigan 48109, kanishka@umich.edu

Vishal Singh
Stern School of Business, New York University, New York, New York 10012, vsingh@stern.nyu.edu

Of the many proposals to reverse the obesity epidemic, the most contentious is the use of price-based interventions such as the fat tax. Previous investigations of the efficacy of such initiatives in altering consumption behavior yielded contradictory findings. In this article, we use six years of point-of-sale scanner data for milk from a sample of over 1,700 supermarkets across the United States to investigate the potential of small price incentives for inducing substitution of healthier alternatives. We exploit a pricing pattern particular to milk in the United States, whereby prices in some geographical regions are flat across whole, 2%, 1%, and skim milk; whereas in other regions they are decreasing with the fat content level. The prevailing price structure is determined at a chain and regional level, and is independent of local demand conditions. This exogenous variation in price structure provides a quasi-experimental set-up to analyze the impact of small price differences on substitution across fat content. We use detailed demographics to evaluate price sensitivity and substitution patterns for different socioeconomic groups. Results show that small price differences are highly effective in inducing substitution to lower calorie options. The impact is highest for low-income households who are also most at risk for obesity. Our results suggest that a selective taxation mechanism that lowers the relative prices of healthier options, such that those price changes are reflected in shelf prices at the point-of-purchase, can serve as an effective health policy tool in the efforts to control obesity.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0917.

Keywords: fat tax; obesity; elasticity; milk pricing; quasi experiment
History: Received: October 8, 2013; accepted: December 29, 2014; Preyas Desai served as the editor-in-chief and K. Sudhir served as associate editor for this article. Published online in *Articles in Advance* July 20, 2015.

1. Introduction

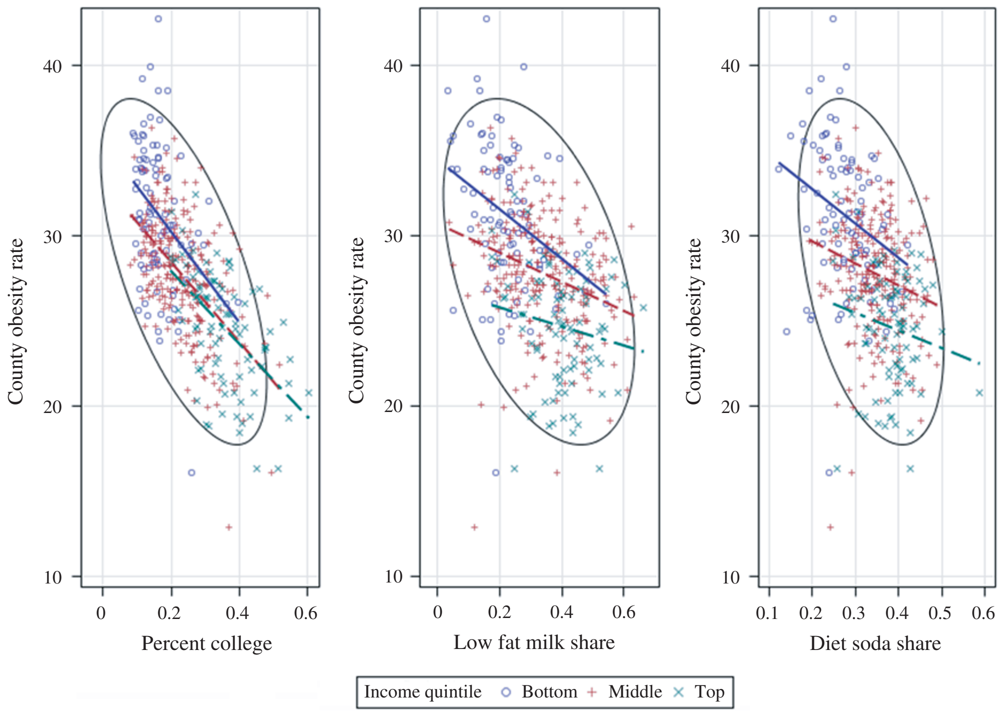
Obesity in the United States has reached epidemic proportions, with two-thirds of adults and one in three children overweight or obese (Ogden and Carroll 2010, Ogden et al. 2010). The condition shows a marked socioeconomic gradient, with significantly higher rates among minority groups and the poor (Flegal et al. 2010, Lantz et al. 1998). Data from the Centers for Disease Control and Prevention (CDC), plotted in Figure 1(A), shows the negative correlation between county level obesity rates and socioeconomic indicators, i.e., income and educational achievement. Although a multitude of environmental and biological factors mediate the observed escalation and disparities in obesity rates, growing evidence points to a chronic imbalance between energy expenditure and dietary intake as one of the leading causes (Cutler et al. 2004, Hill et al. 2003, Swinburn et al. 2011). Figure 1(A) also shows that obesity rates are lower in counties where the market shares of the reduced calorie options for milk (low fat) and carbonated beverages (diet) are higher.[1] (Although this relationship is observed across income levels, it is more pronounced for the lowest level.)

Given the complexity of the problem, reversing the rate of obesity is likely to involve multifaceted strategies at several levels (Gortmaker et al. 2011). In this paper, we investigate the potential of price-based interventions for shifting consumption toward lower calorie options (Brownell 1994). A number of academic studies have been skeptical of the efficacy of such fiscal interventions, with calls for additional empirical research to guide policy (Cash and Lacanilao 2007, Powell and Chaloupka 2009, Thow et al. 2010, Galizzi 2012). A core issue in the debate over taxation as a mechanism against obesity is whether consumers will change consumption in response to price incentives. Because category level demand for food products tends to be inelastic, with elasticity ranges

[1] Figure 1(B) shows the correlation matrix for obesity rates, socioeconomic characteristics, and food consumption choices.

Figure 1 **Obesity Rates, Socioeconomic Characteristics, and Consumption Patterns**

(A) Correlation of county level obesity rates with education, income, and market shares for low fat milk and diet soda. Obesity rates data is from the BRFSS survey conducted by the Centers for Disease Control and Prevention (CDC). Obesity rates are negatively correlated with education, income, and market shares for the lower calorie options (p-value < 0.001 for all correlations).



(B) Correlation matrix for county level obesity rates, socioeconomic characteristics, and market shares for the lower calorie options in milk and diet soda.

	County obesity rate	Percent college	Median income	Low fat milk share	Diet soda share
County obesity rate	1				
Percent college	−0.64	1			
Median income	−0.56	0.70	1		
Low fat milk share	−0.44	0.53	0.46	1	
Diet soda share	−0.42	0.51	0.49	0.84	1

$p < 0.001$ for all correlations.

between −0.27 and 0.81 (Andreyeva et al. 2010), previous empirical studies have generally concluded that small taxes are unlikely to alter purchase behavior (Kuchler et al. 2004, Finkelstein et al. 2010). By contrast, results from controlled experiments show that relative price reductions on lower calorie options are highly effective in shifting demand toward them (Epstein et al. 2010, 2012; French et al. 2001, French 2003). However, a potential problem with the experimental work is that these studies are conducted with small nonrepresentative populations. The objective of this article is to fill this gap in the literature and demonstrate the potential of price-based policy interventions using large scale field data.

To understand the apparent discrepancy in findings across approaches, a few aspects of current tax policies on soft drinks and snacks merit mention.[2] The current levels of state taxes are significantly lower than the price manipulations in controlled experiments (Epstein et al. 2010, French et al. 2001, French 2003). Furthermore, since the taxes are generally levied on the entire product class (e.g., carbonated beverages) rather than on specific items, consumers have limited incentives to substitute within the category (e.g., regular to diet soda). Finally, taxes are usually in the form of post-purchase sales taxes rather than reflected in shelf prices where they are

[2] As of 2014, soda taxes are currently in place in 34 states and Washington, DC, with an average tax rate of 5.2% (www.bridgingthegapresearch.org).

more likely to impact the purchase decision (Chetty et al. 2009).

In this article, we use six years of point-of-sale scanner data for milk from a sample of over 1,700 supermarkets across the United States to investigate the potential of small price incentives for inducing substitution to lower calorie alternatives.[3] We exploit a pricing pattern particular to milk whereby, depending on the geographical region and retail chain, prices across whole, 2%, 1%, and skim milk are either the same (flat) or increasing with fat content (nonflat). Whether a particular retail outlet charges flat or nonflat prices is independent of local demand conditions. This exogenous variation (i.e., not correlated with underlying consumer preferences) provides a quasi-experimental set-up to identify price-induced substitution patterns across fat content.

We find that where prices are flat, i.e., equal across alternatives, the market shares for the high calorie options are significantly higher, particularly in low income areas. With small price differences between the options, we observe a shift in market share toward the lower priced, lower calorie option. The majority of these shifts in demand are achieved with a price difference of just 10% between whole and 2% milk (i.e., approximately 27 cents per gallon). For policy makers debating a fat or sugar tax, this is important because the general conclusion in the existing literature is that a tax of at least 20% (and as high as 50%) is needed to alter consumption behavior (Mytton et al. 2012). The shift to the lower calorie option is particularly strong among low income groups who are also most at risk for obesity. The large discrepancy in market share between high and low income observed under flat prices diminishes as the premium of whole milk over the lower calorie 2% milk increases, and becomes insignificant at a price premium of 15%. Our results suggest that small price differences at the point-of-purchase can be thought of as a nudge (Thaler and Sunstein 2008) to induce substitution to lower calorie options, particularly among at risk low income households.

Whereas our results are consistent with previous experimental work, the nature of the data and the evidence merits attention. Experimental studies are typically conducted in limited settings (e.g., labs or price manipulations in vending machines and cafeterias) and the interventions are studied for a short duration. How consumption behavior will change in response to a tax in the long run cannot be ascertained from these experiments. Our analysis, on the other hand, has the advantage of a true field setting in nationwide markets, observed over several years. What our results establish in a robust manner is the impact of a permanent price change, i.e., mimicking a tax based on fat content, measured over an extended time period. Measurement of the impact of permanent price changes, rather than the outcomes of temporary price changes, is often cited as a critical information need for implementing fat taxes (Cash and Lacanilao 2007, Powell and Chaloupka 2009, Thow et al. 2010, Galizzi 2012).

The analysis presented in the paper supports a selective taxation mechanism designed to induce substitution between options within a narrowly defined product category (e.g., baked versus fried potato chips). This tax should be imposed as an excise tax so that it is reflected in the shelf price at the point-of-purchase, rather than a post-purchase sales tax where it becomes less salient in the decision process (Chetty et al. 2009). The regressive impact of a tax on food (Chouinard et al. 2007, McGranahan and Schanzenbach 2011) is mitigated because the price difference required is small, and the tax is designed to shift choices within a category rather than to discourage consumption of the category as a whole. In a secondary analysis, we examine the welfare implications of altering the relative prices of products while retailer profits remain unaffected. Our analysis shows the inherent trade-offs for different segments of society from such a tax: While economic losses are higher for low income consumers (since they consume a higher proportion of the high calorie options), the health benefits from shifting to the lower calorie option outweigh these costs, resulting in a net welfare gain at every income level.

The rest of the article is organized as follows. Section 2 describes the data used in the study, including features of the milk industry. Section 3 presents the main findings of the paper under various model specifications. Section 4 presents a supplementary analysis to understand the welfare implications of a hypothetical fat tax. The policy implications of our findings and the caveats are discussed in §5.

2. Data

2.1. Retail Scanner Data

The cornerstone of our empirical strategy is comprehensive scanner data provided by IRI (Bronnenberg et al. 2008). The data covers a period of six years, from 2001 to 2006. We observe weekly sales, price, and promotion information for each Universal Product Code (UPC) at the store level. There are a total of 1,708 stores belonging to 101 supermarket chains. There are 447 counties represented in the data, the population

[3] We acknowledge that lower fat and other "diet" options are not necessarily healthier. In general we want to remain agnostic about which is the healthier option (which is for health/nutrition professionals to assess), and focus on showing that price based instruments can be effective in shifting demand between high versus low calorie options.

of which accounts for approximately 50% of the total U.S. population.

The customer base of each store is profiled with an extensive set of demographic variables using zip code level data from the U.S. Census. The demographic profiles show extensive variation across stores in characteristics such as age, income, education, ethnicity, and population density. Summary statistics are reported in Figure 1 in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0917). We collected additional data to characterize local competition and cost factors. This includes the median local hourly wage, the total number of grocery retailers within five miles of each store, and the number of discount grocery retailers (e.g., Walmart Supercenter) within 10 miles of each store. We use a larger radius to measure competition from discount stores since they typically have a larger trading area than regular supermarkets.

2.2. Milk Category

Milk is a ubiquitous commodity sold at four major fat content levels: whole (3.5% fat), 2%, 1%, and skim (less than 0.5% fat). The category is dominated by retailer private labels that account for over 80% of the market share. There are a large number of UPCs representing various brands, sizes, packaging, and fat content. The volume-based market shares by various attributes are as follows:

- Fat content: Whole (31.5%), 2% (34.4%), 1% (15.7%); Skim (18.3%);
- Brand: Private label (80.5%), National brands (19.5%);
- Size: 128 oz (79.3%), 64 oz (20.7%);
- Packaging: Plastic jug (94.3%), Carton (5.7%).

Our analysis uses the store level sales and price data of private label plain milk in the 128 ounce plastic jug at the four major fat content levels. These four products represent 67% of the total volume share of plain milk. We do not include organic, lactose free, and other variants as they are a small share of the market.

2.2.1. Pricing of Milk in the United States. Dairy pricing in the U.S. comprises a complicated combination of market forces and various government regulations. Approximately two-thirds of the total milk in the U.S. is regulated through federal milk marketing orders (FMMO) that were established after the Great Depression. FMMOs set the minimum farm prices of milk that processors and manufacturers must pay to the farmer depending on one of 10 geographic regions (Schnepf 2012). In addition, certain large milk producing states such as California (which accounts for approximately 20% of the milk produced in the U.S.) operate under their own state regulations rather than federal rules.

Whereas prices at the retail level are largely unregulated, they display particular pricing patterns based on chain and geographic region. In approximately one-third of stores, prices are equal (flat) across whole, 2%, 1%, and skim milk. Prices at the remaining stores span an array of nonflat structures that share two key features: (1) Whole milk is either the most or one of the most expensive types (this fails to hold in only 3.2% of observations); and (2) Prices are generally increasing with fat content.[4] Figure 2(A) maps the geographical distribution of retail stores that charge flat or nonflat prices. Figure 2(B) provides examples of the distributions of whole and 2% milk price for four cities. In flat markets, across the six years of data there is almost no difference in price distributions, whereas for nonflat markets the price distribution for 2% milk is shifted lower than whole milk. Our empirical strategy relies on this variation to analyze the impact of small price differences on consumption choice and substitution patterns across fat content.

2.2.2. Factors Accounting for Variation in Price Structure Across Stores. Given the variation in price structure across retailers, a question to address is what drives the retailer's decision to offer flat versus nonflat prices. The observed price structure could be driven by factors such as underlying demand characteristics, competition, actions of downstream processors, regulations, and chain policy. It will be problematic to directly compare outcomes between flat and nonflat pricing structures if this decision is based on the underlying demand characteristics at the store level.

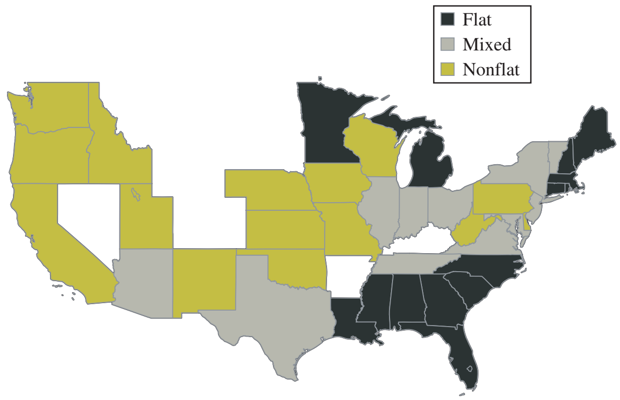
We conduct several analyses to understand what accounts for the variation in pricing patterns across stores. Figure 3(A) compares the demographic profiles served by flat versus nonflat pricing stores. We find no significant differences in any of the characteristics of the customer base. Comparisons of the competitive store environments show no significant differences in the number of competing retailers and large discounters. The difference in wage rates is statistically significant, but the economic significance is small.

Because the price premium of whole (i.e., over 2%) milk is an indicator of whether a store is flat or nonflat, we regress the price ratio of whole to 2% milk on demographics that capture local demand characteristics, measures of the competitive environment, regional fixed effects for FMMOs, and chain-specific fixed effects. None of the included demographic or competitive variables have a significant

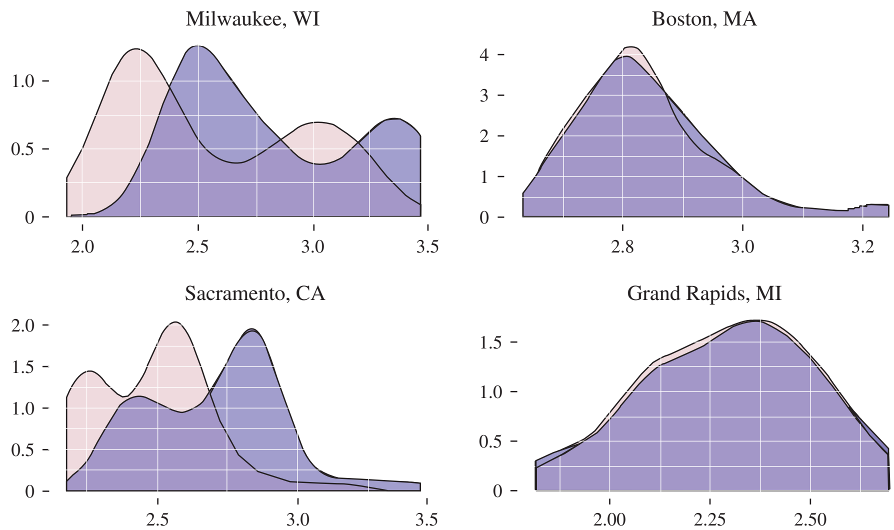
[4] Increasing prices with the level of fat content reflect the underlying wholesale costs of milk and the process by which milk is produced. The fat content of unprocessed raw milk varies with factors such as the breed of cow, the weather, and the cow's feed. After raw milk from different sources is combined, the milk fat is separated from the milk liquid. The components are then reconstituted to produce the standardized milk found at grocery stores. The cost of whole milk is highest because the value of butterfat exceeds the value of the liquid component.

Figure 2 Geographic Variation in the Pricing of Milk Across the U.S.

(A) Geographic distribution of flat and nonflat price structure. In mixed states, both flat and nonflat pricing stores are present, but price structure is consistent across stores within a chain.



(B) Distributions of weekly milk prices for selected cities in flat and nonflat markets. Prices are in dollars per gallon for whole milk (dark) and 2% milk (light) from 2001–2006. In Boston and Grand Rapids, there is a complete overlap in the distribution of whole and 2% milk prices.



effect (see Table 1 in the online appendix). We also conduct a variance decomposition, reported in Figure 3(B), to show how much of the explained variance is accounted for by each factor. The demographic and competitive environment of the stores has limited explanatory power, with chain and marketing order fixed effects explaining almost all of the variance. If the decision to charge flat or nonflat prices were based on the underlying demand conditions, we would expect retail chains to vary their strategy across stores based on the demographic or competitive situation facing the stores. We find no evidence for this in our data.

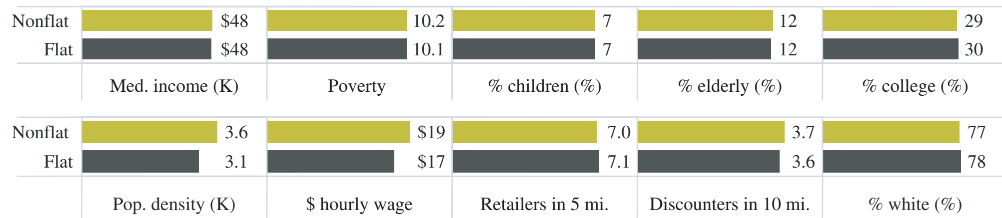
We also investigate the extent to which the price structure is consistent within a chain. For each chain, we compute the proportion of its stores that have flat prices; a value of 1 indicates that all of the chain's stores are flat, while a value of 0 indicates that all of the chain's stores are nonflat. Figure 3(C) plots the distribution of this measure; the peaks in the distribution at the extremes of 0 and 1 indicate that for the majority of chains price structure is consistent across its stores. The distribution of this measure at the chain-state level shows that consistency in pricing structure increases when measured within a state.

To verify that the pricing structure of flat/nonflat is not a special feature of our store level data, we collected prices and sales for milk from the United States Department of Agriculture (USDA) for several U.S. cities. The USDA data matches the IRI store level data quite accurately in terms of both pricing structure as well as relative market shares. Of the 29 cities surveyed, 14 have flat prices at the largest chain store. Moreover, in all of these cities, the second largest chain retail store also has flat prices.[5]

[5] City level retail pricing data from the USDA (http://apps.ams.usda.gov/USDAMIB/Download/DownloadFile.aspx).

Figure 3 (Color online) Flat versus Nonflat Price Structure

(A) Demographics in flat and nonflat markets

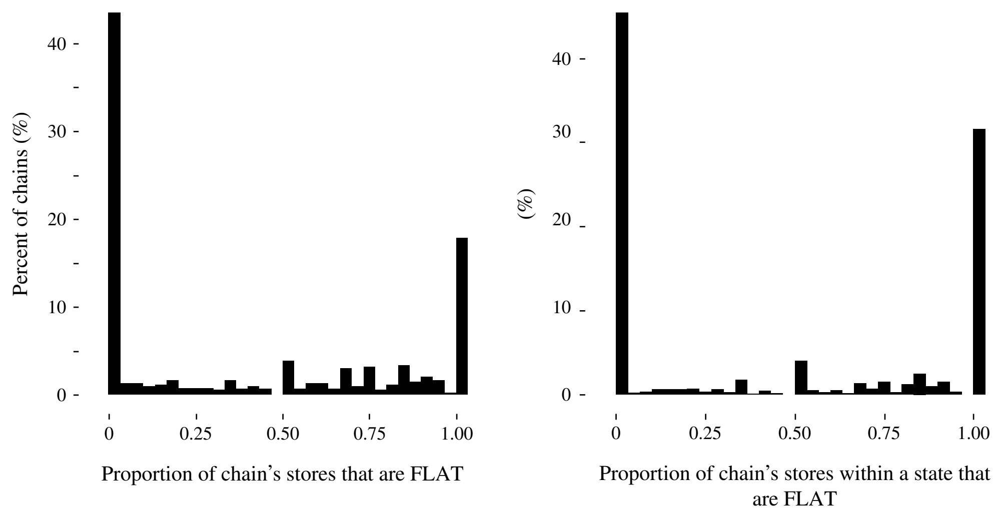


Note. None of the differences are significant at the 0.05 level, except hourly wage.

(B) Variance decomposition: Dependent variable is the price ratio of whole to 2% milk. The table shows the percent of explained variation accounted for by demographics, competitive factors, milk marketing order fixed effects, and chain fixed effects.

% explained variance accounted for by:	(%)
Demographic characteristics: Median income, % children, % white, % college, popn. density	0.16
Competitive environment: Wage, all retailers in five miles, discount retailers in 10 miles	0.32
Marketing order fixed effects	15.44
Chain fixed effects	84.07

(C) Distribution of "percent of stores with flat prices" within a chain, and within a chain-state. The majority of chains are either always flat or always nonflat, with fewer chains adopting mixed policies.



Our analysis suggests that the choice of flat versus nonflat pricing structure is a chain policy at the state level, rather than a store level reaction to local demand conditions. Flat pricing appears to be a form of price lining, i.e., the practice of charging the same price for a set of products to simplify the pricing decision when the products in question are very similar. Nonflat pricing appears to be a form of cost-based pricing, as the retail prices reflect the underlying wholesale costs. In §3, we address how the price structure impacts product choice.

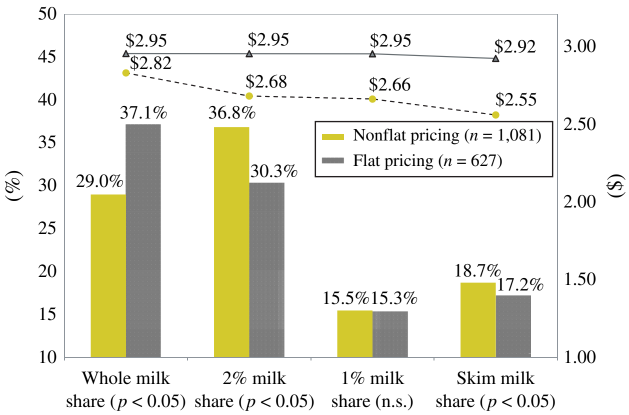
3. Empirical Analysis and Results

3.1. Descriptive Analysis

We begin with summary results to compare the market shares for whole, 2%, 1%, and skim milk under flat and nonflat pricing. As seen in Figure 4, the pricing structure has a significant impact on market shares. Where prices are flat, whole milk has the highest market share (37%). Under nonflat pricing, the price of whole milk is on average 14 cents (5%) higher than the price of 2% milk. This price difference is accompanied by a significant drop in market share of whole milk from 37% in flat pricing stores to 30% in nonflat pricing stores ($p < 0.05$). Most of the substitution is towards 2% milk, the closest substitute in terms of fat content, which sees a significant increase in market share from 29% in flat pricing stores to 37% in nonflat stores. We find no significant difference in the shares for 1% and skim milk across the two formats.

3.1.1. Impact by Income Groups. As noted in §1, obesity rates in the U.S. are significantly higher among

Figure 4 (Color online) Impact of Flat versus Nonflat Pricing: Summary Statistics



Notes. Average market shares and price per gallon by milk type in flat and nonflat pricing stores. p-values represent the significance level for a t-test of equal share in flat and nonflat stores (n.s. indicates not significantly different at the 10% level).

lower socioeconomic status households. Figure 5(A) shows the differences in the market shares of milk between flat and nonflat markets for the lowest and highest income quintiles. We first note that the share of whole milk (the higher calorie option) is larger for low income consumers in both flat and nonflat markets. Second, in nonflat markets, whole milk shares are lower for both income groups, but the reduction is significantly larger for the low income quintile.

We also analyze carbonated beverages which serves as a benchmark because there are no price differences between regular and diet soda within a brand, and promotions are coordinated. Figure 5(B) shows the distribution of market share for diet soda for the highest and lowest income quintiles in flat and nonflat markets. As observed for milk, the share of the lower calorie option, diet soda, is lower in low income areas. We also observe no differences in market share between flat and nonflat markets. This is important because it suggests that there are no unobserved taste differences for lower calorie products in nonflat markets, rather the reason we observe lower shares of whole milk in nonflat markets is because of the pricing structure.

Figure 5(C) plots the correlation between income and college education and the shares of whole milk and diet soda for each store in the data. As income level and education increase, the shares of whole milk decrease and the share of diet soda increases. At lower income and education levels, there are significant differences in whole milk share between flat and nonflat markets. This difference diminishes and disappears as income and education increase. For diet soda, however, there are no differences in market share between flat and nonflat markets.

In summary, Figure 5 shows several patterns that are pertinent to policy. First, there are systematic differences in consumption based on socioeconomic characteristics. Mirroring the higher incidence of obesity at lower income levels, we also observe higher consumption of the high calorie option at the lower income level. Note in particular that when prices are equal across products, low income households are significantly more likely to consume the high calorie option. Finally, there is a large shift in demand toward the lower calorie option when its relative price is lower, particularly for the lower income consumers.

3.2. Regression Analysis

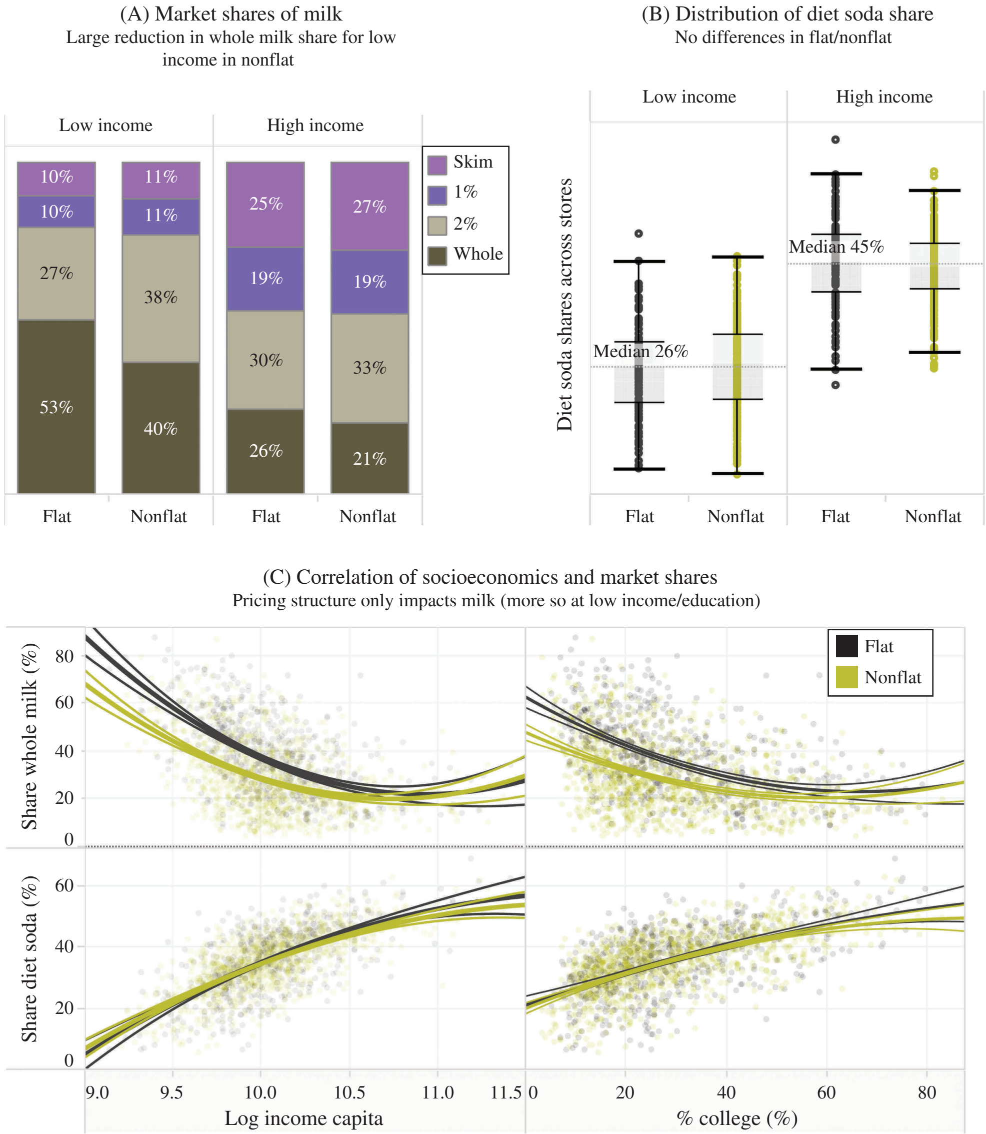
The discussion above suggests that variations in pricing structure lead to significant changes in market share for whole milk. To formalize this, we estimate a series of regression models where the focal outcome variable is the market share of whole milk in each store.[6] We use the logit transformation of whole milk share S^W as the dependent variable: $\ln(S^W/(1-S^W))$, which rescales market share from the (0, 1) interval to the real line.

3.2.1. Own and Cross Price Elasticity for Fat Content. In Model 1, the independent variables are the prices of whole, 2%, 1%, and skim milk, and demographic controls.[7] Figure 6(A) shows the results of this regression (see Online Appendix Table 2 for estimates of control variables). The price coefficients indicate that an increase in whole milk price decreases its share, whereas increases in the prices of lower fat substitutes result in higher shares for whole milk. The parameter estimates are used to compute average price (own and cross) elasticity. Evaluated at the mean, the own price elasticity for whole milk is −3.14, implying that a 1% increase in whole milk price will reduce its share approximately 3%. The closest substitute for whole milk is 2% milk, with a cross price elasticity of 1.14, whereas 1% and skim milk are weaker substitutes. This is consistent with the summary analysis in

[6] We take the most conservative approach and use the aggregated store level market share for analysis. Whereas the data is observed at the store-week level, there is a limited time-series variation in the *relative* prices and shares of milk within a store. In §3.3, we show that the parameter estimates are comparable regardless of level of data aggregation.

[7] This specification does not include chain or location fixed effects. As shown in §2.2.2, the variation in price structure is explained primarily by chain and location fixed effects. This is further demonstrated in Figure 2(A) which maps the geographic consistency in pricing structure, and Figure 3(C) which shows that price structure is consistent within a chain, and even more so within a chain-state. When chain and location fixed effects are included, they absorb most of the variation in the relative price, so that the price coefficients diminish and become insignificant. This is because there is little variation in (relative) prices after controlling for chain and location fixed effects.

Figure 5 **Impact of Flat versus Nonflat Pricing, by Socioeconomic Characteristics**



Notes. High and low income refers to the top and bottom income quintiles based on per capita income. Key message: (1) Impact of pricing structure higher for low socioeconomic classification (SEC), (2) Shares of soda suggest no systematic taste differences between flat and nonflat markets.

Figure 4, where the majority of movement in market share of whole milk under nonflat pricing is to the 2% option.

3.2.2. Nonlinearities in Response. Because the response to a relative price premium (or discount) could vary in a nonlinear fashion, we estimate a second model where we use the price ratio of whole to 2% milk (the closest substitute) to create a sequence of dummy variables. These variables indicate the level of the price premium for whole milk over 2%: No price premium (flat), up to 5%, 5% to 10%, 10% to 15%, and greater than 15%. This specification also allows for the possibility that consumers may respond to a price difference only after it exceeds a certain threshold. The results for Model 2 in Figure 6(A) show that as the premium of whole milk over 2% milk increases, the market share of whole milk falls (see Online Appendix Table 3 for estimates of control variables). However the response is highly nonlinear, with a decreasing marginal impact of increases in the price premium. The majority of the shift in market share away from whole milk is achieved with a nominal price difference of approximately 10% (about 27c per gallon).

Finally, since the response to price differences is likely to vary with demographic characteristics, we estimate a modification of Model 2 by interacting the level of the price premium with income. This is of particular interest given the higher prevalence of obesity among lower income groups (Ogden and Carroll 2010). We create a second set of dummy variables based on income quintiles and interact these

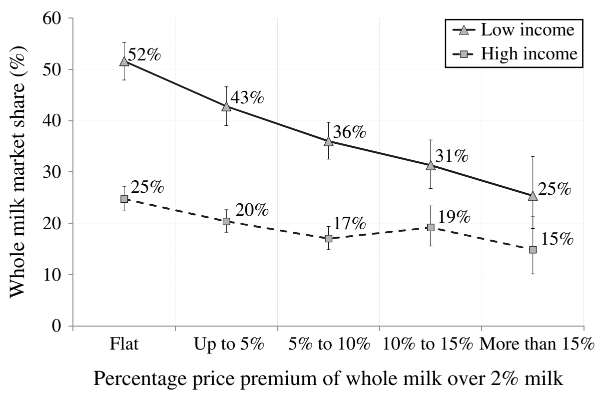
Figure 6 Impact of Flat versus Nonflat Pricing: Regression Results

(A) Parameter estimates for models 1 and 2 show the changes in whole milk share due to price differences. Model 1 results are used to estimate own and cross-price elasticity estimates for whole milk. Model 2 results are used to estimate whole milk market share at different levels of the whole milk price premium (with 95% confidence intervals).

Dependent variable: ln(Whole milk share/(1 − Whole milk share))				
	Model 1		Model 2	
Price parameter	Parameter estimates	Implied elasticity of whole milk	Parameter estimates	Implied whole milk share [95% C.I.] (%)
Prices charged				
Whole milk price	−1.61 (0.11)**	−3.14 (0.22)**		
2% milk price	1.20 (0.21)**	1.14 (0.20)**		
1% price	0.95 (0.15)**	0.40 (0.06)**		
Skim price	−0.08 (0.13)	−0.04 (0.06)		
Whole milk price premium				
Flat			−0.59 (0.03)**	36 [35, 37]
Up to 5%			−0.86 (0.03)**	30 [28, 31]
5% to 10%			−1.20 (0.03)**	23 [22, 24]
10% to 15%			−1.27 (0.05)**	22 [20, 24]
More than 15%			−1.60 (0.09)**	17 [14, 19]
Controls:	*Income, education, race, age, and density*		*Income, education, race, age, and density*	
R-square	0.77		0.76	
Number of observations	1,708		1,708	

Note. Standard errors are in parentheses.
**, Significant at 5%.

(B) Whole milk market share at each level of the price premium for whole over 2% milk, by income group. Estimates are based on Model 3 regression results (full results in the online appendix). High- and low-income refers to the top and bottom quintiles based on per capita income. Vertical bars show 95% confidence intervals.



with the previously defined set of price ratio dummy variables. In Figure 6(B), we use the results of this model to plot the implied market shares of whole milk for the lowest and highest income quintiles at different levels of the whole milk price premium (see Online Appendix Table 4.1 for parameter estimates). Under flat prices, the discrepancy between income groups is large; whole milk share for the low income group (52%) is more than double the high income group (25%). As the whole milk premium increases, the share for both income groups falls, but the response is stronger for the lower income quintile. At a premium of 5%–10%, the market share for low income falls from 52% to 36%, whereas for high income it falls from 25% to 17%. The discrepancy between income groups continues to fall as the premium increases, and is statistically insignificant with a premium of more than 15%.

Whereas our main interest is in understanding how response to the price ratio varies with income, there are also likely differences in response based on other demographics. Online Appendix Table 4.2 shows the results of Model 3 with interactions between the demographics and an indicator for flat pricing. The results show that the elderly have a higher share of whole milk where prices are flat. The response to flat versus nonflat does not appear to vary with the other demographics.

3.2.3. Discussion. The market share changes and elasticity estimates presented here are higher in magnitude compared to those reported in previous research for milk (Chouinard et al. 2007, Gould 1996) and food products in general (Andreyeva et al. 2010). For example, previous research based on dairy data concludes that even a 50% tax would have a limited impact in altering consumption behavior (Chouinard et al. 2007). We note two key differences in our analysis: First, our identification relies on cross-sectional variation in price structures across geographical locations as opposed to time series movements in price within stores. Thus, rather than relying on weekly price fluctuations to estimate price elasticity, our approach more closely mimics the impact on consumption behavior due to a permanent price change across options. Second, we focus on within category elasticity (i.e., substitution between products in the category) which tends to be significantly higher (Bijmolt et al. 2005). In other words, consumers are more likely to switch between alternatives within a category (e.g., different brands of chips) due to price changes, rather than change the level of consumption. These differences, in part driven by data limitations in previous research, are significant because evaluating the feasibility of price based instruments such as taxes or subsidies critically depends on price elasticity estimates.

3.3. Robustness Checks

To demonstrate the robustness of our findings, we conduct several further analyses that consider product selection, endogenous prices, non-Gaussian error shocks, and different levels of time aggregation. We discuss each of these below.

• Product selection: Our main results are based on analysis of private label milk which captures approximately 75% of the volume of milk sold. To check robustness to the selection of milk, we replicate the results using the full set of products, including regional and national brands. Note that the price differential is calculated based on private label milk prices, although the results are similar based on share weighted prices. We find that our estimates, reported in Figure 7(A), are statistically indistinguishable from those in Figure 6(A).

• Endogenous pricing schemes: Our main results assume that pricing schemes are exogenous and uncorrelated with demand shifters. In our discussion on pricing patterns in milk in §2.2 we observed that these patterns tend to be chain and location specific. After controlling for demographics, there is no reason

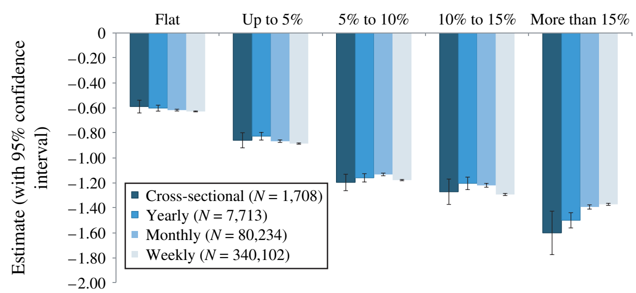
Figure 7 (Color online) Results of Robustness Checks

(A) Robustness of main result to product selection and endogenous prices. Estimates of regression of whole milk share on price premium of whole milk over 2% milk.

	All brands	Endogenous prices
Parameter	Estimate	Estimate
Flat	−0.62 (0.02)	−0.57 (0.04)
Up to 5%	−0.88 (0.03)	−0.76 (0.03)
5% to 10%	−1.16 (0.03)	−1.15 (0.03)
10% to 15%	−1.24 (0.05)	−1.54 (0.07)
More than 15%	−1.46 (0.08)	−1.72 (0.42)
Controls	*Income, poverty, education, race, age, population density*	
No. of observations	1,708	

Note. Standard errors are in parentheses.
**, Significant at 1% level.

(B) Robustness of main result to level of data aggregation. Estimated parameter values and confidence intervals with different levels of data aggregation: Cross-sectional, yearly, monthly, and weekly.



for state level demand shocks for whole milk. Moreover on the supply side, there are production and cost differences across states, therefore we consider state fixed effects as the ideal instrument for price premiums for whole milk over 2%. In our main regression, we project the price premium on a set of dummy variables for levels of the price premiums (flat, up to 5%, 5% to 10%, 10% to 15%, and over 15%). To account for endogeneity, in the first stage we use state fixed effects as instruments for the price premiums. The R^2 in the first stage is 0.62. In the second stage, we use the projected price premiums in the levels, as in the main regression. The parameter estimates from the second stage are shown in the second column of Figure 7(A). These results are similar to the main results presented in Figure 6(A). The test statistic for the Hausman test is 4.15 (not significant at a 0.1 level), therefore we cannot reject the null hypothesis that the price premiums are exogenous.[8]

[8] We present the second stage regression results without accounting for first stage uncertainty. This could be problematic as we bucket the endogenous variables into five levels of price premiums (flat, up to 5%, 5% to 10%, 10% to 15%, and over 15%). Online Appendix Figure 2 shows that our results are unchanged if we bootstrap from the asymptotic distribution in the first stage.

• Time series versus cross-section data: Whereas the data is observed at the store-week level, there is limited time-series variation in the *relative* prices of milk. Consequently, within a store there is limited movement between options. For this reason, we aggregate to the store level and use cross-sectional data for the regression analyses above. The cross-sectional data represents the most conservative approach because using the time-series data increases the sample size and artificially inflates the precision of the estimates. To demonstrate this, Figure 7(B) compares the parameter estimates from the main model using cross-sectional data with the results using time series data, i.e., at the annual, monthly, and weekly levels. Whereas the parameter estimates are stable across levels of aggregation, the confidence intervals reduce in size with lower levels of aggregation.

3.4. Summary of Main Results

Our analysis thus far establishes the following results: Where prices are equal across alternatives, the market share for the higher fat alternative is highest among the available options, and is higher in low income versus high income areas. The market share of the higher fat alternative falls as its price premium relative to the lower fat alternatives increases. Demand is highly elastic, particularly in lower income areas, so that large shifts to the lower calorie alternative are achieved with relatively small price differences. Consequently, the discrepancy in market shares between high and low income areas disappears with a price premium of just 15%.

A key feature of our results is that they are based on market share outcomes observed across a large number of markets and over a long time. Compared with lab experiments (or field studies using vending machines or cafeterias) where the intervention is for a short time, our results show the long term demand response to price differences between the higher and lower calorie alternatives. Similarly, conclusions on the potential efficacy of a fat tax in econometric studies with field data are usually based on simulating the impact of a hypothetical price increase, often outside the range of observed data.

Our results provide strong support for a selective taxation mechanism that creates a price premium for the higher calorie alternative to discourage its consumption. However there are important concerns related to how such a policy would impact consumer welfare and whether the changes can be achieved without impacting retailer profitability. Opposition to tax-based policies is often based on such concerns. In §4 we conduct supplementary analyses that address these issues.

4. Welfare Implications of a Fat Tax Policy

We have shown that when prices reflect a tax on the higher calorie option, market shares shift towards the lower calorie option. Implementation of any initiative that alters the status quo would require cooperation on many fronts. The Danish fat tax introduced in October 2011, and withdrawn a year later following intense opposition and pressure from both consumers and business interests, offers an important example. Whereas initial evidence suggested that the tax was impacting behavior (Jensen and Smed 2013), one of the major reasons cited for the withdrawal was the administrative costs and the negative impact on business interests (Strom 2012).[9] A critical question is whether such a policy can be beneficial to consumers without negatively impacting retailers. The goal of this section is to estimate the welfare implications of imposing a fat-tax policy. We compare the economic disutility from paying a higher price relative to the health benefits of switching to a lower calorie choice. Below, we estimate a structural demand model that can be used to conduct a variety of policy simulations. A key feature of the policy simulations is that the taxes (i.e., price increase) on the higher calorie option (whole milk) are offset by subsidies (i.e., price decrease) to low calorie products, and in a manner by which retailer revenues are unaltered. This is important because implementing a change in tax policy needs to be mindful of the profit implications for retailers.

4.1. Demand Model

An econometric challenge in developing a demand model is that the key variation in the data is from the cross-sectional variation across stores (versus time series variation within a store). Specifically, in our data the variation in pricing structures (flat or nonflat) across stores allows us to estimate price elasticities. However, conditional on a pricing structure (e.g., flat prices), there is little to no movement in relative prices and shares of the different kinds of milk. Consistent with this, we find that store fixed effects explain over 96% of the variation in relative shares in our data. To overcome this, we define a choice model where we can explicitly parse out the identification from both the time-series and cross-sectional structure of the data. We formulate the utility that a consumer i receives from brand (type of milk) j, at retailer r, in month t as

$$u_{ijrt} = \alpha_{jr} + \alpha_{ij} + (\beta^{TS} + \beta_i)P_{jrt} + \mu_j^{TS} FP_{rt} + \gamma^{TS} F_{jrt} + \xi_{jrt} + \epsilon_{ijrt}. \quad (1)$$

[9] A related issue is that production of lower calorie options in certain categories may be costlier. Even for milk where the cost of production is in fact increasing in fat content, retailer profitability may be adversely affected by altering the price gaps.

In Equation (1), α_{jr} are the brand store fixed effects. These fixed effects capture all of the observed and unobserved cross-sectional variation in the data. The coefficient α_{ij} is a random effect of a consumer i's utility for brand j. By construction, these must be mean zero (with the store brand fixed effects) and we assume that the variance of α_{ij} is σ_j.

In Equation (1), P_{jrt} represents the prices of brand j in store r at time t, and β^{TS} is the corresponding mean price coefficient. Because the cross-sectional variation in prices and shares will be absorbed in the store brand fixed effects (α_{jr}), β^{TS} is identified with only time series variation in the data. β_i is the random coefficient on price, with mean zero and variance σ_β. FP_{rt} is an identifier for retailer r charging flat prices at time t, and μ_j^{TS} is the impact of flat pricing on the utility of brand j identified based on time series variation in the data. F_{jrt} is feature advertising, and γ^{TS} is the coefficient of feature on utility; again, this is identified based on time series variations in the data. ξ_{jrt} is an unobserved utility shock that impacts every consumer's utility for brand j at retailer r at time t. Note this is different from the brand-store fixed effects, as it varies over time. A concern is that our observed prices might be correlated with these unobserved shocks. To account for this endogeneity, we instrument for price with state-specific farm cost of milk as the primary instrument.[10] ϵ_{jrt} is assumed to be a type-I extreme value shock.

In our data, we observe a large amount of fluctuation in the prices of milk over six years, but aggregate category demand as well as relative shares across fat content in a store is quite stable. To quantify this we consider a model of total private label volume sales with only store fixed effects. We find the R^2 of this model is 0.92, and that the adjusted R^2 decreases when we add prices. This suggests that the demand for milk (in the price range of the observed data) is not elastic at the aggregate category level, and therefore the impact of price changes is on switching between options in the category, rather than switching to an outside good. For this reason, we do not have an outside option in our choice model.

There are several aspects of behavior that are not captured by our specification. In particular, the consequence of forward-buying (Mela et al. 1998) by strategic customers, and multi-unit sales might be an issue. To some extent the impact of stockpiling may not be so great as milk is a perishable product with high storage costs. To address multiunit sales and stockpiling would however require a more complex modeling approach.

To estimate the first stage model we use a simulated method of moments (see Berry et al. 1995, Nevo 2000). Because we only consider inside utility we consider all utility relative to that for fat free milk. After estimation of the discrete choice model, we run a second stage minimum distance model to recover the parameters identified with the cross-sectional variation in the data, from the following model:

$$\alpha_{j,r} = \alpha_j^{CS} + \alpha_{\text{Chain}(r)}^{CS} + \beta^{CS}\bar{P}_{jr} + \mu_j^{CS}\bar{FP}_r + \gamma^{CS}\bar{F}_{jr} + \delta_j X_r + \nu_{jr}. \tag{2}$$

The dependent variable in the regression is the vector of estimated brand-store fixed effects α_{jr}. Here α_j^{CS} captures brand specific fixed effects, and $\alpha_{\text{Chain}(r)}^{CS}$ are chain fixed effects that capture the mean preference for fat free milk by chain, whereas the brand-store fixed effects capture the difference in preference for the other types of milk versus fat free. In Equation (2), $\bar{P}_{jr}$ captures the average price for brand j at store r, where the average is taken over all time periods. The coefficient β^{CS} represents the price coefficient identified from cross-sectional variation. $\bar{FP}_{jr}$ is the average (over time) value of the flat price indicator for retailer r, and μ_j^{CS} captures the impact of flat pricing on the utility for brand j. The coefficients $\bar{F}_{jr}$ is the average (over time) store feature advertising for brand j in store r, and γ^{CS} captures the impact on utility. The variables X_r are the demographic characteristics of consumers in the store r, and δ_j captures the demographic differences in brand utilities. The coefficients ν_{jr} are unobserved store-brand effects, which are assumed to be uncorrelated with the independent variables in this model. The estimation of the second stage model is done with GLS regression as specified in Nevo (2000, §3.5).

The computational complexity of the demand model makes it difficult to use the full data available for estimation. To estimate the model on a subset of the data, first we randomly selected 25% of the stores in the sample (464 stores), and then sampled one-third of all months of data per store, for an average of 20 months of data per store. This yields 8,910 store-month observations that are used in the model estimation.

4.2. Results

The parameter estimates of our model are shown in Figure 8(A). The main result from this table is the importance of cross-sectional variation to identify the parameters. Consider the price estimates: From just the time series variation in the data, we estimate the price parameter as −0.69, and from just the cross-sectional variation in the data we estimate the price parameter, more than three times greater, as −2.47. The reason for this is the lack of time series variation in *relative* prices and shares in the data. To better understand these differences, we convert these estimates to elasticities. The implied aggregate demand elasticity if we consider only time series variation is

[10] http://www.fsa.usda.gov/FSA/.

Figure 8 Results of Structural Demand Model Estimation

(A) Structural demand model parameter estimates.
*Indicates significance ($\alpha = 0.05$)

Parameter	Estimate
Time series parameters	
Price	−0.690 (0.014)*
Feature	0.051 (0.009)*
Flat price for 1%	−0.006 (0.005)
Flat price for 2%	−0.010 (0.005)
Flat price for whole	−0.017 (0.005)*
Cross-sectional parameters	
Price	−2.472 (0.268)*
Feature	1.417 (0.249)*
Flat price impact on 1%	−0.027 (0.088)
Flat price impact on 2%	−0.409 (0.087)*
Flat price impact on whole	0.126 (0.095)
Intercept for 1%	−0.678 (0.119)*
Intercept for 2%	0.338 (0.119)*
Intercept for whole	0.218 (0.120)
Cross-sectional demographic	
% white impact on 1%	0.049 (0.029)
% white impact on 2%	−0.117 (0.029)*
% white impact on whole	−0.408 (0.029)*
Income impact on 1%	−0.050 (0.026)
Income impact on 2%	−0.265 (0.026)*
Income impact on whole	−0.398 (0.026)*
Children impact on 1%	0.040 (0.028)
Children impact on 2%	0.156 (0.028)*
Children impact on whole	0.104 (0.028)*
Heterogeneity	
Price	0.022 (0.004)*
Intercept for 1%	0.007 (0.001)*
Intercept for 2%	0.016 (0.002)*
Intercept for whole	0.199 (0.025)*

(B) Aggregate demand cross-price elasticity

	With a 1% change in price		
Change in share of	Whole	2%	1%
Whole	−2.80	1.31	1.31
2%	1.39	−2.57	1.39
1%	0.58	0.58	−3.6

−0.73, whereas the estimated elasticity when we consider only cross-sectional variation is −2.27, and the overall estimated elasticity is −2.8. The full elasticity matrix is reported in Figure 8(B). In a recent meta-analysis, Andreyeva et al. (2010) reported the mean price elasticity for whole milk as −0.59 (range −1.68, −0.02). Our estimate from just the time series variation in the data is consistent with this range. We find that explicitly accounting for cross-sectional variation is critical to estimate the elasticity in this category, which (to our knowledge) is ignored in the previous literature.

We see the same trend for the parameters of feature and display and the impact of flat prices on relative utilities. The feature estimate is positive and significant in the cross-sectional estimates whereas it is insignificant in the time series estimates. Our estimates are reasonable for the different demographics, where we find that the percentage of the population that is white and higher income lead to a lower utility for whole milk relative to lower fat milk. Children below the age of 4 lead to a higher utility for whole and 2% milk.

4.3. Welfare Impact of a Tax Policy

Next we use the model results to simulate the impact of a tax policy if stores that charge flat prices switch to charging nonflat. With the change in price structure from flat to nonflat, we expect the market share of whole milk to fall. This simulation is designed to connect the change in relative prices to the consequences in terms of increase in welfare due to health benefits and welfare loss due to higher prices for whole milk (Brownell et al. 2009). To compute the impact of the fat tax requires some assumptions. These are either standard in the medical and nutrition literature or are based on population averages:

- Average consumption of milk is 1 gallon per month[11]
- Calories per 8 ounces of milk by fat content: whole milk—150 calories, 2% milk—122 calories, 1% milk—102 calories, fat free milk—86 calories.
- Impact of calories on weight gain: 3,500 calories result in a gain of one pound of fat (Wishnofsky 1958).
- Impact of weight gain on Body Mass Index (BMI): To compute the change in BMI when weight changes, we use an average height of 1.7 meters.[12]
- Impact of BMI change on healthcare expenditure: Wang et al. (2006) estimate a healthcare cost of $202.3 per BMI change over a 24 month period. Following this, we assume healthcare costs of $8.42 per BMI unit change over one month.

Based on these assumptions we simulate the impact of a 10 cent tax on whole milk. To ensure no aggregate changes in revenue for the retailer, we implement a revenue neutral price rearrangment so that the 10 cent tax on whole milk is offset by a 3.4 cent rebate on all other varieties of milk. Figure 9(A) shows the predicted shares of milk with this simulated tax, and compares the outcome to the actual observed shares. As observed in the previous section, a small change in prices of milk generates a large movement in relative shares as consumers switch from whole milk to 2% milk. We see relatively small changes in the share for 1% and fat free milk.

[11] We consider this as a conservative estimate as the 2001 estimate of average milk consumption is 22.2 gallons per year (http://css.snre.umich.edu/css_doc/CSS08-08.pdf) and the 2009 estimate is 20.6 (http://www.foodnavigator-usa.com/Market/Average-US-milk-consumption-slumps-8-percent-in-past-decade).

[12] We take the average of the mean male and female height in the U.S. (see http://www.cdc.gov/nchs/fastats/bodymeas.htm).

Figure 9 Impact of a Fat Tax on Market Share and Welfare

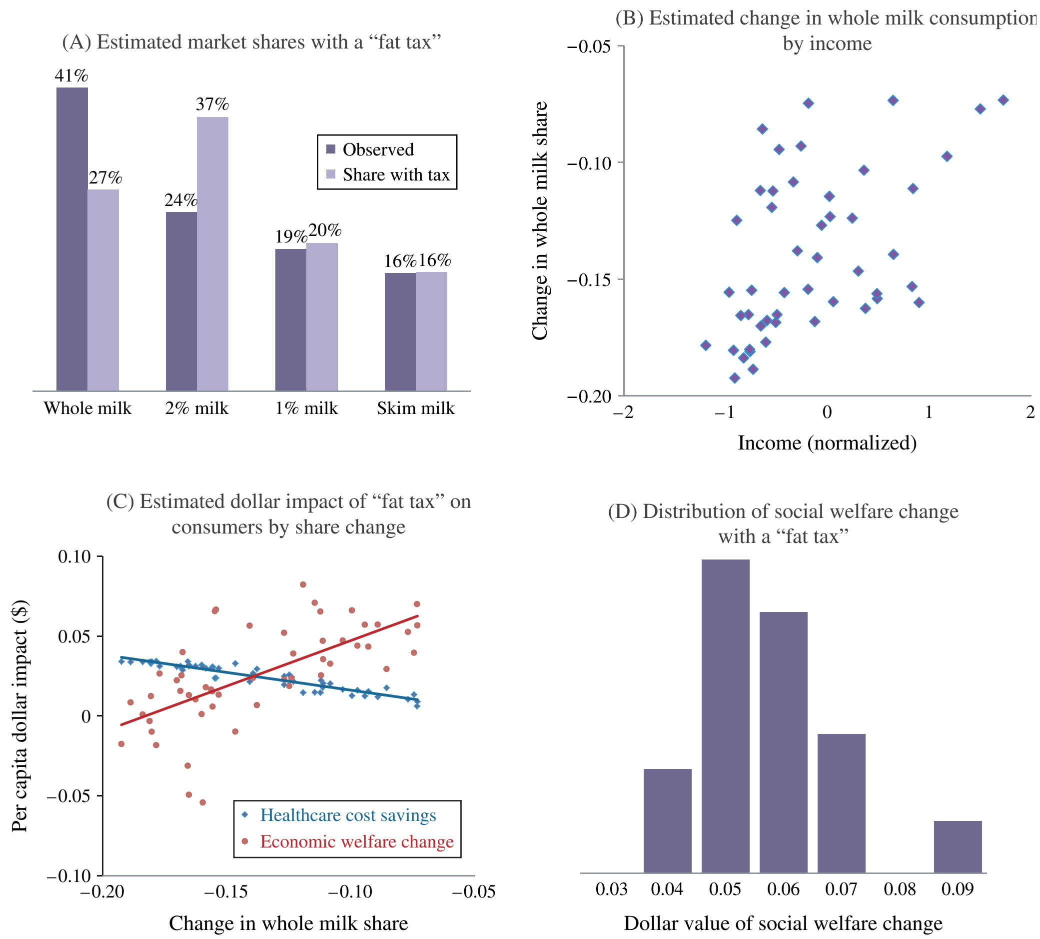


Figure 9(B) shows that the reductions in whole milk share are highest for lower income groups. Based on the predicted share change we can evaluate the implications for per capita dollar change in healthcare costs versus economic welfare, and the per capita total social welfare. Figure 9(C) shows the inherent tradeoffs involved between economic gains or losses versus health benefits. The largest gains in economic welfare are where the change in whole milk share is lowest; these tend to be the higher income areas where the share of lower fat milk is already high, so the gains are from the price reduction on the already preferred milk type. The gains in economic welfare are lowest, and in some cases negative, where the change in whole milk share is highest. This captures the regressive nature of a fat tax because the largest reductions in whole milk share are at the lower income levels. The reduction in whole milk share also yields a relative change in fat consumption. We estimate the calories from milk will reduce by approximately 5% with a fat tax. We monetize this effect in terms of healthcare cost savings. Figure 9(C) also shows that these gains in healthcare cost savings are largest where the change in whole milk share is highest, so the lower income groups benefit most in terms of health effects. Combining the economic and health effects yields the social welfare effect. Figure 9(D) shows the distribution of social welfare change with a fat tax. The support of this distribution is positive, indicating that all groups are better off with the suggested price change. Of particular significance, the welfare is coming from different sources in low and high income markets. In low income markets the positive impact is from the health benefits of the proposed tax, whereas in high income markets the positive impact is from the reduced prices on low fat milk.

5. Policy Implications

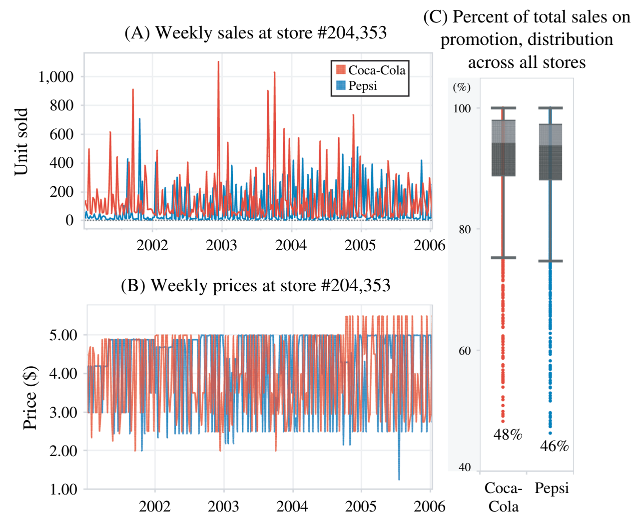
Obesity rates in the U.S. have reached epidemic proportions, with significant consequences for individual health and society at large. Of the various obesity prevention strategies, point-of-purchase interventions in the form of taxes on unhealthy foods have been identified as the most cost effective and as having the largest potential health impact (Vos et al. 2010). The general conclusion from the extant empirical literature is that these taxes need to be substantial, at least 20% and often as high as 50%, to have a meaningful impact (Thow et al. 2010, Mytton et al. 2012). This would be highly regressive since low income consumers spend a greater proportion of their disposable income on food. Our analysis shows that such large taxes may not be necessary since large shifts in demand toward the lower calorie option are achieved with a price gap of just 5%–10%. More important, at risk low income consumers are particularly responsive to the small price differences across options.

Overall, our analysis supports a selective taxation mechanism designed to induce substitution between options within a narrowly defined product category (e.g., baked versus fried chips), rather than to discourage consumption of the category as a whole. This has the additional advantage of mitigating the regressive nature of food taxes since some options within a narrowly defined product category can be made cheaper. These taxes should be imposed as an excise tax so that they are reflected in the shelf price at the point-of-purchase, rather than imposed as a post-purchase sales tax where they become less salient in the decision process.[13]

Current retail pricing practices in the U.S. offer little incentive to choose the lower calorie options since they are either priced the same (low versus high fat yogurt, diet versus regular soda), or in some cases sold at a premium (baked versus regular chips). Our analysis also spotlights the impact of the retailing practice of price-lining (charging the same price for a class of similar products) on product choice: For milk it results in a higher market share for the higher calorie option. To the extent that this is an unintended consequence, it is important for retailers to be made aware of these response patterns.

Estimating welfare effects and monetizing the changes in health indicators requires a number of assumptions. What is established more precisely in our analysis is that small price gaps across options can induce substitution to lower calorie products. These seemingly minor shifts in consumption are of consequence since relatively small changes in energy intake can accumulate over time and lead to substantial changes in weight (Hall et al. 2011). An extensive literature in the behavioral sciences also shows that food choices tend to follow an automatic habitual process (Cohen and Farley 2008, Rothman et al. 2009), presenting an obstacle to altering consumption behavior. The results presented in the paper provide strong evidence

Figure 10 **Pricing and Sales Patterns for Carbonated Beverages in the U.S.**



that small price interventions at the point-of-purchase can counteract such habitual tendencies.

In closing, we point to several caveats of the study. First, our findings are primarily based on milk consumption. Substitution patterns between high and low calorie options (diet versus regular soda, or baked versus fried potato chips) may be quite different for other products. Our analysis focuses on milk because of the particular pricing patterns observed in the U.S. retail market. With most field data, identification of direct substitution across fat or diet attributes is difficult since products within a brand (e.g., Coke and Diet Coke) typically have the same price points and coordinated promotions. Experimental work on changing the relative prices of regular versus diet soda shows that such price manipulations can be effective. In Block et al. (2010), the authors conduct a series of controlled price and education manipulations in a hospital cafeteria in Boston. They find price to be a more effective instrument than educational messages alone. However, the authors acknowledge the need for additional studies with diversified populations to generalize the findings. The high level of consumer responsiveness to the frequent price promotions used in the soda category suggest that price-based instruments can be effective policy tools. As an example, in Figure 10, we plot the weekly price and sales history for a 12-pack of Coca-Cola and Pepsi for a typical store in the data. The response to promotional activity is large. Figure 10(B) shows the distribution (across all stores in the IRI academic data) of the percent of volume sold on promotion: On average promotions account for over 90% of total sales volume for these products.

Another caveat with the suggested policy of taxation of selected products is that consumers may substitute calories to other nontargeted categories. For

[13] Proposals for such excise taxes on targeted products (e.g., one cent per ounce tax on beverages with added caloric sweeteners) have been made by health policy advocates (Brownell et al. 2009), and are currently under consideration in several countries and states in the U.S.

example, a tax on high fat milk or regular soda may lead people to switch to high calorie alternatives in other categories. In general, this is a difficult empirical issue to address as one would need to observe the entire consumption basket including food consumption outside of supermarket purchases. For some categories, it may also be desirable to "demarket" the entire category rather than shift consumption to a less harmful option. Although the success achieved in combatting tobacco use provides valuable lessons, the food industry is significantly more diverse and not limited to a subset of the population. Understanding how food categories can be "demarketed" is a valuable area for future research.

A final caveat relates to the database used in the analysis. The stores included in the database represent a broad spectrum of demographic profiles. Nevertheless coverage of the poorest areas that are served by small, independent grocers will be limited, as these stores do not have the capabilities to record and transmit UPC level sales data. This further relates to the limited shopping options available in such locations, which further exacerbates the incidence of obesity. The alternatives available in these extremely poor neighborhoods are not observed, and we cannot be certain of whether the outcomes observed in our analysis will extend to these areas.

Despite the shortcomings listed above, our study provides strong, field-based empirical support to the findings from experimental research (Epstein et al. 2012) on the efficacy of price in altering consumption behavior. A key strength of our analysis is that it relies on consumption decisions observed over an extended time period, rather than the response to a temporary intervention in a limited setting.

The analysis and results presented in the paper support the calls by health policy advocates and medical practitioners for the use of price-based instruments as a health policy tool to combat obesity (Jacobsen and Brownell 2000, Nestle 2002). Note also that the options that are better for health outcomes is an unresolved issue with on-going debate and research. Recent evidence suggests that higher fat options are more conducive to weight loss (Holmberg and Thelin 2013), and that the negative consequences of artificial sweeteners outweigh the benefits of calorie reduction (Swithers 2013). This is an important issue for the medical and nutrition research community to resolve. The contribution of this paper is to show that small price differences are effective in shifting demand between the available alternatives.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0917.

Acknowledgments

The authors would like to thank seminar participants at Carnegie Mellon University, Columbia University, Cornell University, London Business School, SICS conference at University of California, Berkeley, University of Michigan, and Yale University. The authors would also like to thank Raymond Fisman for comments and suggestions.

References

Andreyeva T, Long MW, Brownell KD (2010) The impact of food prices on consumption: A systematic review of research on the price elasticity of demand for food. *Amer. J. Public Health* 100:216–222.

Berry S, Levinsohn J, Pakes A (1995) Automobile prices in market equilibrium. *Econometrica* 63:841–890.

Bijmolt T, van Heerde H, Pieters RJ (2005) New empirical generalizations on the determinants of price elasticity. *J. Marketing Res.* 42:141–156.

Block J, Chandra A, McManus K, Willet W (2010) Point-of-purchase price and education intervention to reduce consumption of sugary soft drinks. *Amer. J. Public Health* 100:1427–1433.

Bronnenberg B, Kruger M, Mela C (2008) Database paper—The IRI marketing data set. *Marketing Sci.* 27:745–748.

Brownell KD (1994) Get slim with higher taxes. *New York Times* (December 15):A29.

Brownell KD, Farley F, Willett WC, Popkin BM, Chaloupka FJ, Thompson JW, Ludwig DS (2009) The public health and economic benefits of taxing sugar-sweetened beverages. *New England J. Medicine* 361:1599–1605.

Cash S, Lacanilao R (2007) Taxing food to improve health: Economic evidence and arguments. *Agricultural Resource Econom. Rev.* 36:174–182.

Chetty R, Looney A, Kroft K (2009) Salience and taxation: Theory and evidence. *Amer. Econom. Rev.* 99:1145–1177.

Chouinard HH, Davis DE, LaFrance JT, Perloff JM (2007) Fat taxes: Big money for small change. *Forum Health Econom. Policy* 10:Article 2.

Cohen D, Farley T (2008) Eating as an automatic behavior. *Preventing Chronic Disease* 5:A23.

Cutler DM, Glaser E, Shapiro J (2004) Why have Americans become more obese. *J. Econom. Perspectives* 17:93–118.

Epstein LH, Dearing KK, Roba LG, Finkelstein E (2010) The influence of taxes and subsidies on energy purchased in an experimental purchasing study. *Psych. Sci.* 21:406–414.

Epstein LH, Jankowiak N, Nederkoorn C, Raynor HA, French SA, Finkelstein E (2012) Experimental research on the relation between food price changes and food-purchasing patterns: A targeted review. *Amer. J. Clinical Nutrition* 95:789–809.

Finkelstein EA, Zhen C, Nonnemaker J, Todd JE (2010) Impact of targeted beverage taxes on higher- and lower-income households. *Arch. Internal Medicine* 170:2028–2032.

Flegal KM, Carroll MD, Ogden CL, Curtin LR (2010) Prevalence and trends in obesity among US adults, 1999–2008. *J. Amer. Medical Assoc.* 303:235–241.

French SA (2003) Pricing effects on food choices. *J. Nutrition* 133:841S–843S.

French SA, Jeffery RW, Story M, Breitlow KK, Baxter JS, Hannan P, Snyder MP (2001) Pricing and promotion effects on low-fat vending snack purchases: The CHIPS study. *Amer. J. Public Health* 91:112–117.

Galizzi MM (2012) Label, nudge or tax? A review of health policies for risky behaviours. *J. Public Health Res.* 1(1):14–21.

Gortmaker SL, Swinburn BA, Levy D, Carter R, Mabry PL, Finegood DT, Huang T, Marsh T, Moodie ML (2011) Changing the future of obesity: Science, policy and action. *Lancet* 378: 838–847.

Gould BW (1996) Factors affecting US demand for reduced-fat fluid milk. *J. Agricultural Resource Econom.* 21:68–81.

Hall KD, Sacks G, Chandramohan D, Chow CC, Wang YC, Gortmaker SL, Swinburn BA (2011) Quantification of the effect of energy imbalance on body weight. *Lancet* 378:826–837.

Holmberg S, Thelin A (2013) High dairy fat intake related to less central obesity: A male cohort study with 12 years' follow-up. *Scandinavian J. Primary Health Care* 31:89–94.

Hill J, Wyatt H, Reed G, Peters J (2003) Obesity and the environment: Where do we go from here? *Science* 299(5608):853–855.

Jacobsen M, Brownell KD (2000) Small taxes on soft drinks and snack foods to promote health. *Amer. J. Public Health* 90: 854–857.

Jensen JD, Smed S (2013) The Danish tax on saturated fat—Short run effects on consumption, substitution patterns and consumer prices of fats. *Food Policy* 42:18–31.

Kuchler F, Tegene A, Harris JM (2004) Taxing snack foods: What to expect for diet and tax revenues. Current Issues in Economics of Food Markets. Agricultural Information Bulletins 33607, United States Department of Agriculture, Economic Research Service. http://www.ers.usda.gov/media/306707/aib74708_1_.pdf.

Lantz PM, House JS, Lepkowski JM, Williams DR, Mero RP, Chen J (1998) Socioeconomic factors, health behaviors, and mortality: Results from a nationally representative prospective study of US adults. *JAMA* 279:1703–1708.

McGranahan L, Schanzenbach D (2011) Who would be affected by soda taxes? Essays on Issues March 284. Federal Reserve Bank of Chicago, Chicago.

Mela CF, Jedidi K, Bowman D (1998) The long-term impact of promotions on consumer stockpiling behavior. *J. Marketing Res.* 35:250–262.

Mytton OT, Clarke D, Rayner M (2012) Taxing unhealthy food and drinks to improve health. *British Medical J.* 344:2831.

Nestle M (2002) *Food Politics: How the Food Industry Influences Nutrition and Health* (University of California Press, Berkeley, CA).

Nevo A (2000) A practitioner's guide to estimation of random-coefficients logit models of demand . *J. Econom. Management Strategy* 9:513–548.

Ogden C, Carroll MD (2010) Prevalence for overweighy, obesity and extreme obesity among adults: United States, trends 1976–1980 through 2007–2008. *National Center for Health Statistics*. http://www.cdc.gov/nchs/data/hestat/obesity_adult_07_08/obesity_adult_07_08.pdf.

Ogden CL, Lamb MM, Carroll MD, Flegal KM (2010) Obesity and socioeconomic status in children and adolescents: United States, 2005–2008. *National Center for Health Statistics*. http://www.cdc.gov/nchs/data/databriefs/db51.pdf.

Powell LM, Chaloupka FJ (2009) Food prices and obesity: Evidence and policy implications for taxes and subsidies. *Milbank Quart.* 87:229–257.

Rothman AJ, Sheeran P, Wood W (2009) Reflective and automatic processes in the initiation and maintenance of dietary change. *Ann. Behavioral Medicine* 38:S4–S17.

Schnepf R (2012) Dairy policy proposals in the 2012 farm bill. *CRS Report for Congress* (September 18):R42736. http://www.idfa.org/docs/default-source/not-blank/crs-report-dairy-policy-proposals-in-the-2012-farm-bill39699a9c41746fcd88eaff000002c0f4.pdf?sfvrsn=0.

Strom S (2012) Fat foods tax is repealed in Denmark. *New York Times* (November 13):B4. http://www.nytimes.com/2012/11/13/business/global/fat-tax-in-denmark-is-repealed-after-criticism.html.

Swinburn BA, Sacks G, Hall KD, McPherson K, Finegood DT, Moodie ML, Gortmaker SL (2011) The global obesity pandemic: Shaped by global drivers and local environments. *Lancet* 378:804–814.

Swithers S (2013) Artificial sweeteners produce the counterintuitive effect of inducing metabolic derangements. *Trends Endocrinology Metabolism* 24:431–441.

Thaler R, Sunstein C (2008) *Nudge: Improving Decisions About Health, Wealth and Happiness* (Yale University Press, New Haven, CT).

Thow AM, Jan S, Leeder S, Swinburn B (2010) The effect of fiscal policy on diet, obesity and chronic disease: A systematic review. *Bull. World Health Organ.* 88:609–612.

Vos T, Carter R, Barendregt J, Mihalopoulos C, Veerman L, Magnus A, Cobiac L, Bertram M, Wallace A (2010) Assessing cost effectiveness in prevention (ACE-Prevention): Final Report. University of Queensland, Brisbane and Deakin University, Melbourne. Accessed June 23, 2015, http://dro.deakin.edu.au/eserv/DU:30030306/carter-assessingcost-2010.pdf.

Wang F, McDonald T, Bender J, Reffitt B, Miller A, Edington DW (2006) Association of healthcare costs with per unit body mass index increase. *J. Occupational Environ. Medicine* 48:668–674.

Wishnofsky M (1958) Caloric equivalents of gained or lost weight. *Amer. J. Clinical Nutrition* 6:542–546.