

Will a Fat Tax Work?*

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Abstract

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 US to investigate the potential of small price incentives for inducing substitution to healthier alternatives. We exploit a pricing pattern particular to milk in the US, whereby prices in some geographical regions are flat across Whole, 2%, 1% and Skim milk; while 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 setup 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 socio-economic 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.

Keywords: Fat Tax, Obesity, Elasticity, Milk Pricing, Field Experiment

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1 Introduction

Obesity in the US has reached epidemic proportions, with two-third 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 amongst minority groups and the poor (Flegal et al. 2010, Lantz et al. 1998). Data from the Centers for Disease Control, plotted in Figure 1A, shows the negative correlation between county level obesity rates and socioeconomic indicators - 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, Glaser and Shapiro 2004, Hill et al. 2003, Swinburn et al. 2011). Figure 1A 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 raised skepticism on the efficacy of such fiscal interventions, with calls for additional empirical research to guide policy (Cash and Lacañilao 2007, Powell and Chaloupka 2009, Thow et al. 2010, Galizzi 2014). A core issue in the debate over taxation as a mechanism against obesity is whether consumers will change consumption in response to price incentives. Since category level demand for food products tends to be inelastic - with elasticity ranges be-

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

tween -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, Tegene and Harris 2004, Finkelstein et al. 2010). In 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, Epstein et al. 2012, French et al. 2001, French 2003). However, a potential problem with the experimental work is that these studies are conducted with small non-representative populations. The objective of this article is to fill this gap in the literature and demonstrate the potential of price-based policy interventions using a 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 mention². 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, they give consumers 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 more likely to impact the purchase decision (Chetty, Looney, and Kroft 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 US 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

²As 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)

³We 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 to shift demand between high versus low calories options.

fat content (non-flat). Whether a particular retail outlet charges flat or non-flat prices is independent of local demand conditions. This exogenous variation (i.e. not correlated with underlying consumer preferences) provides a quasi-experimental setup to identify price-induced substitution patterns across fat content.

We find that where prices are flat - 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 (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, Clarke and Rayner 2012). The shift to the lower calorie option is particularly strong amongst 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 calories options, particularly amongst the at-risk low-income households.

While 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 – 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 Lacañilao 2007, Powell and Chaloupka 2009, Thow et al. 2010, Galizzi 2014).

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, Looney, and Kroft 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 keeping the retailer profits 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 outweighs these costs, resulting in a net welfare gain at every income level.

The rest of the article is organized as follows. In the next section, we describe 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 the concluding section.

2 Data

2.1 Retail Scanner Data

The cornerstone of our empirical strategy is a comprehensive scanner data provided by IRI (Bronnenberg, Kruger, and Mela 2008). The data covers a period of six years, from 2001 to 2006. We observe weekly sales, price, and promotion information for each 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 of which accounts for approximately 50% of the total US population.

The customer base of each store is profiled with an extensive set of demographic variables using zip code level data from the US 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 appendix figure 1. We collected additional data to characterize local competition and cost factors. This includes the median local hourly wage, the total number of grocery retailers located within 5 miles of each store, and the number of discount grocery retailers (e.g. Wal-Mart Supercenter) located 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 an 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 which 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: 128oz (79.3%), 64oz (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 US

Dairy pricing in the US comprises a complicated combination of market forces and various government regulations. Approximately two-thirds of the total milk in the US 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 ten 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 US) operate under their own state regulations rather than federal rules.

While 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 non-flat structures which 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 2A maps

⁴Increasing 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.

the geographical distribution of retail stores that charge flat or non-flat prices. In Figure 2B, we show 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 the distributions of price, while for non-flat markets the price distribution for 2% milk price 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 non-flat prices. The observed price structure could potentially 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 non-flat 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 3A compares the demographic profiles served by flat versus non-flat pricing stores. We find no significant differences in any of the characteristics of the customer base. Comparisons of the competitive environments of the stores 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.

Since the price premium of whole over 2% milk is an indicator of whether a store is flat or non-flat, we regress the price ratio of whole to 2% milk on demographics which 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 effect (see Appendix Table 1). We also conduct a variance decomposition, reported in Figure 3B, 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 non-flat 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 the chain's stores are non-flat. Figure 3C 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/non-flat is not a special feature of our store level data, we collected prices and sales for milk from the USDA for several US cities. The data from USDA matches the IRI store level data quite accurately in terms of both the 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

Our analysis suggests that the choice of flat versus non-flat 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' - 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. Non-flat pricing appears to be a form of cost-based pricing, as the retail

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

prices reflect the underlying wholesale costs. In the next section, 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 non-flat 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 non-flat 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 non-flat 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 non-flat 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 the introduction, obesity rates in the US are significantly higher among lower socioeconomic status households. Figure 5A shows the differences in the market shares of milk between flat and non-flat 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 non-flat markets. Second, in non-flat 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 5B shows the distribution of market share for diet soda for

the highest and lowest income quintiles in flat and non-flat 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 non-flat markets. This is important because it suggests that there are no unobserved taste differences for lower calorie products in non-flat markets, rather the reason we observe lower shares of whole milk in non-flat markets is because of the pricing structure.

Figure 5C 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 non-flat 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 non-flat 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 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: $\ln(\frac{S^W}{1-S^W})$, 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 6A shows the results of this regression (see Appendix Table 2 for estimates of control variables). The price coefficients indicate that an increase in whole milk price decreases its share, while 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, while 1% and skim milk are weaker substitutes. This is consistent with the summary analysis in Figure 4, where the majority of movement in market share of whole milk under non-flat pricing is to the 2% option.

3.2.2 Non-Linearities in Response

Since the response to a relative price premium (or discount) could vary in a non-linear 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

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

⁷This specification does not include chain or location fixed effects. As shown in section 2.2.2, the variation in price structure is explained primarily by chain and location fixed effects. This is further demonstrated in Figure 2A which maps the geographic consistency in pricing structure, and Figure 3C 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 the chain and location fixed effects.

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 6A show that as the premium of whole milk over 2% milk increases, the market share of whole milk falls (see Appendix Table 3 for estimates of control variables). However the response is highly non-linear, 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 with the previously defined set of price ratio dummy variables. In Figure 6B, 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 Appendix Table 4.1 for parameter estimates). Under flat prices, the discrepancy between income groups is large - whole milk share for low-income (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%, while 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%.

While 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. Appendix table 4.2 shows the results of Model 3 with interactions between the demo-

graphics and an indicator for flat pricing. The results shows that the elderly have higher share of whole milk where prices are flat. The response to flat versus non-flat 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 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 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 7A, are statistically indistinguishable from those in Figure 6A.

- 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 section 2.2 we observed that these pricing patterns tend to be chain and location specific. After controlling for demographics, there is no reason for state level demand shocks for whole milk. Moreover on the supply side, there are production and cost difference 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 7A. These results are similar to the main results presented in Figure 6A. 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

- Time series versus cross-section data: While the data is observed at the store-week

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

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 7B compares the parameter estimates from the main model using cross-sectional data with the results using time series data: at the annual, monthly and weekly level. While the parameter estimates are stable across level 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. As a consequence, 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 period. In comparison to lab experiments (or field studies using vending machines or cafeteria) where the intervention is for a short time period, 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 the next section 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 which 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. While 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 dis-utility from paying a higher price relative to the health benefits of switching to a lower calorie choice. In what follows, we estimate a structural demand model which can be used to conduct a variety of policy simulations. A key feature of the policy simulations is that the taxes (price increase) on the higher calorie option (whole milk) are offset by subsidies (price decrease) to low-calorie products— in a manner that

⁹A 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.

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 non-flat) 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. In order 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:

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

In equation 1, α_{jr} are the brand-store fixed effects. These fixed effects capture all the observed and unobserved cross sectional variation in the data. 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 the variance of α_{ij} is σ_j .

P_{jrt} represents the prices of brand j in store r at time t , and β^{TS} is the corresponding mean price coefficient. Since 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 instrument¹⁰. 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 6 years, but aggregate category demand as well 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, Jedidi and Bowman 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 multi-unit sales and stockpiling would however require a more complex modelling approach.

The estimation of the first stage model is done using simulated method of moments (see BLP 1995, Nevo 2000). Since 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

¹⁰<http://www.fsa.usda.gov/FSA/>

a second stage minimum distance model to recover the parameters identified with the cross-sectional variation in the data, from the following model.

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

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 $\alpha_{Chain(r)}^{CS}$ are chain fixed effects which capture the mean preference for fat free milk by chain, while the brand store fixed effects capture the difference in preference for the other types of milk versus fat-free. \bar{P}_{jr} captures the average price for brand j at store r, where the average is taken over all time periods. β^{CS} represents the price coefficient identified from cross sectional variation. $\bar{F} \bar{P}_{jr}$ 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. \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. X_r are the demographic characteristics of consumers in the store r, and δ_j captures the demographic differences in brand utilities. 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) section 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 8910 store-month observations which are used in the model estimation.

4.2 Results

The parameter estimates of our model are shown in Figure 8A. 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 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 -0.73, while 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 8B. 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 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 while it is insignificant in the time series estimates. Our estimates are reasonable for the different demographics, where we find that 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 non-flat. With the change in price structure from flat to non-flat, we expect market share of whole milk to fall. The purpose of this simulation is 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 month¹¹
- 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 gain of 1 pound of fat (Wishnofsky 1958).
- Impact of weight gain on 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 health care expenditure: Wang et al. (2006) estimate a health care cost of \$202.3 per BMI change over a 24 month period. Following this, we assume health care 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

¹¹We 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>)

¹²We take the average of the mean male and female height in the US (see <http://www.cdc.gov/nchs/fastats/bodymeas.htm>)

price rearrangement so that the 10 cent tax on whole milk is offset by a 3.4 cent rebate on all other varieties of milk. Figure 9A 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.

Figure 9B 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 health care costs versus economic welfare, and the per capita total social welfare. Figure 9C shows the inherent trade-offs 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 health care cost savings. Figure 9C also shows that these gains in health care 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 9D 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. Importantly 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, while in high income markets the positive impact is from the reduced prices on low fat milk.

5 Policy Implications

Obesity rates in the US 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 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 importantly, 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

¹³Proposals for such excise taxes on targeted products (e.g. 1 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 US.

Current retail pricing practices in the US 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 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 US 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 be able to generalize the findings. The high level of consumer responsiveness to the frequent price promotions employed in the soda category do 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 10B 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 non-targeted categories. For 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 which 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 extreme 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 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). It is also important to note that which options 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.

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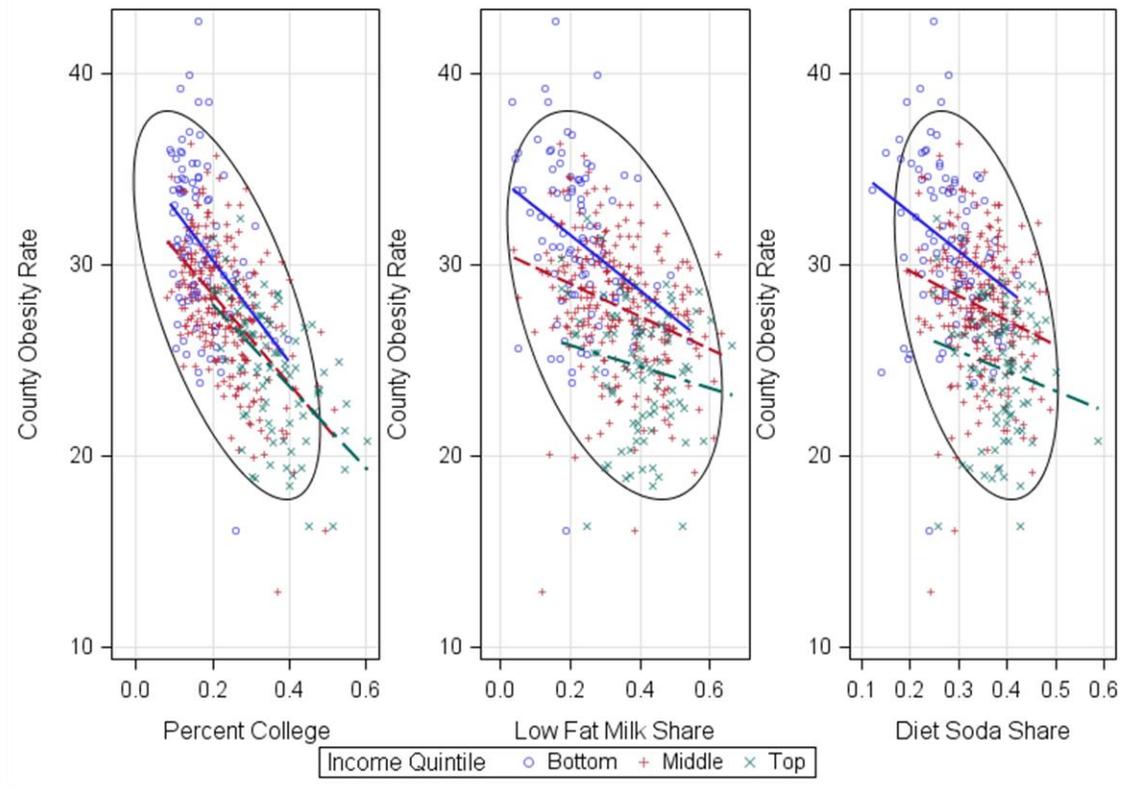
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Figure 1: Obesity Rates, Socioeconomic Characteristics and Consumption Patterns

A: Correlation of county level obesity rates with education, income and market shares 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 <.001 for all correlations).



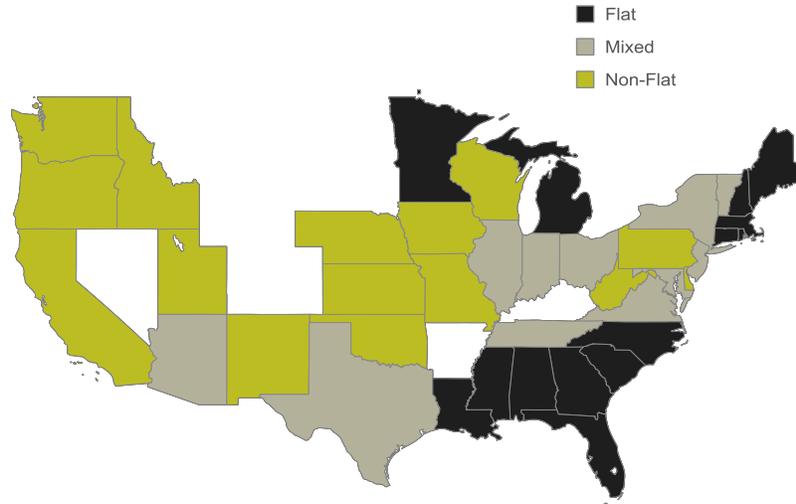
B: Correlation matrix for county level obesity rates, socioeconomic characteristics, and market shares for the lower calorie options in milk and soda. (p<.001 for all correlations).

| | 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 | | |
| LowFat Milk Share | -0.44 | 0.53 | 0.46 | 1 | |
| Diet Soda Share | -0.42 | 0.51 | 0.49 | 0.84 | 1 |

Figure 2: Geographic Variation in the Pricing of Milk across the US

A: Geographic distribution of flat and non-flat price structure.

In mixed states, both flat and non-flat 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 non-flat markets. Prices are dollars per gallon for whole milk (dark) and 2% milk (light) from 2001-2006. In Boston and Grand Rapids, there is complete overlap in the distribution of whole and 2% milk prices.

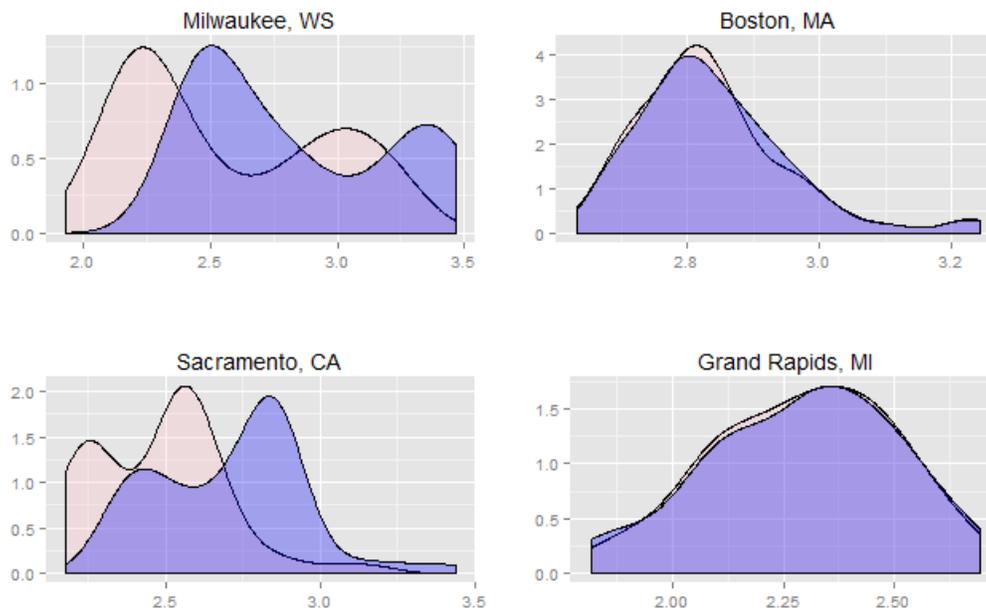


Figure 3: Flat versus Non-Flat Price Structure

A: Demographics in Flat & Non-Flat Markets. Note: None of the differences are significant at 0.05 level, except hourly wage.

| | | | | | |
|---------|--------------|----------------|--------------------|-----------------------|-----------|
| NonFlat | \$48K | 10.2 | 7% | 12% | 29% |
| Flat | \$48K | 10.1 | 7% | 12% | 30% |
| | Med. Income | Poverty | % Children | % Elderly | % College |
| NonFlat | 3.6K | \$19 | 7.0 | 3.7 | 77% |
| Flat | 3.1K | \$17 | 7.1 | 3.6 | 78% |
| | Pop. Density | \$ Hourly Wage | Retailers in 5 mi. | Discounters in 10 mi. | % White |

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: <i>Median Income, % Children, % White, % College, Popn. Density</i> | 0.16% |
| Competitive Environment: <i>Wage, All retailers in 5 miles, Discount retailers in 10 miles</i> | 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 non-flat, with fewer chains adopting mixed policies.

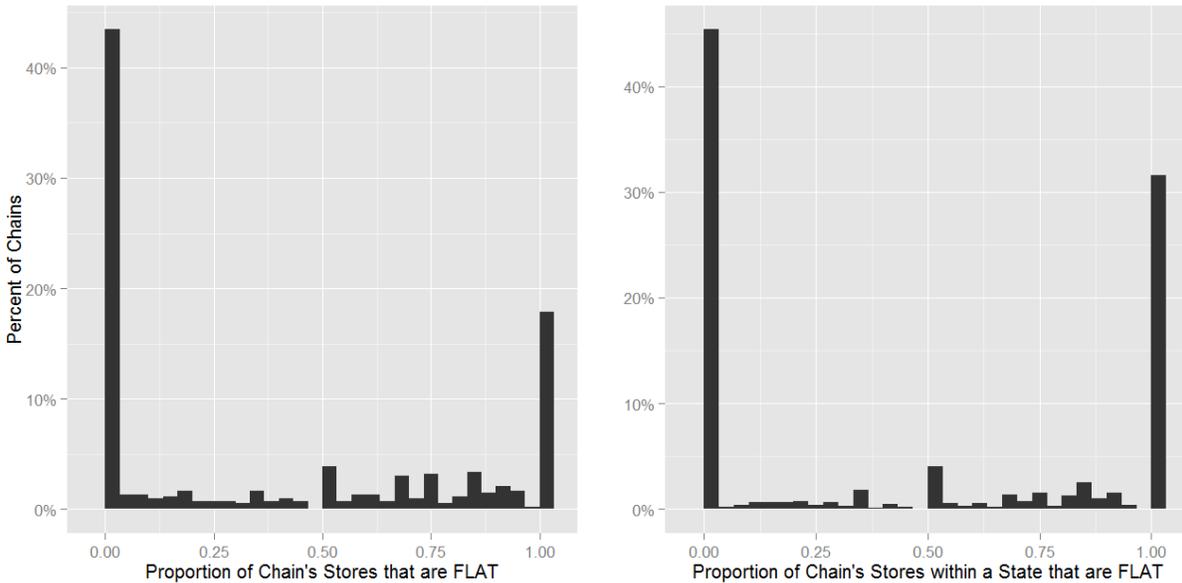


Figure 4: Impact of Flat versus Non-Flat Pricing: Summary Statistics

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

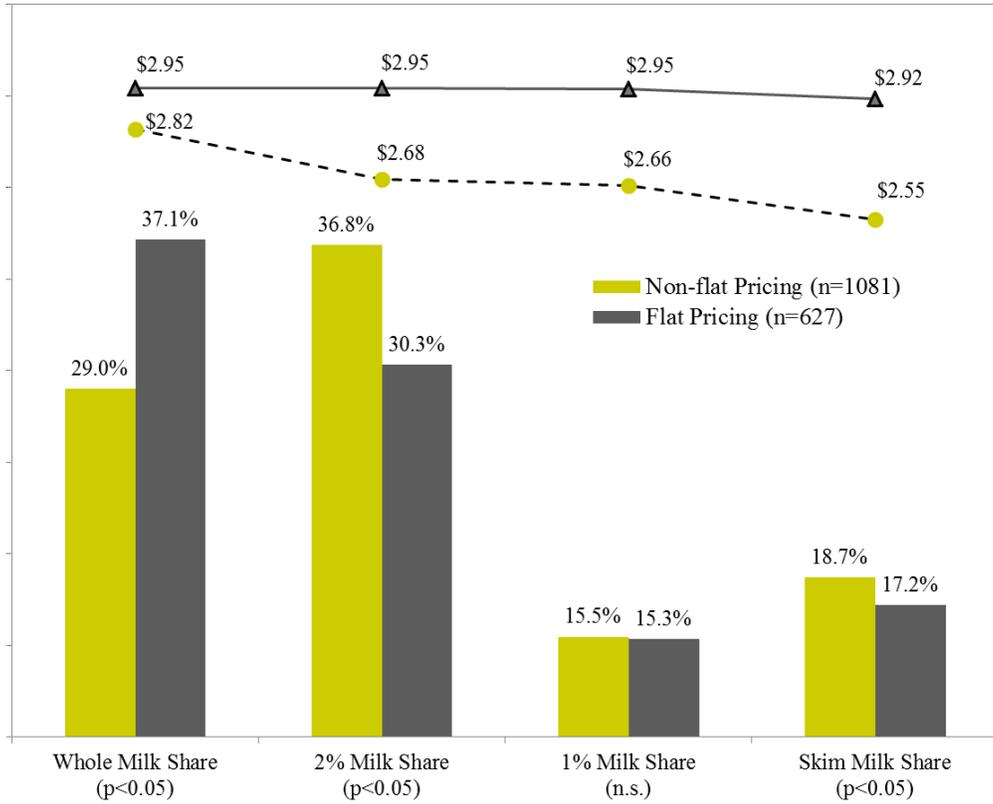
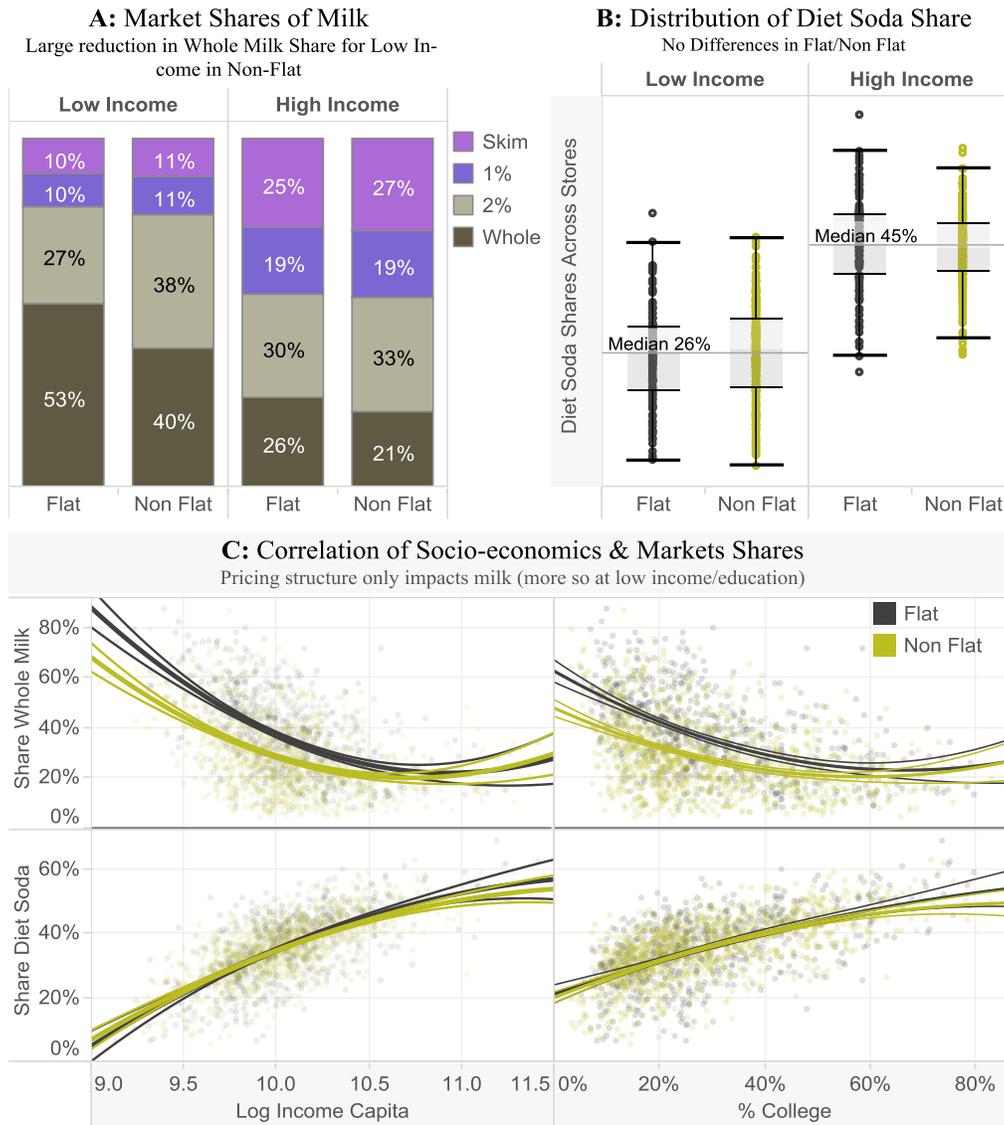


Figure 5: Impact of Flat versus Non Flat Pricing, by Socioeconomic Characteristics
 Note: High and low income refers to the top and bottom income quintiles based on per capita income.



Key Message: (1) Impact of pricing structure higher for low SEC, (2) Shares of soda suggest no systematic taste differences between flat and non-flat markets.

Figure 6: Impact of Flat versus Non-Flat 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). Standard errors are in parentheses. ** represents significant at 5%.

Dependent variable: $\ln(\text{Whole milk share}/1-\text{Whole milk share})$

| Price parameter | Model 1 | | Model 2 | |
|---------------------------------|--|----------------------------------|--|-------------------------------------|
| | Parameter Estimates | Implied Elasticity of Whole Milk | Parameter Estimates | Implied whole milk share [95% C.I.] |
| <i>Prices charged</i> | | | | |
| 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) | | |
| <i>Whole milk price premium</i> | | | | |
| Flat | | | -0.59 (0.03)** | 36% [35%, 37%] |
| Upto 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: | <i>Income, Education, Race, Age, and Density</i> | | <i>Income, Education, Race, Age, and Density</i> | |
| R-square | 0.77 | | 0.76 | |
| Number of observations | 1,708 | | 1,708 | |

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 appendix). High- and low-income refers to the top and bottom quintiles based on per capita income. Vertical bars show 95% confidence intervals.

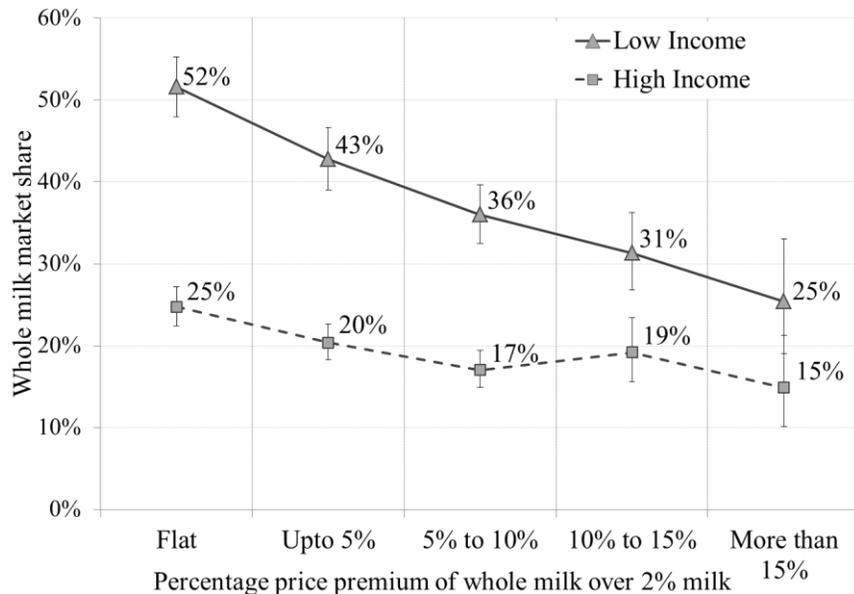


Figure 7: Results of Robustness Checks

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. Standard errors are in parentheses and ** indicates significant at 1% level.

| | All Brands | Endogenous Prices |
|----------------|---|-------------------|
| Parameter | Estimate | Estimate |
| Flat | -0.62 (0.02) | -0.57 (0.04) |
| Upto 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 | |
| # observations | 1,708 | |

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.

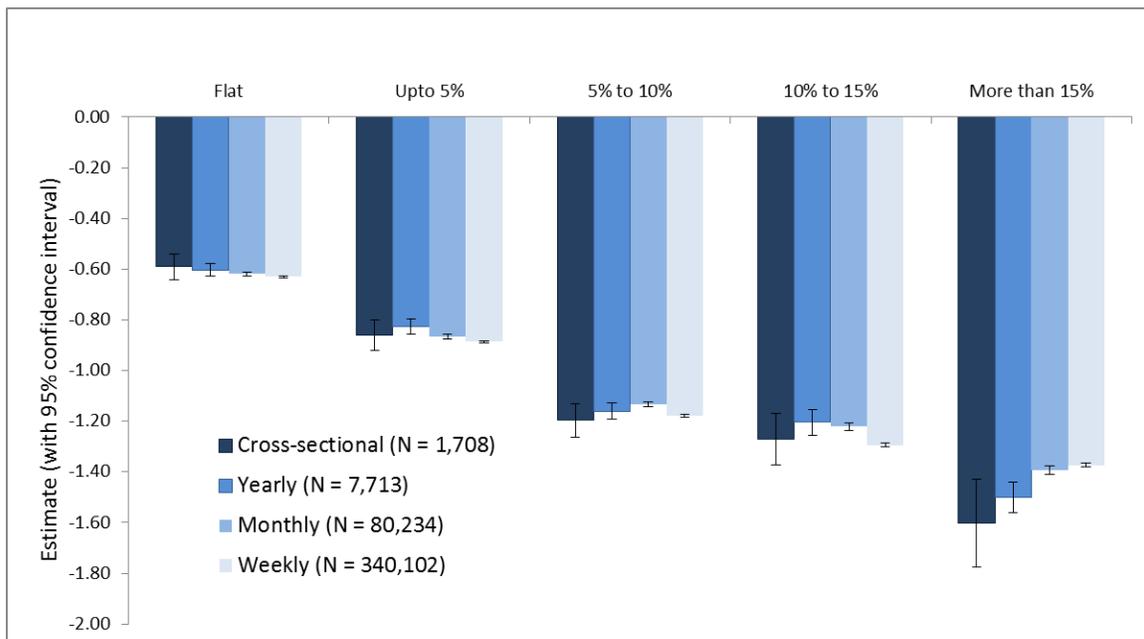


Figure 8: Results of Structural Demand Model Estimation

A. Structural demand model parameter estimates. *Indicates significance ($\alpha=.05$)

| 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 WH | -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

| Change in Share of: | With a 1% change in price: | | |
|---------------------|----------------------------|-------|-------|
| | Whole | 2% | 1% |
| Whole | -2.80 | 1.31 | 1.31 |
| 2% | 1.39 | -2.57 | 1.39 |
| 1% | 0.58 | 0.58 | -3.36 |

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

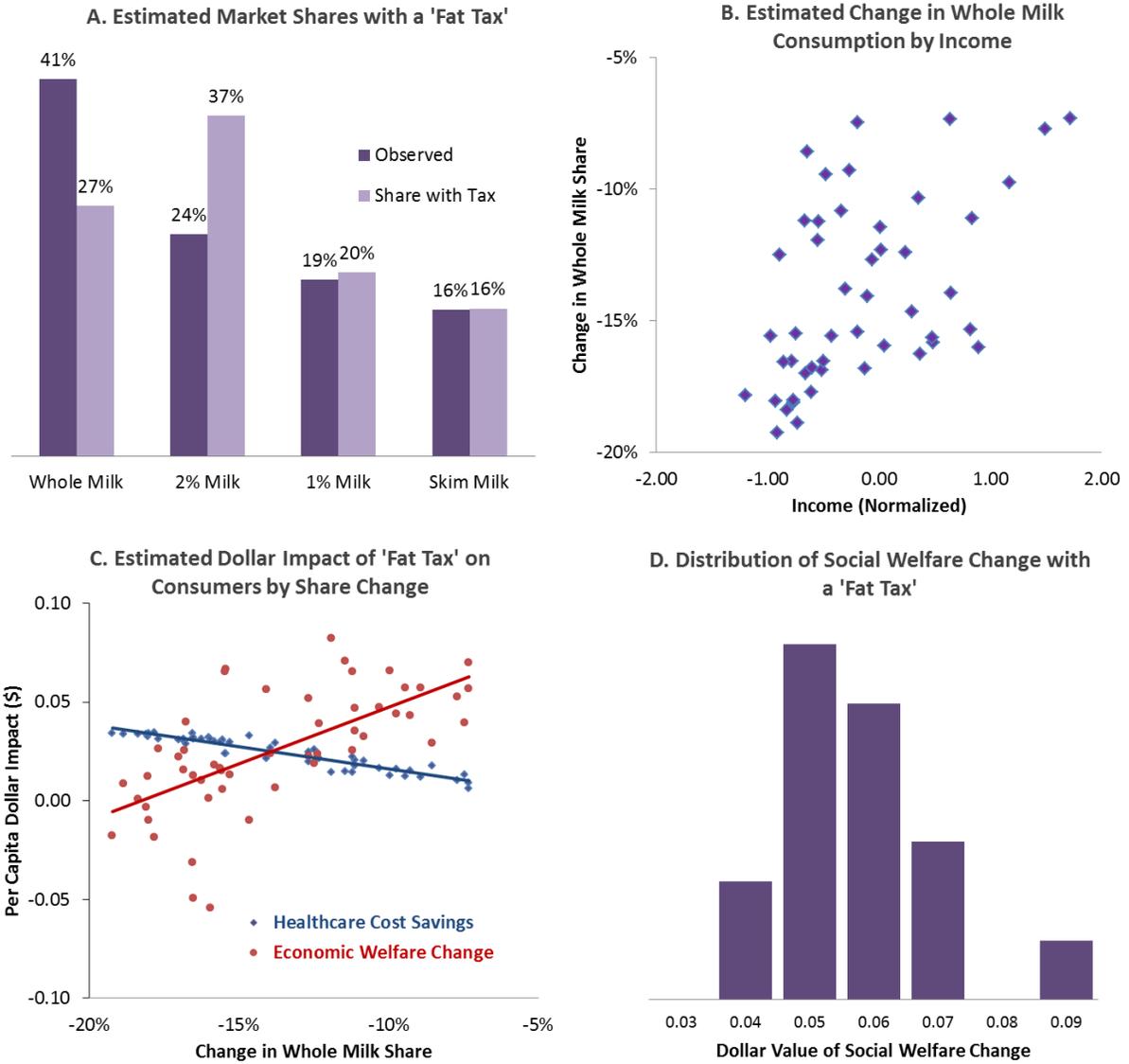


Figure 10: Pricing and Sales Patterns for Carbonated Beverages in the US

Weekly price and sales history for the highest selling UPC (12-pack cans) for Coca-Cola and Pepsi at a typical store. The plot shows high level of promotional activity and large consumer response to promotions. Across all stores and weeks in the data (500,000+ observations), price promotions account for over 90% of sales for both products.



Will a Fat Tax Work? Online Appendix

December 19, 2014

Table 1: Price ratio of Whole to 2% milk: (1) Regression and (2) Variance Decomposition.

| | (1) | | (2) |
|------------------------------------|----------|-----------|------------------------|
| | Estimate | Std Error | Variance Decomposition |
| Intercept | 1.0393 | -0.006 | |
| Median Income | -0.0017 | -0.002 | 0.06% |
| % Children | -0.0003 | -0.001 | 0.00% |
| % College | -0.0005 | -0.002 | 0.01% |
| % White | -0.0014 | -0.001 | 0.09% |
| Population Density | -0.0003 | -0.001 | 0.00% |
| Wage | 0.0028 | -0.002 | 0.14% |
| All retailers within 5 miles | -0.0002 | -0.001 | 0.00% |
| Discount retailers within 10 miles | -0.0021 | -0.001 | 0.18% |
| Marketing Order Fixed Effects | Included | | 15.44% |
| Chain Fixed Effects | Included | | 84.07% |
| R square | 0.658 | | |

Table 2: Full results for Model 1: (1) Full results of regression of logit transform of whole milk market share on prices of whole, 2%, 1% and skim milk, and demographic controls. (2) Implied elasticity of demand for whole milk with respect to prices of whole, 2%, 1% and skim milk. Standard errors are in parentheses. ** indicates significant at 1% level.

| Parameter | (1) Parameter Estimate | | (2) Implied Elasticity of Whole Milk Share: | |
|------------------------|------------------------|----------|---|----------|
| Price estimates | | | | |
| 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) |
| Demographics | | | | |
| Intercept | -1.97 | (0.11)** | | |
| Low income | 0.12 | (0.05)** | | |
| High Income | -0.16 | (0.04)** | | |
| % Poverty | 0.11 | (0.02)** | | |
| % College | -0.13 | (0.02)** | | |
| % White | -0.29 | (0.02)** | | |
| % Children | 0.03 | (0.02) | | |
| % Elderly | 0.04 | (0.02)** | | |
| Population density | 0.02 | (0.01) | | |
| R-square | 0.77 | | | |
| Number of observations | 1708 | | | |

Table 3: Full results for Model 2: (1) Results of regression of logit transformation of whole milk share on price premium of whole milk over 2% Milk. A series of dummy variables are used to indicate the premium of whole milk over 2% milk. (2) Estimated whole milk market share at different levels of the premium of whole milk over 2%** indicates significant at 1% level.

| Parameter | (1) | | (2) | |
|----------------------------|-----------|----------|----------------------------|------------|
| | Parameter | Estimate | Estimated whole milk share | [95% C.I.] |
| Whole milk price premium : | | | | |
| Flat | -0.59 | (0.03)** | 36% | [35%, 37%] |
| Upto 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%] |
| Low income | 0.13 | (0.05)** | | |
| High Income | -0.12 | (0.04)** | | |
| % Poverty | 0.10 | (0.02)** | | |
| % College | -0.13 | (0.02)** | | |
| % White | -0.33 | (0.02)** | | |
| % Children | 0.01 | (0.02) | | |
| % Elderly | 0.05 | (0.02)** | | |
| Population density | 0.02 | (0.01) | | |
| R-square | 0.76 | | | |
| Number of observations | 1708 | | | |

Table 4: Full results for Model 3: (1) Results of regression of whole milk share on price premium of whole milk over 2% milk interacted, by income. To capture differences in response to the price premium across income group, dummy variables indicating the premium of whole milk over 2% milk are interacted with dummy variables for income. Standard errors are in parentheses. ** indicates significant at 1% level. (2) Results including interactions between demographics and Flat indicator.

| (1) | | | | | | |
|----------------------------|------------|----------|--|----------|-------------|----------|
| Parameter | Low Income | | Medium Income | | High Income | |
| Whole milk price premium : | | | | | | |
| Flat | -0.42 | (0.06)** | -0.58 | (0.03)** | -0.77 | (0.06)** |
| Upto 5% | -0.77 | (0.07)** | -0.83 | (0.04)** | -1.02 | (0.06)** |
| 5% to 10% | -1.05 | (0.07)** | -1.22 | (0.04)** | -1.25 | (0.08)** |
| 10% to 15% | -1.26 | (0.11)** | -1.30 | (0.07)** | -1.10 | (0.12)** |
| More than 15% | -1.56 | (0.19)** | -1.65 | (0.11)** | -1.41 | (0.22)** |
| | | | | | | |
| % Poverty | | | 0.10 | (0.02)** | | |
| % College | | | -0.13 | (0.02)** | | |
| % White | | | -0.32 | (0.02)** | | |
| % Children | | | 0.01 | (0.02) | | |
| % Elderly | | | 0.05 | (0.02)** | | |
| Population density | | | 0.02 | (0.01) | | |
| R-square | 0.76 | | | | | |
| Number of observations | 1708 | | | | | |
| | | | | | | |
| (2) | | | | | | |
| | Low Income | | Medium Income | | High Income | |
| Whole milk price premium: | | | | | | |
| Flat | -0.42 | (0.06)** | -0.62 | (0.02)** | -0.52 | (0.06)* |
| Up to 5% | -0.83 | (0.07)** | -0.86 | (0.03)** | -0.87 | (0.07)* |
| 5% to 10% | -1.14 | (0.07)** | -1.25 | (0.03)** | -1.07 | (0.08)* |
| 10% to 15% | -1.33 | (0.10)** | -1.33 | (0.06)** | -0.97 | (0.12)* |
| More than 15% | -1.63 | (0.18)** | -1.70 | (0.1)** | -1.26 | (0.21)* |
| Demographics | | | Demographic Interactions with Flat Indicator | | | |
| % Poverty | 0.06 | (0.02)* | | | -0.08 | (0.04) |
| % College | -0.25 | (0.03)* | | | -0.07 | (0.04) |
| % White | -0.33 | (0.02)* | | | -0.02 | (0.03) |
| % Children | -0.06 | (0.02)* | | | 0.02 | (0.04) |
| % Elderly | -0.02 | (0.02) | | | 0.08 | (0.03)* |
| Population Density | 0.06 | (0.03)* | | | -0.03 | (0.03) |
| | | | | | | |
| R-square | 0.78 | | | | | |
| Number of Observations | 1708 | | | | | |

Figure 1: Distributions of Local Demographic and Competitive Characteristics

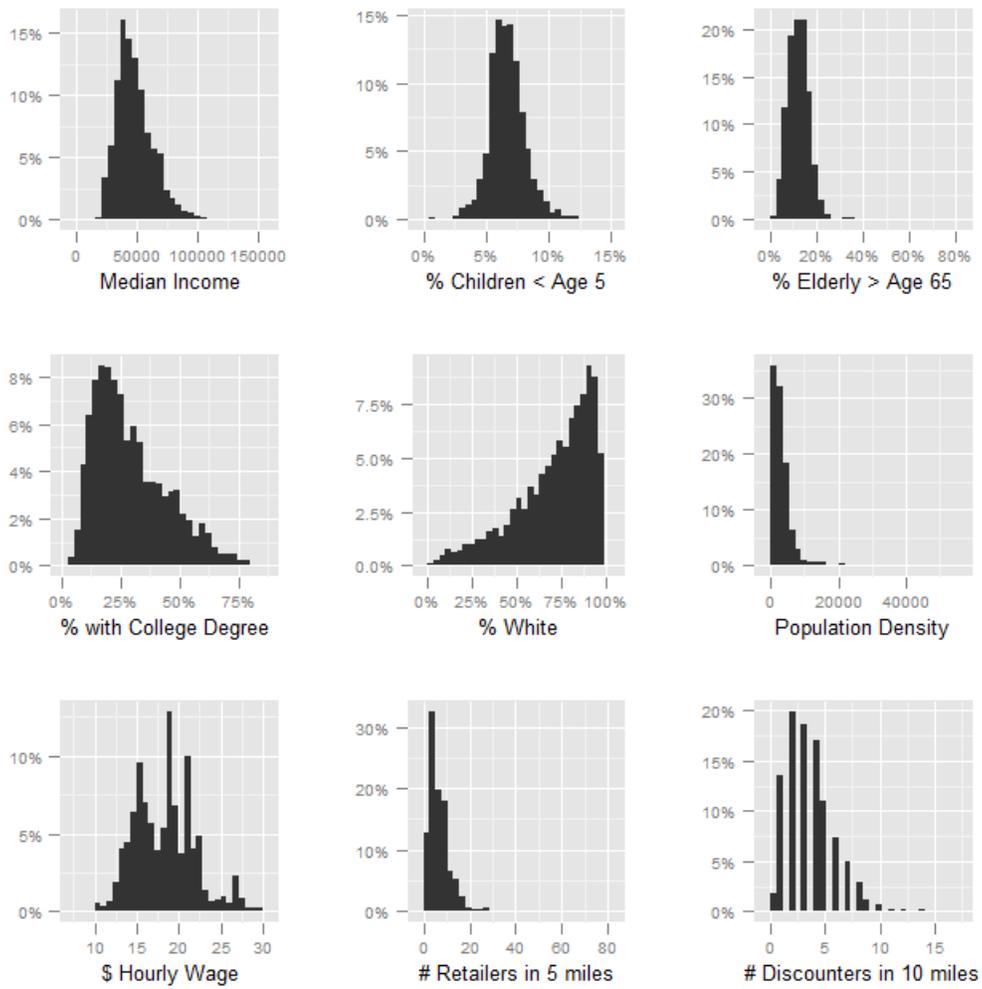


Figure 2: Distribution of second stage parameter estimates after accounting for first-stage estimation error.

