The Incidence of Grocery Taxes in U.S. Food and Factor Markets

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Abstract

We study the incidence of county-level grocery sales taxes across the United States from 2010-2019. We find substantial grocery tax over-shifting to consumers. On average, a grocery tax that generates $1 in government revenue leads to a $1.33 rise in tax-inclusive consumer food prices. This tax over-shifting is even higher for lower-income households and shoppers at discount and dollar stores. The grocery tax incidence varies significantly among foods, with over-shifting highest for perishable staples. The increased retail margins arising from grocery tax over-shifting do not translate into increased earnings for food retail workers or higher prices farmers receive.

Keywords: Food Sales Taxes, Tax Incidence, Retail Food Prices, Demand Analysis

JEL Codes: H22, L81, Q11, D12

*Zhao, Kaiser and Barrett: Cornell University; Zheng: University of Kentucky. Zhao is the corresponding author at jz877@cornell.edu. We thank three anonymous reviewers and various seminar audiences for helpful comments on earlier drafts. Our analyses are based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. This research received no financial support. The authors declare no conflicts of interest.

1 Introduction

Approximately one-third of all United States (U.S.) counties assess a state, county, or combined sales tax on food purchased at a retail outlet. Such grocery taxes are widely considered distributionally regressive because, per Engel's Law, low-income households spend a larger proportion of their income on food than do higher income families.

The distributional effects also turn, however, on the incidence of grocery taxes.[1] Standard welfare theory predicts that the tax incidence between consumers and retailers under perfect competition depends on the relative price elasticities of demand and supply; whichever party is less price responsive bears more of the tax burden (Jenkin 1872; Harberger 1962). Conversely, grocery taxes might be especially regressive if firms with market power face convex demand curves, enabling them to raise (tax-exclusive) product prices so that consumers not only shoulder the full tax burden but also pay extra for the same foods, despite no change in food retailers' marginal cost, a phenomenon known as 'tax over-shifting' (Anderson et al. 2001; Bonnet and Réquillart 2013; Weyl and Fabinger 2013; Pless and van Benthem 2019). Given widespread unease about grocery tax regressivity, rising concerns about market power in a range of U.S. industries (Berry et al. 2019), and the paucity of current evidence on this topic (Besley and Rosen 1999), the incidence of U.S. grocery taxes seems a timely, policy-relevant topic for study.

We are aware of only three previous studies of grocery tax pass-through to consumers on several food items, all of which found tax over-shifting on most food products. Besley and Rosen (1999) examine sales tax pass-through for a very small set of food and non-food products based on data from the 155 largest cities in the U.S.. They find tax over-shifting for most food items, including bananas, bread, milk, eggs, Crisco, and Coke. Politi and Mattos (2011) study ad-valorem tax pass-through on retail prices for ten food products – beans, beef, bread, butter, coffee, flour, milk, rice, soybean oil, and sugar – in Brazil's 16 states from 1994-2008. Finally, Gračner et al. (2022) estimate a roughly 60% average pass

[1] Grocery taxes could also have indirect effects through induced changes in food consumption patterns that affect health and food security outcomes (Allcott et al. 2019; Zheng et al. 2021; Cawley and Frisvold 2023; Wang et al. 2023) or through general equilibrium effects. We abstract from those mechanisms in this paper.

through for taxes on energy-dense food in Mexico between 2012 and 2016, with consumers shouldering the full tax burden, with or without an over-shift markup, on almost all taxed food products.

The first contribution of this paper is a comprehensive examination of grocery tax pass-through across all food categories in the U.S. We constructed a panel dataset of U.S. grocery food tax rates at the county level, which we merge with NielsenIQ Homescan household food purchase data at the product (UPC)-level for 2010 through 2019. These data enable us to estimate grocery tax pass-through rates using individual transactions observations on specific food products. Our results show considerable over-shifting of grocery taxes to consumers. Specifically, a one dollar increase in grocery tax revenues to state or local government leads to a \$1.33 increase in the tax-inclusive price, on average. Grocery taxes thereby increase retail margins on food items, which could lead to additional revenue gains for retailers, given price inelastic demand for food items.

Our second contribution is to identify important heterogeneity in grocery tax over- shifting by household and store types and by product groups. Lower-income, White, Hispanic or Asian households, and shoppers at discount, drug, warehouse stores, or especially dollar stores – retail formats that disproportionately serve lower-income customers (Stern et al. 2015) – face greater grocery tax over-shifting than do higher-income or Black or Native American consumers at conventional grocery or convenience stores. Highly perishable staple products like fluid milk exhibit the highest rates of tax over-shifting.

Our third contribution links grocery taxes with underlying factor markets, namely retail worker earnings and farm-level product prices, to gain a more complete understanding of who benefits from grocery tax over-shifting. In partial equilibrium, grocery tax over-shifting to consumers implies an increase in food retail workers' and product suppliers' marginal revenue product, without any corresponding increase in fixed or marginal costs. In 2022, almost 45% of consumer expenditures on food for home consumption accrued to agri-food value chain workers and half of food retailers' gross revenue that accrued to food retailers passed through to workers (USDAERS, 2023). Given the strong evidence we find of grocery tax over-shifting, do any of the increased retail margins to retailers with market power pass through to their workers or suppliers? In partial equilibrium with competitive labor markets, an exogenous positive shock to prices increases the marginal revenue product of labor and therefore should translate into greater food retail worker earnings, whether through increased wage rates, hours worked, or both. Yet a growing body of research suggests that retailers possess significant demand-side market power in wage-setting, with many grocery store employees earning wages close to the statutory minimum (Berger et al., 2022; Bachmann and Frings, 2017; Greenhalgh-Stanley et al., 2018). Further, food retailers employ a modest minority of hourly wage workers in any geographic market, and without competitive upward wage pressure, in general equilibrium food retail employers may be able to retain the full increase in retail margins. Indeed, we find no impact of grocery taxes on county-level grocery store workers' earnings; indeed, the point estimates are negative but statistically insignificant. These results are consistent both with others' recent findings that employers exercise market power (De Loecker et al. 2020; Azar et al. 2022; Berger et al., 2022; Card 2022; Yeh et al. 2022) and with the observation that food retail has insufficient impact on local labor markets to affect wage rates in general equilibrium.

Similar arguments apply to agricultural commodities that undergo minimal processing. For example, our product-level estimates identify fluid milk as the product with the highest rate of grocery tax over-shifting, and in 2022, 51 percent of the consumer price of fresh milk purchased for consumption at home accrued to farmers.[2] Higher fluid milk retail margins caused by a grocery tax therefore imply non-negligible increases in the returns to fluid milk. But whether that translates into higher farmgate prices for dairy farmers depends on how well the local milk market is integrated with broader national markets and consumer demand response to higher prices caused by county- or state-level increases in grocery taxes. We find no significant impact of grocery taxes on the county-level Class I minimum milk price received by farmers.

Some state and local governments rely on grocery taxes for an important part of their revenues. But the incidence of those taxes appears quite regressive. The main finding of this research is that grocery tax over-shifting leads to substantial pre-tax retail price increases among food items, while the magnified tax burden falls disproportionately on consumers,

[2]Per USDA-ERS at https://www.ers.usda.gov/data-products/price-spreads-from-farm-to-consumer/highlights-and-interactive-charts/, accessed 15 May 2024.

especially lower-income households and patrons of dollar stores, with no discernible gains flowing to workers or farmers.

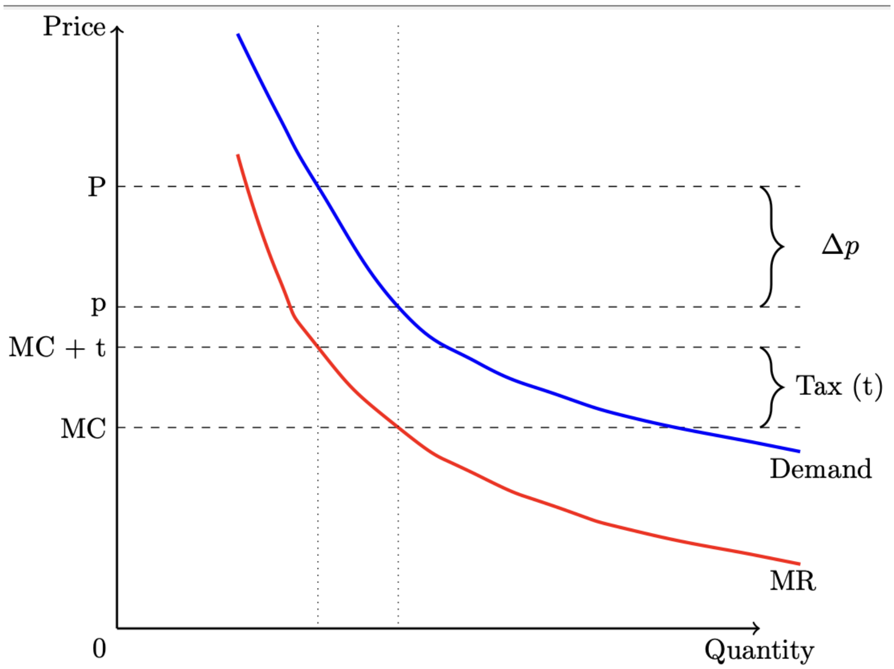
2 Analytical Framework for Estimating Grocery Tax Pass-Through

This section briefly summarizes the existing microeconomic theory of tax pass-through so as to help readers understand how to interpret the empirical results that follow.

A. Decomposition of Tax Over-shifting

Under In the presence ofa convex demand curve, Pless and van Benthem (2019) illustrates the over- shifting for the case of a subsidy. We illustrate the counterpart scenario for a tax over- shifting in Figure 1. When a tax (t) is introduced, the marginal cost curve shifts upward from MC to $MC + t$. Facing convex consumer demand, a firm with market power increases price by $P - p = \Delta p > t$. This is the definition of tax over-shifting because it implies that the tax-exclusive price $P - t > p$. This occurs because the less elastic demand at higher quantities allows the firm to pass through more than the full amount of the tax to consumers, thus increasing the final price by more than the tax imposed.

Figure 1. Tax Over-Shifting with a Highly Convex Demand Curve



Weyl and Fabinger (2013) and Pless and van Benthem (2019) show the tax pass-through for monopoly and symmetric, imperfect competition, respectively as:

$$(1) \quad \frac{dP}{dt} = \frac{1}{1 + \frac{\varepsilon_D - 1}{\varepsilon_S} + \frac{1}{\varepsilon_{ms}}}$$

$$(2) \quad \frac{dP}{dt} = \frac{1}{1 + \frac{\theta}{\varepsilon_\theta} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}$$

where t and P denote a tax expressed in per-unit format, and the tax-inclusive price, respectively. The elasticity parameter ε_D is the elasticity of demand, ε_S represents the elasticity of supply (i.e., of the inverse marginal cost curve), ε_{ms} reflects the curvature of the demand function, θ is a market conduct parameter ranging from zero (perfect competition) to one (pure monopoly), which is invariant to the changes in P, and the parameter ε_θ reflects how the conduct parameter varies as the quantity produced changes. See Weyl and Fabinger (2013) or Genakos and Pagliero (2022) for further details and discussion. These equations show that, with a sufficiently convex demand curve, the pass-through rate $\frac{dP}{dt}$ can exceed 1, meaning the price increase Δp is greater than the tax t itself. This is tax over-shifting, the phenomenon for which we test.

B. Tax Pass-Through for Ad Valorem Taxes

Since the grocery sales tax is an ad valorem tax (τ), we follow Besley and Rosen's (1999) derivation of a per-unit-tax equivalent measure of sales tax pass-through. Consider the following model, in which the logarithm of the tax-exclusive price, p^*, is regressed on sales tax, τ, and control variables, X, which includes an intercept term.

$$(3) \quad \ln p^* = \beta_1 \tau + \beta_2 X$$

Multiplying both sides of the equation by p^* yields

$$(4) \quad p^* \ln p^* = p^* \left(\beta_1 \tau + \beta_2 X\right).$$

Totally differentiating equation (4) leads to

$$(5) \quad dp^* \ln p^* + dp^* = \beta_1 d \left(p^* \tau\right) + \beta_2 X dp^*,$$

or equivalently,

$$(6) \quad \frac{dp^*}{d\,(p^*\tau)} = \frac{\beta_1}{1 + \ln p^* - \beta_2 X} = \frac{\beta_1}{1 + \beta_1 \tau}.$$

Using the fact that the tax-inclusive price, $P = p^*(1+\tau)$, equation (6) can be expressed as:

$$(7) \quad \frac{dP}{d\,(p^*\tau)} = 1 + \frac{dp^*}{d\,(p^*\tau)} = 1 + \frac{\beta_1}{1 + \beta_1 \tau}.$$

Equation (7) estimates how much the tax-inclusive price, P, increases given an increase in tax revenue $d(p^*\tau)$ from an increase in the ad valorem tax rate, τ. Equation (7) is comparable to the tax pass-through in the previous sub-section focusing on a unit tax (t), thus we use this expression to estimate tax pass-through per dollar of grocery tax revenue generated for the taxing jurisdiction.

3 Data

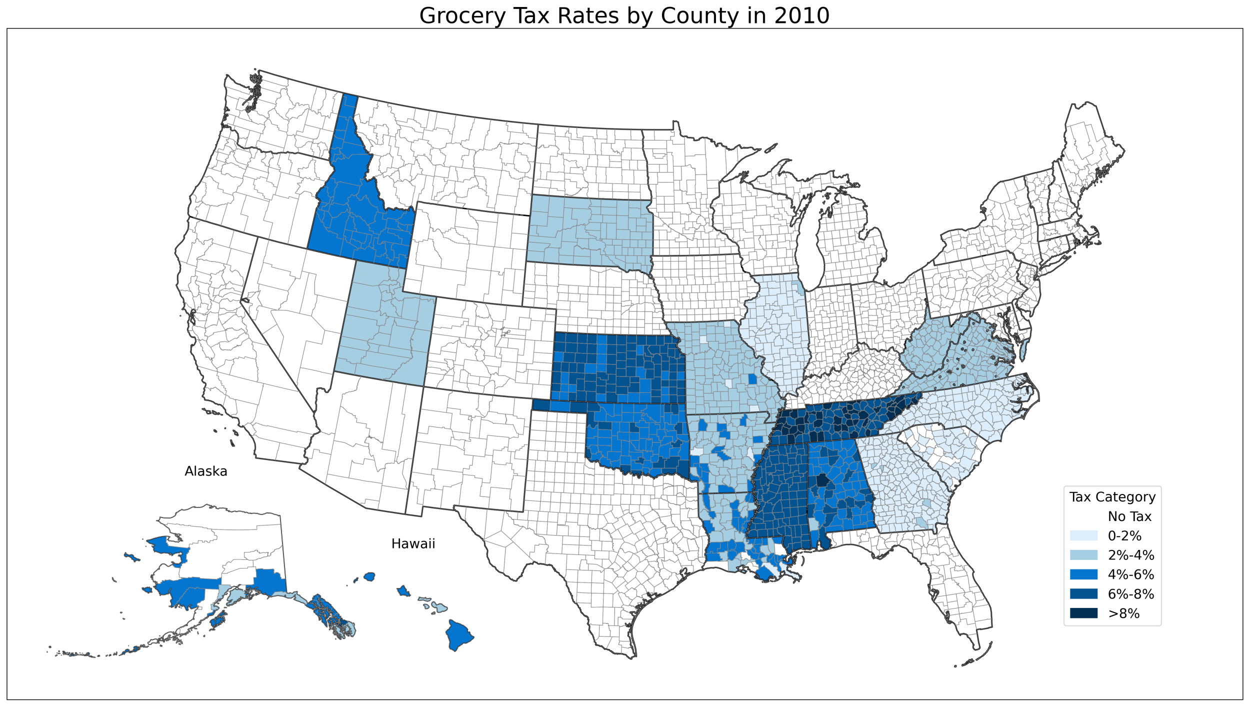
Our analysis relies on two data sets for the estimation of grocery tax pass-through rates, and then two other data sets to explore whether grocery taxes impact grocery workers' earnings or the price farmers get from milk sales.

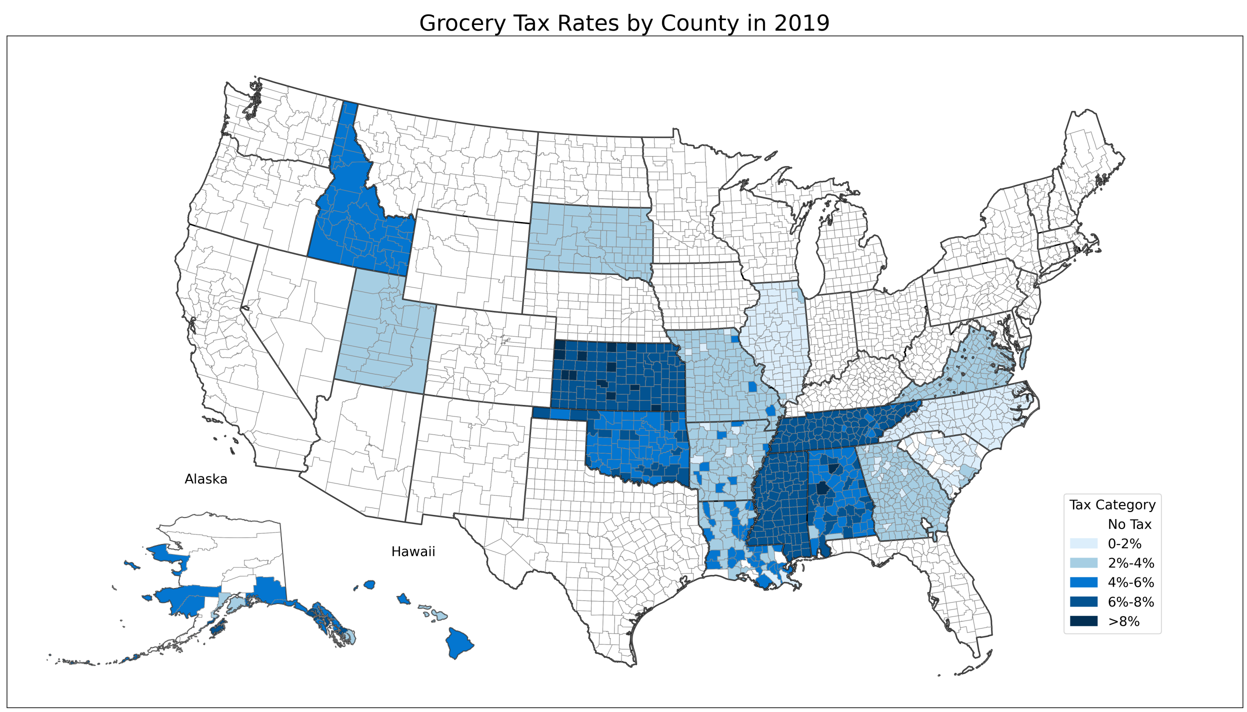
A. State and County Food Sales Taxes

We assembled data on U.S. county-level food sales tax rates 2010 through 2019. The total grocery tax rate in each county is the combination of the state and county-level tax rates, obtained from Tax-Rates.org and various websites of state and county Departments of Revenue. The data contain all the historical rates and the dates of tax rate changes.

The maps in Figure 2 highlight important variations in grocery tax rates, 2010 to 2019. In 2010, the highest grocery tax rates, particularly those in the 6%-8% range and above, were concentrated in southern states such as Alabama, Mississippi, and Tennessee. These states have historically maintained higher grocery tax rates than the rest of the country. Some states in the Midwest and South experienced notable shifts in their grocery tax rates over our study period. In states like Kansas and Tennessee, many counties exhibited an increase in grocery taxes, from lower tax rates (0%-4%) to higher ones (4%-8%) by 2019. These shifts reflect local policy responses to evolving fiscal conditions or changing political priorities that prompted increased grocery tax rates. In contrast, West Virginia eliminated its grocery tax in July 2013. [3]

Figure 2. US Grocery Tax Rates By County in 2010 and 2019





[3] https://www.salestaxinstitute.com/resources/west-virginia-introduces-phaseout-grocery-food-tax

Over our 2010-2019 study period, 19 different states had at least one county with a positive grocery tax rate in at least one year. The highest combined state and county rate was 9% in some counties of Alabama (Table A1). The average combined (state plus county) rate among counties with a positive grocery tax was 4.3% in 2019. Eight states impose taxes on food with the same rate as the general sales tax: Alabama (8%), Mississippi (7%), Kansas (6.5%), Idaho (6%), Tennessee (5%), Oklahoma (4.5%), South Dakota (4.5%), and Hawaii (4%). [4] Six states collected food sales taxes at a reduced rate compared to general sales taxes: Utah (3%), Virginia (2.5%), North Carolina (2%), Arkansas (1.5%), Missouri (1.225%), and Illinois (1%). Four states do not impose grocery taxes at the state level but have specific counties that do: Alaska, Georgia, Louisiana, and South Carolina. West Virginia abolished grocery taxes in 2013.

Our econometric strategy (discussed below) includes county, month, and universal product code (UPC) fixed effects. The pass-through rates we identify therefore come from inter-household variation within counties, months and products. Over this period, the largest state-level tax change occurred in 2013 when over 30 counties in Georgia increased their food sales taxes by 3 percentage points. The smallest change occurred in Kansas, when the state reduced the food sales tax by 0.15 percentage points in early 2014. No changes occurred in Hawaii, Idaho, Mississippi, North Carolina, South Dakota, or Utah during this period. Variation in grocery tax rates within counties over time arises due to a range of macroeconomic and political factors – e.g., state-level legislative changes, county and state fiscal conditions – that should be independent of the individual consumer-by-product-level transactions data we use to identify grocery tax pass-through rates. Thus county-level intertemporal changes in grocery sales tax rates (reported in Appendix Table A2) generate the identifying variation of interest. This should easily satisfy the conditional independence assumption necessary to identify the causal effects of grocery taxes on tax-exclusive retail prices.

[4] Five of these states (KS, ID, TN, OK, and HI) offer a tax credit to low-income households to offset the tax costs, although it is unclear how much redemption occurs.

B. NielsenIQ Consumer Panel

We use food purchases and household demographic data from NielsenIQ Homescan Consumer Panel (NHCP) from January 1, 2010, to December 31, 2019. NielsenIQ data offer a nationally representative longitudinal panel of 40,000 to 60,000 U.S. households annually (Harding et al., 2012). Though households may rotate in and out of the panel over time, over 80% of the households remain in the sample each year. NHCP provides a wealth of information on grocery food transactions such as product brand, size, store type, coupon usage, zip code, price, and other product and store characteristics. In addition, it includes household socioeconomic characteristics such as income. Appendix Table A3 describes these data.

The transaction-level, decade-long NHCP data take up over 700 GB. To keep estimation computationally manageable, we employed a supervised machine learning algorithm using 5% bootstrapped samples, with 500 replicates. We report mean parameter estimates from the empirical distribution of bootstrapped parameter estimates and report the standard deviations of the bootstrapped distribution as the standard errors of those estimates. As shown in Table A3 for a sample generated by bootstrap, we include 15,825,274 transactions made by 145,794 households in all the 50 states plus the District of Columbia. This includes 329,678 distinct UPCs. The distribution of food categories is shown in Appendix Figure A1. Around one-half of the observed transactions are dry grocery products (e.g., cereal, breakfast food, crackers, cookies). The next two major categories are dairy products (fluid milk, cheese, etc.), and fresh produce (fruits and vegetables).

C. Grocery Store Workers' Earnings

We obtain county-level average earnings data for food retail workers, by store type, from the Quarterly Workforce Indicators (QWI) dataset for 2010-2019, from the United States Census Bureau's Longitudinal Employer-Household Dynamics program. We follow the North American Industry Classification System (NAICS) codes, using categories for Grocery and Related Product Merchant Wholesalers (4244), Grocery and Convenience Retailers (4451), Specialty Food Retailers (4452), and Warehouse Clubs, Supercenters, and Other General Merchandise Retailers (4552).

D. Class I Farmgate Milk Prices

The Class I milk price is the minimum price U.S. dairy farmers receive each month. It varies across U.S. counties based on the federal milk marketing order system authorized by the Agricultural Marketing Agreement Act of 1937. The Class I milk price thus provides a lower bound indicator of a key input cost for milk retailers. We obtained county-month-level Class I milk price data from USDA Agricultural Marketing Service. [5]

4 Estimation Strategy

Our regressions follow a straightforward estimation strategy. We treat grocery tax rates as exogenous, which is almost surely true for the UPC-level, individual consumer purchase data that underpin our tax pass-through estimates. The reduced-form regression of pre-tax (i.e., tax- exclusive) unit prices on the grocery sales taxes is:

$$\text{(8)} \quad \ln(p_{uijm}) = \beta_0 + \beta_1 \tau_{jm} + \eta C_{jm} + \theta X_{im} + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm}$$

where $\ln(p_{uijm})$ is the natural logarithm of the pre-tax (i.e., tax-exclusive) price paid for food product (UPC code) u by household i in county j in month (and year) m . The ad-valorem tax for food groceries in county j and in month m, τ_{jm} , expressed in proportional terms (i.e., in the [0,1] interval), is our key variable of interest. Per Besley and Rosen (1999), the semi-log specification allows us to assess the degree of tax pass-through; a positive β_1 indicates over-shifting.[6] We include the vector C_{jm} to account for measurable cost-of-living differences, including median apartment rent, average commercial electricity rate, and state minimum wage (Leung 2021). X_{im} is a vector of household characteristics, including income, and household head race and educational attainment. We also include fixed effects to control for time-invariant mean differences in prices across county (δ_j) , UPC (α_u) , and month-year (φ_m) . The error term is ε_{uijm} has the usual properties. Standard errors are clustered at the county level to alleviate concerns about residual serial correlation. Using product and

[5] https://www.ams.usda.gov/resources/price-formulas

[6] Note that we do not include any measure of market power – like the Herfindahl index – due to endogeneity to the same conditions that might cause grocery taxes and because the relationship between market concentration and prices is fundamentally ambiguous even in the presence of market power (Berry et al. 2019).

county fixed effects, our identification comes from within-product price changes in response to within-county tax changes over time.

We also estimate a version that includes household fixed effects as a robustness check; most household characteristics necessarily drop out because they do not change over time. Since those characteristics – e.g., race, income category – hold considerable interest, our preferred specification does not include household fixed effects. We also interact household characteristics and store-specific retail channel information with grocery taxes so as to test for potentially heterogenous price responses across customers (where White, low-income households are the baseline category) or store channels, with grocery stores as the benchmark to compare against discount stores, Warehouse Clubs, convenience stores, dollar stores, and drug stores.

5 Grocery Tax Pass-Through Estimates

The first column of Table 1 displays the main baseline results. The estimated β_1 coefficient is 0.338, significant at the one percent level. Food retailers significantly over-shift grocery taxes to retail consumers through price markups, on average. Following equation (7) – drawing on Besley and Rosen (1999) – we can estimate how much the tax-inclusive retail price increases per dollar of added government tax revenue. In our baseline model (Table 1, column 1), using the average grocery tax rate of 4.3% for counties that collected grocery taxes in 2019 ($\tau = 0.043$), we estimate that for every dollar of grocery tax revenue collected by government, the average retail tax-inclusive price paid by consumers increases by $1.33 across all grocery food products.

Across robustness checks (Table A4) with (1) no household fixed effect nor household-level control variables, (2) household fixed effects with no other household-level controls, and (3) demographic and other control variables with household fixed effects, the β_1 estimated coefficient remains positive, statistically significant, and quite similar in magnitude, ranging from 0.265 to 0.396, none significantly different from our baseline estimates.

We test for heterogeneous grocery tax over-shifting by interacting the grocery tax variable with household characteristics, store characteristics, or both (Table 1, columns 2-5). Starting from equation (7), and given an ational average grocery tax rate of 4.3% (0.043), conditional on having any grocery tax, is sufficiently small to approximate the pass-through rate as $1+\beta_1$, this results in a pass-through rate of 1.381 for low-income households as the reference group. The highest income levels experience a statistically significant 23 percent lower grocery tax pass throughover-shifting than the lowest income households (column 2).

Table 1. Regression Results on Tax Pass-through, by Household Demographics and Store Channels

Dependent Variable: ln (Pre-tax Unit Price)	(1) Baseline Result	(2) By Income	(3) By Store Types	(4) By Race	(5) All Interaction Terms
Grocery Tax	0.338***	0.381***	0.189	0.372***	0.265**
	(0.124)	(0.131)	(0.125)	(0.124)	(0.129)
Grocery Tax * Median Income		-0.041			-0.029
		(0.047)			(0.046)
Grocery Tax * High Income		−0.086*			-0.071
		(0.052)			(0.051)
Grocery Tax * Discount Stores			0.336***		0.337***
			(0.052)		(0.051)
Grocery Tax * Warehouse Club			0.620***		0.627***
			(0.108)		(0.108)
Grocery Tax * Convenience Store			-0.056		-0.04
			(0.421)		(0.421)
Grocery Tax * Dollar Store			1.257***		1.265***
			(0.197)		(0.196)
Grocery Tax * Drug Store			0.312*		0.324***
			(0.157)		(0.324)
Grocery Tax * Black				−0.181***	−0.215***
				(0.067)	(0.065)
Grocery Tax * Hispanics				0.055	0.038
				(0.088)	(0.088)
Grocery Tax * Asians				-0.077	-0.069
				(0.171)	(0.171)
Grocery Tax * Other Races				−0.282**	−0.303***
				(0.113)	(0.112)
Month Fixed Effects	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y
UPC Fixed Effects	Y	Y	Y	Y	Y
Household Fixed Effects	N	N	N	N	N
Household Characteristics	Y	Y	Y	Y	Y
County-Level Economic Controls	Y	Y	Y	Y	Y
Number of Clusters	2,894	2,894	2,894	2,894	2,881

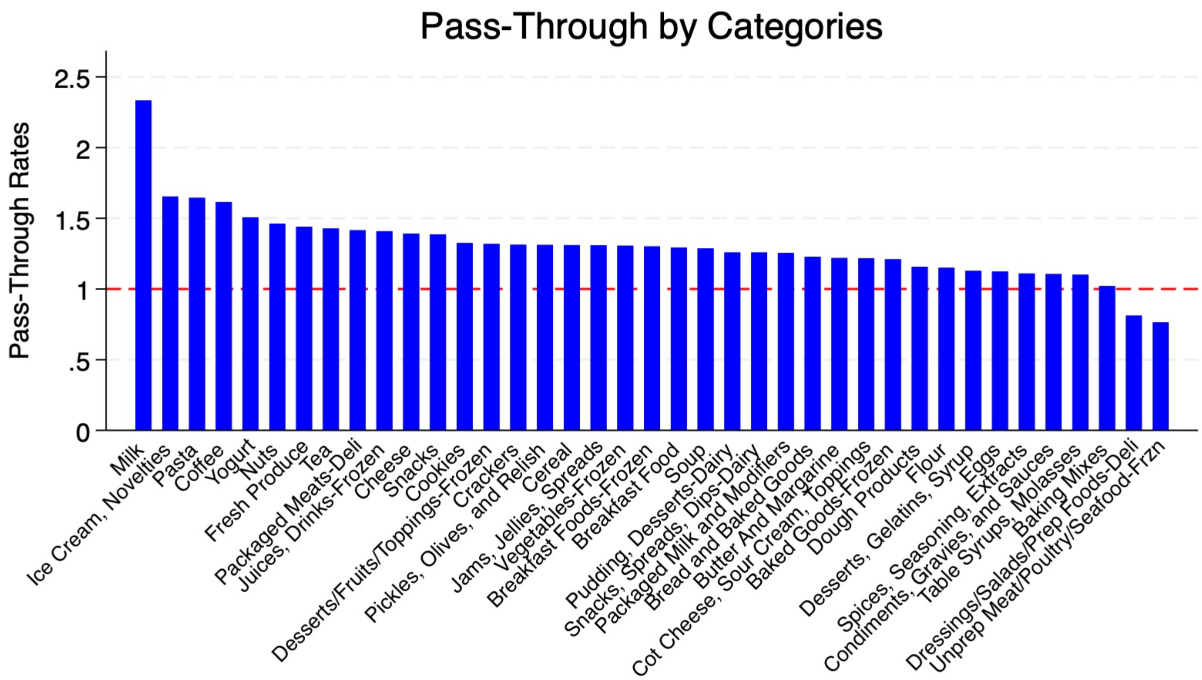
Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. N=14,383,111.

This result may seem counter-intuitive since the price elasticity of food demand typically declines (in absolute value) with income. This may reflect lower income households having less flexibility to travel to alternative food retail outlets, as compared to higher income households, although we cannot test this hypothesis with these data. That conjecture is consistent, however, with the striking heterogeneity we see in grocery tax over-shifting by store type. We find that drug stores, discount stores, warehouse club stores, and especially dollar stores – all disproportionately frequented by lower-income consumers – all over-shift grocery taxes significantly more than do grocery stores or convenience stores. The estimated tax coefficient for discount stores (column 3) is 34 percentage points higher than conventional grocery stores, 62 percentage points higher for warehouse clubs, and 126 percentage points higher for dollar stores. This indicates that dollar stores exhibit nearly double the tax pass-through compared to regular grocery stores.

The store categories that have the highest rates of grocery tax over-shifting are frequented disproportionately by White households. Indeed, we find that households with Black household heads experience only half the pass-through rate of those with White household heads, and those with Other Race (mainly Native American) household heads face almost no statistically significant grocery tax pass-through at all, with an estimated coefficient slightly above zero (1.09) as shown in column 4. Once we allow for different tax rate coefficients by income, race, and store type, the heterogeneity by income shrinks in magnitude and becomes statistically insignificant, while the racial differences increase both in magnitude and proportional to the baseline white, lower-income households (column 5).

Considerable variation in tax shifting exists among major product categories. Table A5 and Figure 3 show the estimates of pass-through rates that come from interacting the grocery tax with various product categories (spreads, jellies, and jams are the baseline product group). Fresh milk products have the highest over-shifting. This is not surprising because fresh milk products are perishable staples and tend to be among the most price inelastic of all grocery items, with estimated price elasticities of -0.045 (Kaiser, Streeter, and Liu, 1988), -0.039 (Schmit and Kaiser, 2004), and - 0.154 (Zheng and Kaiser, 2008). For milk products, an increase in the ad valorem tax rate equivalent to one dollar of tax revenue increases the retail tax-inclusive milk price by $2.33.

Figure 3. Grocery Tax Pass-Through Rates by Food Categories



At the opposite extreme, frozen unprepared meat and seafood have the lowest tax incidence for consumers. For that product category, a tax increase equivalent to one dollar raises the tax-inclusive price by only \$0.76; retailers absorb a non-trivial portion of the tax burden. A similar result holds for salads and deli, where one dollar of tax revenue raises the tax-inclusive price by \$0.81. These latter two results reflect product categories with significantly greater price elastic demand; for example, recent estimates for deli ham range from –1.3 to -1.6 (Lusk and Tonsor, 2016).

Of the 40 different food product categories we study (Table A5), only two – deli salads and prepared foods, and unprepared frozen meat – exhibit evidence of incomplete grocery tax pass-through to consumers. Taxes pass through fully on baking mix products, i.e., there is no over-shifting but the full grocery tax incidence falls on consumers. We find statistically significant evidence of grocery tax over-shifting for the other 37 product categories. The magnitudes vary, but the breadth of the grocery tax over-shifting effect is striking. We also check for variations across six food categories as classified by Nielsen IQ and find meaningful and statistically significant differences between, for example, dairy products, dry goods, and packaged meats – all with large, statistically significant over-shifting – and fresh produce (Table A6).

6 Model Diagnostic Checks

We subject these estimates to a range of robustness checks, reported in the Online Appendix. First, we assumed that grocery taxes are exogeneous, following prior studies on sales taxes (Rohlin and Thompson, 2018; Zheng et al., 2021; Zhao et al., 2021). We exploit the panel nature of the data to conduct a placebo test in which we add future tax rates, τ_{jm+1} , to equation (8):

$$\ln\left(p_{uijm}\right) = \beta_0 + \beta_1\tau_{jm} + \beta_2\tau_{jm+1} + \eta C_{jm} + \theta X_i + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm}. \tag{9}$$

If the grocery tax is strictly exogeneous, then prices should not respond to future tax changes, i.e., β_2 should equal zero. As shown in Table A7, the β_2 estimate is indeed statistically insignificantly different from zero, while the β_1 remains substantially unchanged and statistically significant at the 1 % level.

Second, our model requires parallel trends across counties since in essence it is a differences-in-differences estimator. So, we include county-specific time trends:

$$\ln\left(p_{uijm}\right) = \beta_0 + \beta_1\tau_{jm} + \eta C_{jm} + \theta X_i + \beta_j\left(\delta_j * \mathit{trend}\right) + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm} \tag{10}$$

where $\delta_j * \mathit{trend}$ is the county-specific, monthly linear trend. We also try county-specific quarterly and annual linear trends. If the estimated tax impact is not sensitive to the inclusion of county-specific trends, that reinforces the credibility of our findings. Appendix Table A8 shows our tax coefficients change little in magnitude, and not at all in statistical significance, from the version that does not include county-specific trends.

We also estimate an event study model. During our study period, several counties and states changed grocery sales tax rates multiple times. These multiple treatments could confound inference, so we restrict analysis to only the 144 counties that increased their grocery tax only once in our study period and compare these to a control group of counties with no grocery tax. The event study plots of the post-treatment effects (up to six months after) are consistent with our main results (Figure A2). After a county observed its only tax increase over the decade, tax- exclusive food prices increased, significantly so in two out of six months, even with the low power of this small subsample. No statistically significant pre-trend exists. We also find that the post-change tax increase estimates are equal to or higher than the corresponding tax decrease estimates (Figure A3). While this suggests the possibility of asymmetry consistent with the exercise of market power, the difference is not statistically significant, possibly due to insufficient power to detect such asymmetries given only 144 positive counties and 181 negative changes in the data.

Finally, we conduct a placebo test in which we randomize the assignment of grocery taxes among counties, keeping the other independent variables unchanged. This mechanically breaks the hypothesized causal correlation between grocery taxes and pre-tax prices in each county, generating a randomized pseudo-treatment that should have no impact on pre-tax food prices unless some spurious correlation exists (Christian and Barrett 2024). We bootstrap the grocery tax variable 500 times and plot the kernel densities of the resulting coefficient estimates and their p-values in Figure A4, and report results in Table A9. In only 4% of the 500 regression instances (20 times), did we observe p-values under 0.05. This exercise suggests that the estimated impact of grocery taxes on pre-tax food prices is not spurious. All in all, our core results stand up well to all the robustness checks we tried.

7 Who Captures the Retail Price Markups?

Our main finding is that food retailers significantly over-shift grocery taxes to consumers. For all food items, on average, the results indicate that an ad valorem tax sufficient to raise one dollar of revenue increases the retail tax-inclusive price by $1.33. Grocery food taxes create a significant revenue windfall for food retailers, with the amount depending on product mix and the price elasticities of demand for the food products on their shelves.

We can estimate how induced tax-exclusive price increases impact retailer revenues using the food product category-specific price elasticity of demand estimates of Okrent and Alston (2012), which range from -0.05 for dairy, to -0.31 for meat and eggs, to -0.58 for cereals and bakery, to -0.79 for fruits and vegetables. Additionally, we incorporate the budget shares of food product categories provided in their Table 1. Okrent and Alston (2012) relied on the Consumer Expenditure Survey and Consumer Price Indices to classify food groups, which differs from Nielsen's classification. We therefore established a one-to-one correspondence between Okrent and Alston (2012)'s product categories and those of the Nielsen Consumer Panel (Table A10). This permits us to merge budget shares and price elasticity estimates from Okrent and Alston (2012) with pass-through rates derived from our estimated regression coefficients based on Nielsen data so as to estimate the retail revenue effects of grocery tax changes.

For instance, in Alabama, grocery food taxes raised approximately $500 million in 2021.[7] That implies a grocery tax windfall of $80 million, calculated with the equation in the footnote. [8] In Mississippi, the 7% tax on food generates between $267 million and $315 million annually in tax revenue for the state, but also brings up to $42-50 million for grocery retailers due to over-shifting.[9] Other states' estimated tax revenue yield and grocery retailers' windfall revenue increases net of tax payments are shown in Table 2. Column 2 expands the grocery tax revenue to include all states, while Column 3 calculates the revenue windfall with weighted average revenue gains, incorporating budget shares and price elasticities derived from Okrent and Alston (2012).

These estimates raise an important question. When firms manage to pass on more than the full amount of a tax to consumers, do they retain the entire financial windfall, or do they share it? Specifically, do food retailers use this additional revenue to increase wages for their workers, or do they pass some of it along to upstream suppliers and farmers? The distribution of this windfall within the marketing chain is crucial to understanding the broader economic impacts of tax pass-through.

[7]https://wbhm.org/2021/why-alabama-lawmakers-just-wont-give-up-the-grocery-tax/

[8]Calculating the revenue change with the budget share and price elasticities, we find the total revenue of retailers increase by Grocery Tax Revenue * $\sum[BudgetShare_i * (1 - PriceElasticity_i * TaxPassThrough_i) - 2]$, which amounts to Grocery Tax Revenue * 0.159 on average nationwide.

[9]https://mississippitoday.org/2021/01/21/key-house-leader-says-mississippi-should-cut-highest-in-nation-grocery-tax/

Table 2. Grocery Revenue for Stores Located in State-Wide Positive Grocery Taxes in 2019

States	Tax Revenue	Tax Revenue Windfall
AL#	500	80
AR	450	72
HI#	270	43
ID#	79	13
IL	400	64
KS#	450	72
MO	70	11
MS#	315	50
NC#	400	64
OK#	300	48
SD#	104	17
TN	272	43
UT	200	32
VA	600	95

Food items are taxed at the full rate as sales tax.

* Tax revenue in Million USD.

*Alaska, Georgia, Louisiana, and South Carolina exempt food sales taxes at the state level, but groceries can still be subject to local sales taxes.

*Sources: State Departments of Revenue, tax.org, and taxfoundation.org.

A. Earnings of Grocery Store Workers

To answer the first part of that question, we regress earnings by food retail outlet employees on the grocery food tax and a similar set of country-level covariates used as control variables in the prior regressions:

$$\text{(11)} \quad \ln(\,Earnings_{\,ijq}) = \beta_0 + \beta_1 \tau_{jq} + \eta C_{jq} + \delta_j + \alpha_i + \gamma_q + \varepsilon_{ijq}$$

where the dependent variable is the logarithm of the average earnings of employees in food stores in industry i in county j in quarter (and year) q . The variable τ_{jq} is the ad-valorem grocery tax, C_{jq} is again a vector of measurable cost-of-living differences, and we include county, industry, and quarter-year fixed effects. The standard errors are clustered at the county level.

Table 3. Estimated Grocery Tax Pass-through to Average Worker Earnings

Dependent Variable: ln (Earnings)	(1)	(2)	(3)	(4)
Grocery Tax	-0.668	-0.557	-0.223	0.107
	(1.022)	(0.643)	(0.638)	(0.682)
Commercial Electricity Price			-0.007^{**}	-0.001
			(0.003)	(0.003)
Median Rent			0.0005^{***}	0.0009^{***}
			(0.00005)	(0.00005)
Minimum Wage			0.004	0.008^{**}
			(0.003)	(0.004)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	N	Y	Y	N
Economic Controls	N	N	Y	Y
Number of Clusters	2,693	2,693	2,693	2,693
N	149,328	149,328	134,279	134,279

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.

The main finding is that the grocery food taxes have no impact on food retail worker earnings (Table 3). We also run this regression separately by food store types, including grocery and merchant wholesalers, conventional grocery stores, specialty food stores, and warehouse clubs. We find no significant impact of the grocery food tax on average worker earnings in any type of retail food outlet (Table A11). Although half of the revenue accruing to food retailers is accounted for by labor costs (USDAERS, 2023), none of the significant revenue windfall food retailers enjoy for grocery tax over-shifting accrues to their workers.

B. Farmer Milk Prices

Food price changes induced by grocery taxes might impact the prices farmers in that county receive for commodities, perhaps especially for relatively lightly processed products like fresh, fluid milk, the food with the highest estimated grocery tax pass-through rate. We therefore estimate the pass-through of grocery taxes to the Class I milk prices as follows:

$$(12) \quad \ln\left(PI_{jm}\right) = \beta_0 + \beta_1 \tau_{jm} + \eta C_{jm} + \delta_j + \varphi_m + \varepsilon_{jm}$$

where the dependent variable is the logarithm of the Class I milk price in county j and month (and year) m , constructed by combining the national minimum monthly price and the county price differential. The rest remains the same as in the earnings model.

The results of the milk price model show that grocery food taxes have no impact on Class I milk prices (Table 4). Indeed, the point estimates are consistently negative and insignificant. Despite the tax-inclusive price of milk rising an estimated \$ 2.33 for every dollar of grocery tax revenue raised, and more than half of retail fluid milk prices flowing back to farmers, on average, dairy farmers do not seem to receive a higher price due to grocery taxes.

Table 4. Estimated Pass-through to Class 1 Milk Prices

	(1)	(2)	(3)	(4)
Dependent Variable: ln (Class 1 Milk Price)				
Grocery Tax	-0.299		-0.271	-0.290
	(0.320)	(0.329)	(0.413)	(0.398)
Commercial Electricity Price			0.0003	0.0003
			(0.003)	(0.0003)
Median Rent			-0.00003	-0.00002
			(0.00003)	(0.00003)
Minimum Wage			0.002	0.002
			(0.002)	(0.002)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	N	Y	Y	N
Economic Controls	N	N	Y	Y
Number of Clusters	2,893	2,893	2,893	2,893
N	373,320	373,320	373,311	373,311

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.

8 Discussion

We find that food retailers significantly over-shift grocery taxes onto consumers. We also find evidence of heterogeneous tax pass through based on consumer income and race, as well as by type of retail outlet. Specifically, African American and Other Race (i.e., Native American) households face significantly lower tax over-shifting than low-income White households do, while retailers that generally offer lower prices– i.e., warehouse, discount, and dollar stores – more substantially over-shift grocery taxes onto customers than grocery or convenience stores do. Tax pass-through rates also vary among food product categories. Highly price inelastic demand product categories like milk exhibit the greatest over-shifting while more price elastic products like frozen, unprepared meat and seafood had the lowest tax pass through.

Finally, although food retailers enjoy considerable price markup from grocery tax over-shifting, food retail workers and dairy farmers do not share any of this incremental revenue.

By process of elimination, it appears that food retailers accrue all the windfall gains from the grocery tax.

The major implication of these results is that sales taxes on foods appear even more regressive than previously thought. Not only does the flat, ad valorem rate feature of grocery sales taxes harm lower income relative to higher income households because the poor spend a larger share of their income on food, but we show that grocery taxes also increase tax-exclusive foods prices, and disproportionately so for lower-income households, especially those shopping at discount, dollar and warehouse format food retail outlets. This amplifies the regressive nature of the grocery sales tax, and this should be considered in any policy debate on whether to reduce or repeal their usage by local governments. Policy makers should look at ways to lessen the burden of this tax on lower income households. Lowering or eliminating the grocery tax would be one way to deal with this problem. However, doing so would reduce tax revenue, and government officials would need to look at alternative revenue generating options if it lowered grocery taxes.

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9 Online Appendix

Figure A1. Transactions by NielsenIQ Department

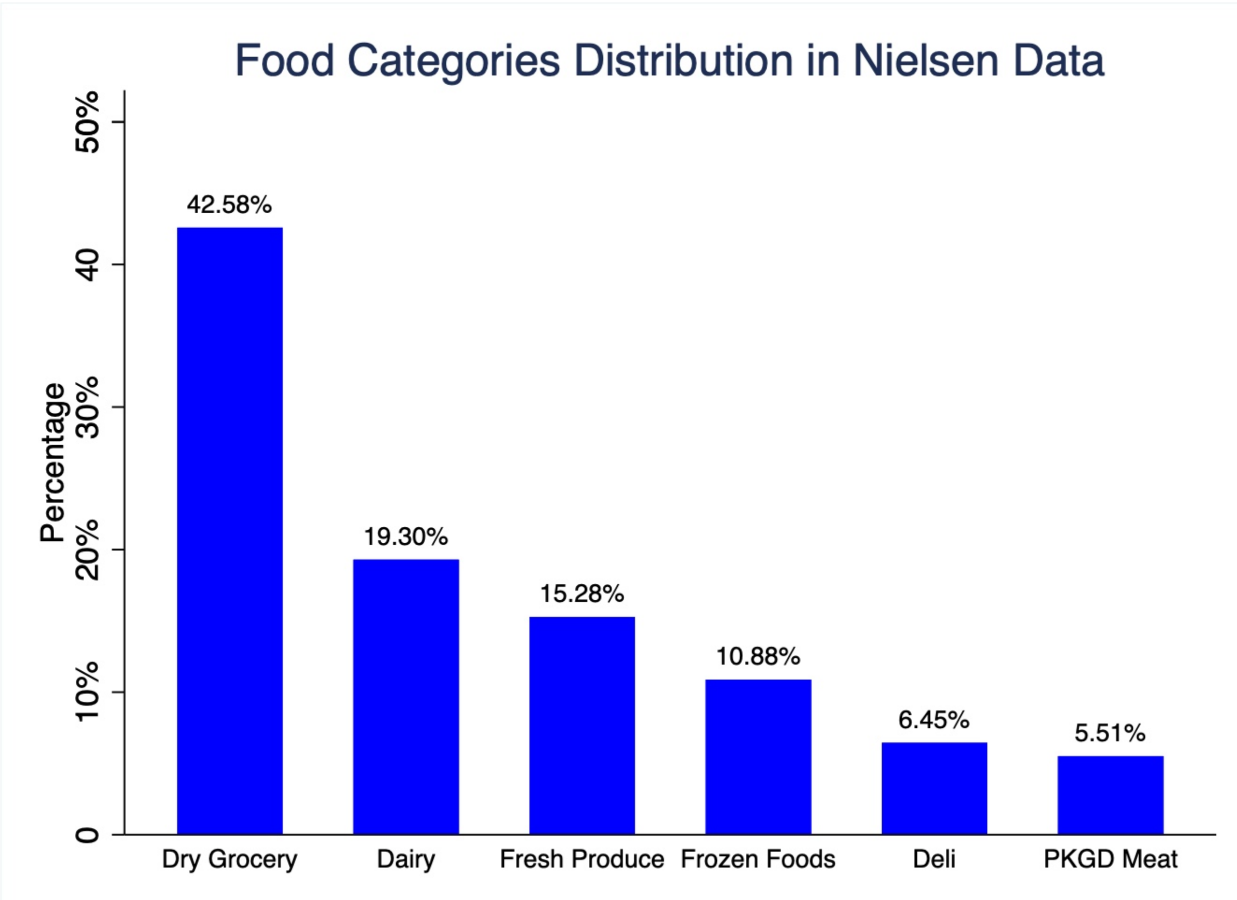

Figure A2. Event Study of Single Tax Increase

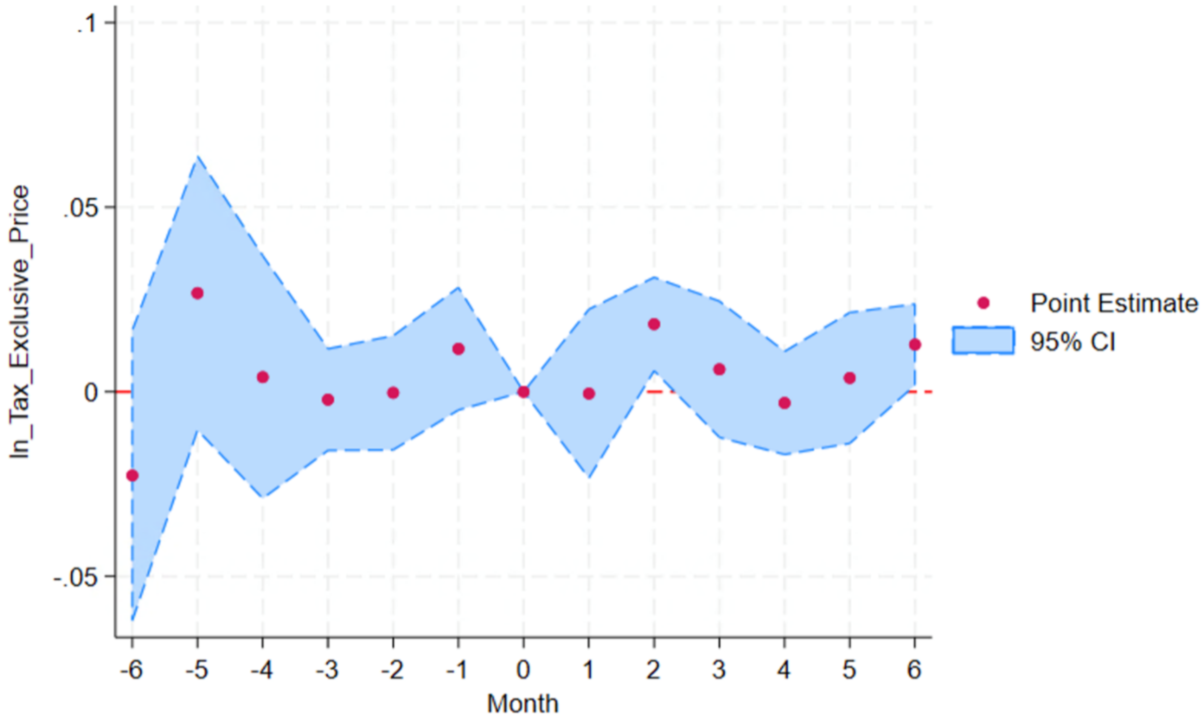

Figure A3. Event Study of Grocery Tax Increase vs Decrease

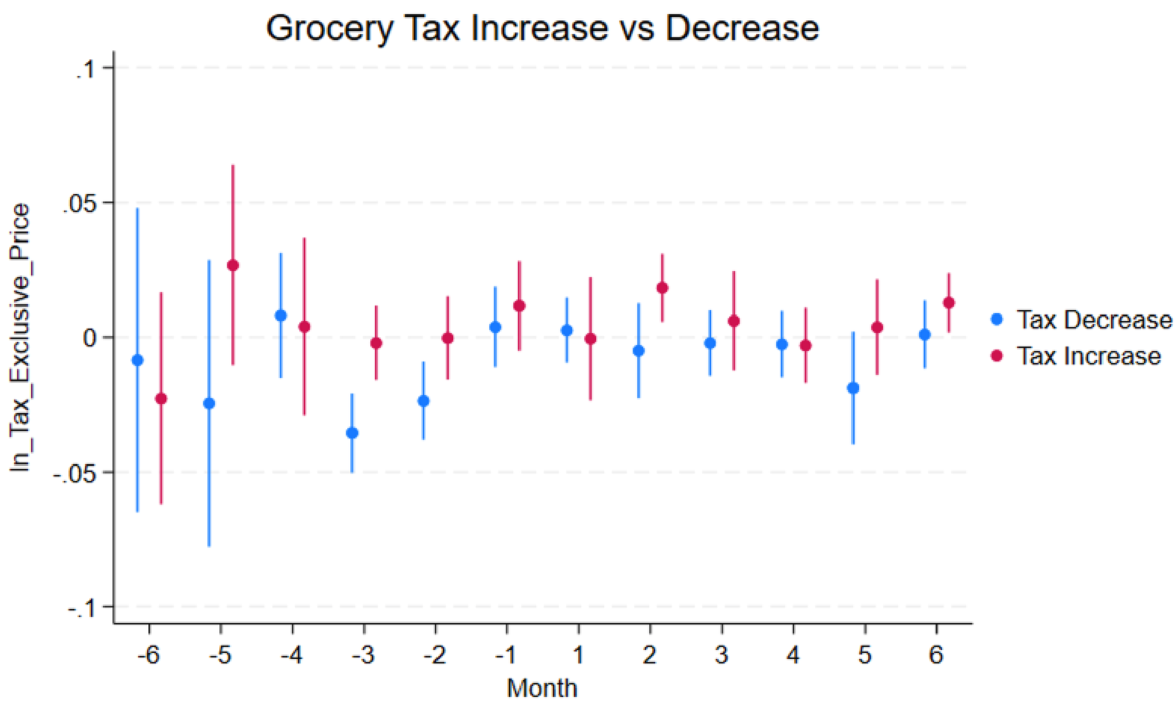

Figure A4. Distribution of Placebo Test Coefficient Estimates

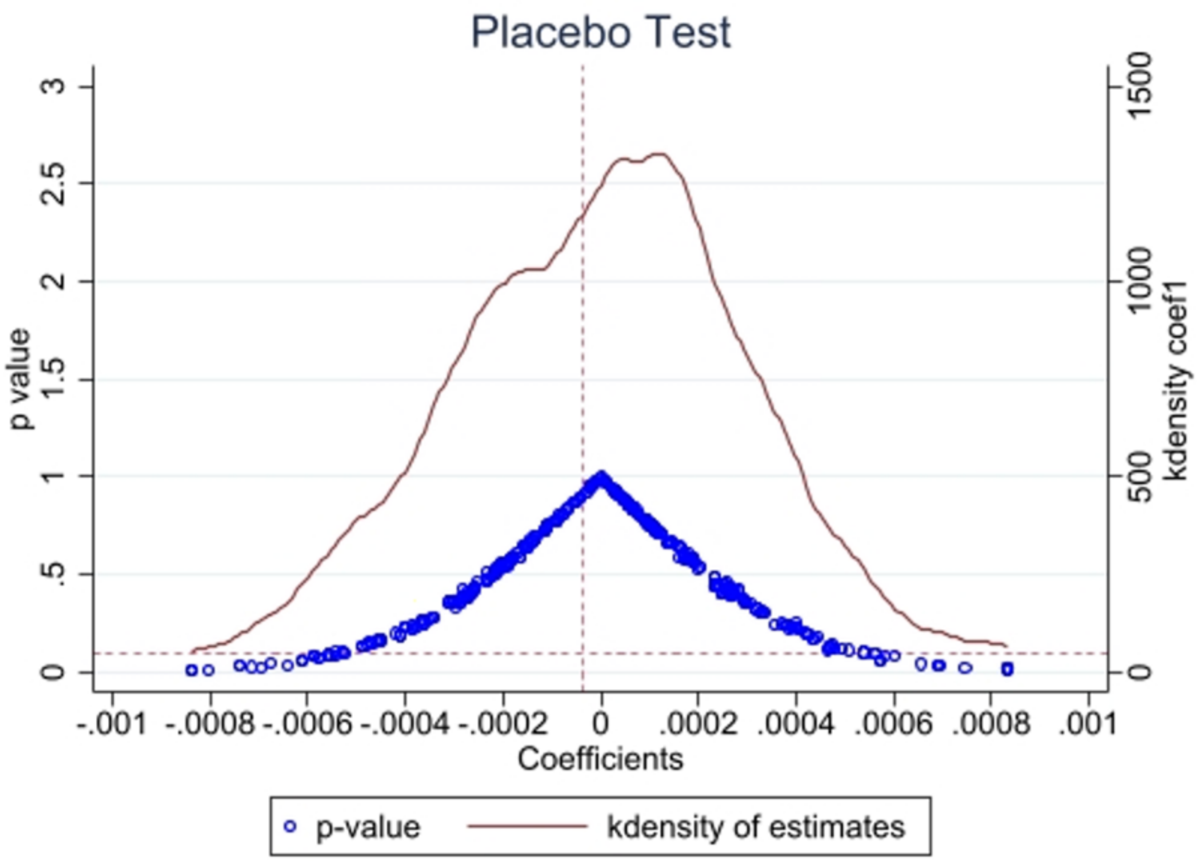

Table A1. States With Food Sales Taxes in 2019

State	Min Food Tax Rate	Max Food Tax Rate	Mean Food Tax Rate	# Counties with Food Sales Tax	# Counties with NO Food Sales Tax	Mean General Sales Tax Rate	Tax Food at Reduced Rate	Counties Follow Home Rule
AL	4%	9%	6.19%	67	0	6.19%	N	Y
AK	2.5%	7%	5.4%	16	13	5.4%	N	Y
AR	1.5%	4.75%	3.2%	75	0	8.21%	Y	Y
GA	1%	4%	3.4%	158	0	7.39%	Y	Y
HI	4%	4.5%	4.25%	5	0	4.25%	N	Y
ID	6%	6%	6%	44	0	6%	N	N
IL	1%	2.25%	1.09%	102	0	6.9%	Y	Y
KS	6.5%	8.73%	7.54%	105	0	7.54%	N	Y
LA	1%	6%	4.3%	60	4	9.41%	Y	Y
MS	7%	7%	7%	82	0	7%	N	N
MO	1.725%	4.91%	2.95%	114	0	5.94%	Y	Y
NC	2%	2%	2%	100	0	6.85%	Y	Y
OK	4.5%	7%	5.7%	77	0	5.7%	N	Y
SC	1%	3%	1.35%	34	12	7.91%	Y	Y
SD	4%	4%	4%	66	0	4%	N	N
TN	5.5%	6.75%	6.51%	95	0	9.51%	Y	Y
UT	3%	3%	3%	25	0	6.46%	Y	Y
VA	2.5%	2.5%	2.5%	95	0	5.35%	Y	Y

Note: The other states did not collect food sales taxes from 2010 to 2019.

Table A2. States with Food Sales Tax Changes from 2010 to 2019

State	Min Change	Max Change	# Counties Changed Tax	# Times Tax Changes in State	# Counties Did NOT Change Tax
AL	−2%	1%	19	24	48
AK	0	1%	3	3	15
AR	−1%	2%	75	137	0
GA	0	3%	185	257	1
IL	0	1.25%	6	6	96
KS	−0.15%	2%	105	327	0
LA	−1.55%	1%	11	11	49
MO	0	2.5%	87	148	27
OK	0	1.25%	44	60	33
SC	0	1%	3	3	31
TN	−1%	0.5%	95	284	0
WV	−1%	0	55	110	0

Note: The other states did not change food sales tax rates from 2010 to 2019.

Table A3. Descriptive Statistics of Analysis Variables

Variable	# Observations	Mean	SD
Total Grocery Taxes		0.009	0.019
Household Income			
< $ 30,000		0.175	0.379
$30,000-$69,999		0.422	0.494
≥ $ 70,000		0.403	0.491
Race			
White		0.807	0.394
Hispanic		0.060	0.238
Black		0.084	0.277
Asian		0.026	0.160
Other Race		0.023	0.022
Head Education			
Less than HS		0.021	0.142
HS Graduate		0.246	0.431
Some College		0.305	0.460
Bachelor and plus		0.429	0.495
Store Channels		0.626	0.990
Grocery Store			0.205
Discount Store			
Warehouse Club		0.190	
Convenience Store		0.004	0.060
Dollar Store		0.017	0.128
Drug Store		0.009	0.091
Market Consentration			
HHI_sales		0.548	0.345
Monthly Ave. Wages			
Food Retails Total		2366.628	1964.817
Grocery Stores		2342.740	536.806
General Merchandise		2340.491	522.744
Grocery Wholesales		2424.327	3945.604
Specialty Food Stores		2364.096	462.077
Milk			
Regulated Milk Price		19.922	2.525
# Transactions	15,825,274		
# Households	145,794		
# UPC Codes	329,678		

Table A4. Baseline Regression Results with Different Specifications

Dependent Variable: ln (Pre-tax Unit Price)	(1) No Household or Demographics	(2) Household FE	Household FE + Demographics
Grocery Tax	0.396***	0.283**	0.265**
	(0.114)	(0.112)	(0.117)
Year FE	Y	Y	Y
Month FE	Y	Y	Y
County FE	Y	Y	Y
UPC FE	Y	Y	Y
Household FE	N	Y	Y
Demographics	N	N	Y
Store Channels	N	N	Y
Number of Clusters	2,894	2,894	2,894
N	15,825,274	15,824,881	14,382,738

Table A5. Interactions by Product Categories

Dependent Variable: ln (Pre-Tax Unit Price)	(1) No Trend or Controls	(2) County Trend	(3) Controls	(4) Trend + Controls
Total Grocery Tax	0.321**	0.319***	0.314**	0.307**
	(0.126)	(0.129)	(0.148)	(0.139)
Grocery Tax * Product Category (Baseline Product = Jams, Jellies, Spreads)				
1. Dry Grocery				
1.2 Soup	0.007	0.007	-0.023	-0.027
	(0.071)	(0.071)	(0.076)	(0.077)
1.3 Baking Mixes	-0.213***	-0.209***	-0.293***	-0.290***
	(0.071)	(0.071)	(0.075)	(0.075)
1.4 Breakfast Food	0.045	0.044	-0.018	-0.022
	(0.085)	(0.085)	(0.094)	(0.094)
1.5 Cereal	0.048	0.047	0.001	0.0008
	(0.077)	(0.077)	(0.087)	(0.088)
1.6 Coffee	0.293**	0.312**	0.318**	0.336**
	(0.124)	(0.123)	(0.147)	(0.144)
1.7 Condiments, Gravies, and Sauces	-0.183***	-0.176**	-0.208***	-0.205***
	(0.069)	(0.070)	(0.076)	(0.077)
1.8 Desserts, Gelatins, Syrup	-0.147**	-0.142**	-0.185**	-0.181**
	(0.073)	(0.074)	(0.082)	(0.083)
1.9 Flour	-0.165*	-0.163*	-0.163	-0.168*
	(0.092)	(0.093)	(0.100)	(0.101)
1.10 Nuts	0.180**	0.193**	0.157*	0.163**
	(0.078)	(0.078)	(0.082)	(0.081)
1.11 Packaged Milk and Modifiers	0.034	0.025	-0.057	-0.066
	(0.075)	(0.074)	(0.078)	(0.077)
1.12 Pasta	0.374***	0.371***	0.349***	0.340***
	(0.086)	(0.086)	(0.102)	(0.103)
1.13 Pickles, Olives, and Relish	0.041	0.046	0.002	0.002
	(0.077)	(0.077)	(0.078)	(0.080)
1.14 Spices, Seasoning, Extracts	-0.168**	-0.165**	-0.204***	-0.210***
	(0.073)	(0.074)	(0.079)	(0.079)
1.15 Table Syrups, Molasses	-0.132	-0.136	-0.213**	-0.219**
	(0.089)	(0.090)	(0.093)	(0.094)
1.16 Tea	0.137*	0.139*	0.122	0.120
	(0.072)	(0.072)	(0.082)	(0.081)
1.17 Bread and Baked Goods	-0.053	-0.044	-0.084	-0.080
	(0.077)	(0.077)	(0.086)	(0.084)
1.18 Cookies	0.042	0.040	0.015	0.007
	(0.076)	(0.075)	(0.081)	(0.079)
1.19 Crackers	0.017	0.018	0.003	-0.003
	(0.080)	(0.081)	(0.091)	(0.089)
1.20 Snacks	0.131*	0.137*	0.079	0.082
	(0.074)	(0.073)	(0.081)	(0.078)

2. Frozen Foods	(1)	(2)	(3)	(4)
2.1 Baked Goods-Frozen	-0.006	0.0009	-0.102	-0.100
	(0.079)	(0.080)	(0.091)	(0.092)
2.2 Breakfast Foods-Frozen	-0.019	-0.007	-0.009	-0.002
	(0.075)	(0.076)	(0.084)	(0.085)
2.3 Desserts/Fruits/Toppings-Frozen	0.042	0.048	0.009	0.009
	(0.083)	(0.084)	(0.092)	(0.093)
2.4 Ice Cream, Novelties	0.389***	0.397***	0.359***	0.365***
	(0.078)	(0.079)	(0.086)	(0.087)
2.5 Juices, Drinks-Frozen	0.073	0.098	0.102	0.145
	(0.129)	(0.130)	(0.152)	(0.153)
2.6 Unprep Meat/Poultry/Seafood-Frzn	-0.543***	-0.518***	-0.547***	-0.529***
	(0.114)	(0.112)	(0.128)	(0.124)
2.7 Vegetables-Frozen	0.001	0.004	-0.004	-0.004
	(0.065)	(0.066)	(0.072)	(0.073)
3. Dairy				
3.1 Butter And Margarine	-0.062	-0.050	-0.093	-0.085
	(0.070)	(0.073)	(0.079)	(0.082)
3.2 Cheese	0.073	0.087	0.084	0.100
	(0.068)	(0.068)	(0.078)	(0.075)
3.3 Cot Cheese, Sour Cream, Toppings	-0.048	-0.051	-0.094	-0.094
	(0.071)	(0.072)	(0.074)	(0.074)
3.4 Dough Products	-0.107	-0.106	-0.156*	-0.161*
	(0.085)	(0.087)	(0.095)	(0.096)
3.5 Eggs	-0.113	-0.104	-0.190*	-0.182*
	(0.099)	(0.098)	(0.111)	(0.109)
3.6 Milk	1.102***	1.106***	1.100***	1.107***
	(0.130)	(0.123)	(0.142)	(0.130)
3.7 Pudding, Desserts-Dairy	-0.071	-0.074	-0.053	-0.055
	(0.139)	(0.139)	(0.171)	(0.171)
3.8 Snacks, Spreads, Dips-Dairy	0.110	0.117	-0.053	-0.044
	(0.107)	(0.109)	(0.115)	(0.117)
3.9 Yogurt	0.207***	0.211***	0.204**	0.208***
	(0.072)	(0.071)	(0.080)	(0.079)
4. Deli				
4.1 Dressings/Salads/Prep Foods-Deli	-0.417***	-0.389***	-0.501***	-0.476***
	(0.135)	(0.137)	(0.154)	(0.157)
5. Packaged Meat				
5.1 Packaged Meats-Deli	0.111	0.126	0.109	0.123
	(0.076)	(0.073)	(0.086)	(0.080)
5.2 Fresh Meat	0.220***	0.239***	0.199***	0.214***
	(0.085)	(0.083)	(0.095)	(0.092)
6. Fresh Produce				
6.1 Fresh Produce	0.199	0.203	0.135	0.139
	(0.157)	(0.133)	(0.178)	(0.139)

Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
County Trends	N	Y	N	Y
Economic Controls	N	N	Y	Y
Number Of Clusters	2,894	2,894	2,693	2,693
N	$15,822,571$	15,820,365	$13,239,830$	$13,236,650$

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level. FE stands for fixed effects.

Table A6. Regression Results by Food Product Categories

Dependent Variable: ln (Pre-tax Unit Price)	(1) Dry Grocery	(2) Frozen Foods	(3) Dairy	(4) Deli	(5) Packaged Meat	(6) Fresh Produce
Grocery Tax	0.434***	0.218	0.361**	0.181	0.451**	-0.400
	(0.137)	(0.223)	(0.183)	(0.706)	(0.258)	(0.263)
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y	Y	Y
Household FE	N	N	N	N	N	N
Household Characteristics	Y	Y	Y	Y	Y	Y
County-Level Economic Controls	Y	Y	Y	Y	Y	Y
Number of Clusters	2,881	2,833	2,866	2,773	2,821	2,832
N	6,260,339	1,516,471	2,718,673	894,372	810,814	2,182,136

Table A7. Strict Exogeneity Test

Dependent Variable: ln (Pre-tax Unit Price)	(1)
Grocery Tax in the current year	0.387^{***}
	(0.113)
Grocery Tax in one year later	0.176
	(0.110)
Year FE	Y
Month FE	Y
County FE	Y
UPC FE	Y
Household FE	N
Demographics	Y
Store Channels	Y
Number of Clusters	2,894
N	$12,341,097$

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.

Table A8. County Group Specific Trends

Dependent Variable: n (Pre-tax Unit Price)	County Linear Trend by Year	(2) County Linear Trend by quarter	County Linear Trend by month
Grocery Tax	0.420**	0.402**	0.404**
	(0.178)	(0.179)	(0.179)
Year FE	Y	Y	Y
Month FE	Y	Y	Y
County FE	Y	Y	Y
UPC FE	Y	Y	Y
Household FE	N	N	N
Demographics	Y	Y	Y
Store Channels	Y	Y	Y
Number of Clusters	2,894	2,894	2,894
N	$15,822,571$	$15,822,571$	$15,822,571$

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.

Table A9. Placebo Test based on Shuffling Taxes

	(1)
Dependent Variable: ln (pre-tax prices)	
Grocery Tax	-0.000000375
	(0.00033)
Year FE	Y
Month FE	Y
County FE	Y
County Trend	N
Economic Controls	Y
Number of Clusters	2,894
N	14,382,738

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.

Table A10. Concordance Table Mapping Product Codes between Nielsen IQ Consumer Panel and Okrent and Alston (2012)

Nielsen IQ	Okrent and Alston (2012) and Budget Shares	Product Groups	Budget Shares under Column 2 Categories	Own Elasticity
Dry Grocery	Cereals/bakery (16.6%)	Flour, flour mixes	4.4%	0.07
		Breakfast cereals	19.01%	-1.05
		Rice, pasta	10.18%	-0.07
		Non-white bread	11.26%	-0.59
		White bread	7.69%	-1.54
		Biscuits, rolls, muffins	9.15%	-0.21
		Cakes, cookies	17.91%	-1.20
		Other bakery products	20.41%	-0.55
	Nonalcoholic beverages (7.5%)	Coffee, tea	17.44%	-0.12
		Carbonated beverages	35.07%	-0.30
		Noncarbonated Beverages	45.2%	-0.44
	Other FAH (27.6%)	Sugar, sweets	18.75%	-0.56
		Fats, oils	16.81%	-0.21
		Soups	5.93%	0.19
		Snacks	3.73%	-1.14
		Condiments, sauces, season	15.26%	-1.92
		Miscellaneous FAH	22.37%	-1.48
Frozen Foods	Nonalcoholic beverages (7.5%)	Frozen beverages	2.29%	-0.61
	Other FAH (27.6%)	Frozen meals	17.15%	-1.05
Dairy	Dairy (12.1 %)	Cheese	31.66 %	-0.70
		Frozen dairy desserts	17.35 %	-0.23
	Meat and Eggs (28.8%)	Milk	36.74%	-0.10
		Other dairy	14.25%	-1.04
		Eggs	4.8%	-0.24
Deli	Fruits and vegetables (16.9%)	Proc. fruits, vegetables	23.4%	-0.77
Packaged Meat	Meat and eggs (28.8%)	Beef	29.09%	-0.70
		Pork	20.23%	-1.26
		Other Red Meat	13.03%	-1.05
		Poultry	18.11%	-0.81
		Fish	14.75%	-0.84
Fresh Produce	Fruits and vegetables (16.9%)	Apples	6.99%	-0.58
		Bananas	6.57%	-1.01
		Citrus	7.84%	-1.10
		Other Fresh Fruit	17.59%	-0.90
		Potatoes	6.64%	-0.42
		Lettuce	4.88%	-0.84
		Tomatoes	6.95%	-0.58
		Other fresh vegetables	19.43%	-0.94

Table A11. The Average Earnings Model by Industry

Dependent Variable: ln (Earnings)	(1) Grocery and Merchant Wholesalers	(2) Grocery Stores	(3) Specialty Food Stores	(4) Warehouse Clubs
Grocery Tax	-0.759	-0.215	1.115	0.748
	(1.551)	(0.798)	(0.978)	(1.063)
Commercial Electricity Price	-0.0003	-0.007	0.003	0.004
	(0.008)	(0.005)	(0.007)	(0.005)
Median Rent	0.0001	0.00003	0.00008	0.0001
	(0.00009)	(0.00007)	(0.00006)	(0.00008)
Minimum Wage	0.004	0.002	-0.001	-0.004
	(0.006)	(0.005)	(0.006)	(0.004)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	N	N	N	N
Economic Controls	Y	Y	Y	Y
Number of Clusters	2,180	2,664	1,998	2,615
N	31,612	35,825	33,103	33,739

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. FE stands for fixed effects.