

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 grocery tax revenue leads to a \$1.44 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 nor higher farmgate prices for farmers.

Keywords: Price Analysis, Retail, Over-shifting, Sales Taxes, Tax Incidence

JEL Codes: H22, L81, Q11, D12

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1 Introduction

Approximately one-third of all United States (U.S.) counties assess a state, county, or combined sales tax on grocery 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 higher-income families do.

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). 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 & Réquillart, 2013; Weyl & Fabinger, 2013; Pless & 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 & Rosen, 1999), the incidence of U.S. grocery taxes is a timely, policy-relevant topic to study.

A rich empirical literature estimates the tax incidence for numerous products. For example, Powell et al. (2021) conduct a meta-analysis of local sugar-sweetened beverage taxes based on 26 estimates from 22 studies published between 2015 and 2021 (Bleich et al., 2020; Cawley & Frisvold, 2017; Cawley et al., 2018, 2020a,b, 2021; Falbe et al., 2015, 2020; Jones-Smith et al., 2020; Leider et al., 2021; Léger & Powell, 2021; Marinello et al., 2020, 2021; Powell & Leider, 2020; Powell et al., 2020; Roberto et al., 2019; Rojas & Wang, 2021; Saelens et al., 2020; Seiler et al., 2021; Silver et al., 2017; Zhang & Palma, 2021). The authors estimate an average pass-through rate to consumers of 70 percent, with the results ranging from 10 percent (Zhang & Palma, 2021) to 121 percent (Bleich et al., 2020). The literature on the incidence of cigarette excise taxes is smaller due to limited accurate data on retail

¹Grocery 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 & Frisvold, 2023) or through general equilibrium effects. We abstract from those mechanisms in this paper.

cigarette prices (Barzel, 1976; Harding et al., 2012), but most studies find tax over-shifting. For instance, Hanson & Sullivan (2009) finds that a one-cent increase in cigarette taxes increases prices by between 1.13 and 1.18 cents based on a phone survey of cigarette retailers. Similarly, Sullivan & Dutkowsky (2012) finds that a \$1 increase in the excise tax increases local cigarette prices between \$1.07 and \$1.14. In addition, Stolper (2016) estimates a 124 percent pass-through rate for gasoline taxes to consumers. Marion & Muehlegger (2011) estimates that a one-cent increase in the state and federal gasoline tax rates leads to increased retail prices by 1.22 cents and 1.1 cents, respectively.

We are aware of only three previous studies of grocery tax pass-through to consumers on a handful of grocery food items, all of which found tax over-shifting on most food products. Besley & 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 sales tax over-shifting for most food items they study, including bananas, bread, milk, eggs, Crisco, and Coke. Politi & Mattos (2011) examine the pass-through of ad-valorem taxes 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. They find that full tax shifting occurred for only three of the ten goods (beans, butter, and flour), while tax over-shifting occurred for only one product (sugar). Finally, Gračner et al. (2022) estimates a roughly 60% average pass-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. To our knowledge, no studies have examined grocery tax pass-through for all food items or comprehensively for all counties in the United States, which is the focus of our study.

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 state and county level grocery food tax rates across the U.S., which we merge with NielsenIQ Homescan household food purchase data at the product (Universal Product Code, UPC)-level from 2010-2019. These data enable us to estimate grocery tax pass-through rates using individual transaction 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 \$1.44 increase in the tax-inclusive price, on average. Grocery taxes thereby increase retail margins on food items, which could lead to additional revenue (and presumably profit) 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 headed 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 back to retailers’ factor markets, namely retail worker earnings and farm-level product prices. The prior literature on tax pass-through focuses exclusively on the distribution of the tax burden between retailers and final consumers. If anything other than complete pass-through to consumers occurs, however, then the grocery tax affects retailer profits - either positively or negatively - which could impact firms’ payments to input suppliers and workers. Labor is the single largest expense for food retailers. In 2022, almost 45% of consumer expenditures on food for home consumption accrued to agri-food value chain workers, and half of the gross revenue that accrued to food retailers passed through to workers as compensation ([United States Department of Agriculture Economic Research Service, 2023](#)). In partial equilibrium with competitive labor markets, an exogenous positive shock to prices increases the marginal revenue product of labor and might therefore 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 & 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 a general equilibrium, food retail employers may be able to retain the full increase in retail margins. So the factor market impacts, if any, of grocery taxes are fundamentally

an empirical question. We find no association of grocery tax rates with county-level grocery store workers' earnings, consistent with the observation that food retail is a small share of the labor market and thus grocery tax-induced changes to retailer profits have a negligible impact on local labor markets in general equilibrium.

Similar arguments apply to agricultural commodities that undergo minimal processing. Our product-level estimates identify fluid milk as the food item with the highest rate of grocery tax over-shifting. 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 higher marginal retailer revenue per unit of fluid milk in partial equilibrium. Whether that translates into higher farmgate prices for dairy farmers depends on a range of factors, including how well the local milk market is integrated with broader national markets, consumer demand response to higher prices caused by changes in grocery taxes, etc. We find no significant impact of grocery taxes on the county-level Class I minimum milk price received by farmers. Just as with labor markets, commodity markets that supply food retail outlets seem unaffected by grocery taxes.

Some state and local governments rely on grocery taxes for an important part of their revenues. The incidence of those taxes appears quite regressive, not just because of the low income elasticity of demand for food but also because grocery tax over-shifting leads to substantial increases in pre-tax retail food prices, while the magnified tax burden falls disproportionately on consumers, 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 established microeconomic theory of tax pass-through so as to help readers understand how to interpret the empirical results that follow. We first offer a brief prose description for those who prefer to skip the formal derivations in the subsequent two sub-sections.

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

Governments rely on retail firms to collect sales taxes assessed on consumers at the time of product purchase. In competitive markets, retailers adjust the tax-exclusive price so that consumers ultimately shoulder anywhere from 0-100% of the tax incidence. The greater the price elasticity of supply relative to demand (in absolute value terms), the greater the tax pass-through rate to consumers. The more inelastic party to the exchange bears more of the tax burden, but neither reaps windfall gains from the imposition of a sales tax.

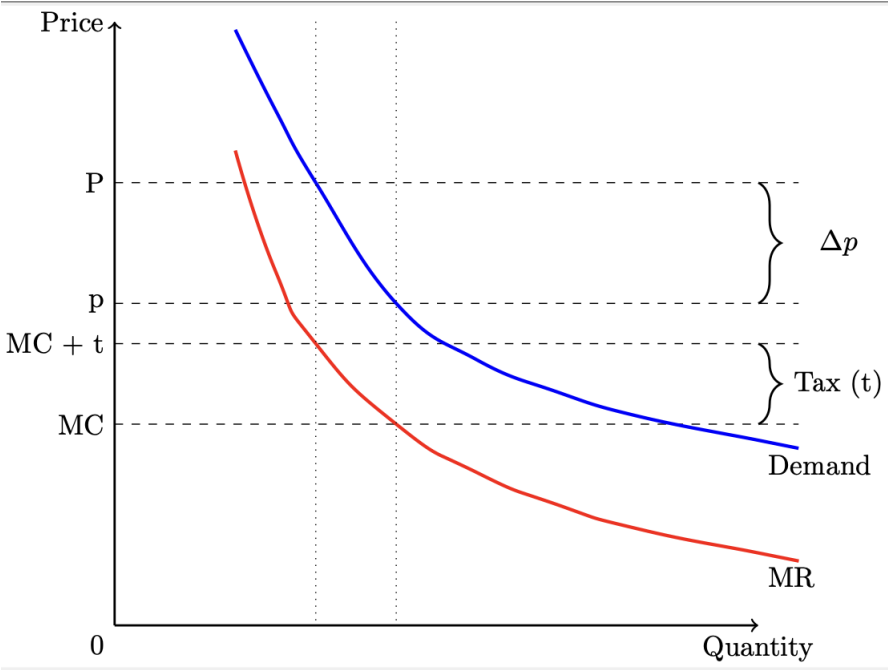
A range of studies find pass-through estimates exceeding 100%, however (Besley & Rosen, 1999; Delipalla & O'Donnell, 2001; Kenkel, 2005). One reason could be the lower consumer salience of grocery taxes because they are not included in the posted prices shoppers see, merely assessed at the moment of sale (Chetty et al., 2009). Analysts typically interpret findings of over-shifting, however, as signaling imperfect competition because it reveals that firms can not only shift the full tax burden onto the consumer but can also increase the tax-exclusive price, thereby boosting profits. Such tax over-shifting depends not only on sufficiently price-inelastic demand but also that demand be sufficiently convex that firms' optimal mark-ups increase at higher prices (Weyl & Fabinger, 2013; Pless & Van Benthem, 2019). Under such conditions, Pless & Van Benthem (2019) shows that tests for over-shifting provide a "simple but underutilized test for market power". The next sub-section illustrates more formally how a firm with market power facing a sufficiently convex demand can over-shift a sales tax. The subsequent sub-section explains how one can decompose the resulting price changes into tax pass-through and retail mark-up, the latter of which generates tax over-shifting.

A. Decomposition of Tax Over-shifting

In the case of a firm with market power facing a convex consumer demand curve, Pless & Van Benthem (2019) illustrates the over-shifting in the presence of a subsidy. We illustrate the counterpart scenario of tax over-shifting in Figure 1, using a lump sum tax for ease of illustration only; the intuition also holds for ad valorem taxes, like the grocery taxes we study. The intuition explaining tax over-shifting is that when a tax, t , is introduced, the marginal cost curve shifts upward from MC to $MC + t$. A firm with market power - i.e., that sets prices such that marginal revenue equals marginal cost - increases price by

$P - p \equiv \Delta p > t$ due to the convexity of demand.³ Convexity implies that demand is not iso-elastic; in particular, those consumers with the highest willingness to pay exhibit more price inelastic demand than do consumers with lower willingness to pay. Convex demand seems a reasonable assumption in the case of food, the willingness to pay for which is highest among consumers with more income, who are also typically less responsive to price changes. The result $\Delta p > t$ defines tax over-shifting because it implies that the tax-exclusive price, $P - t$ exceeds the pre-tax price, p . The less price elastic demand at higher prices allows the firm to pass through more than the full amount of the tax to consumers who remain after the price rise by increasing the final price by more than the tax imposed.

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



Weyl & Fabinger (2013) and Pless & Van Benthem (2019) show the tax pass-through for monopoly as:

$$\frac{dP}{dt} = \frac{1}{1 + \frac{\epsilon_D - 1}{\epsilon_S} + \frac{1}{\epsilon_{ms}}} \tag{1}$$

³A firm with market power facing concave demand would optimally under-shift the tax onto consumers.

where t and P denote a tax per unit, and the tax-inclusive price, respectively. The parameter ε_D represents the price elasticity of demand, ε_S represents the price elasticity of supply (i.e., of the inverse marginal cost curve), ε_{ms} reflects the curvature of the demand function. For symmetric, imperfect competition, the tax pass-through is shown as:

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

where 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 & Fabinger \(2013\)](#) or [Genakos & Pagliero \(2022\)](#) for further details and discussion. These derivations show that, with a sufficiently convex demand curve, the pass-through rate $\frac{dP}{dt}$ can exceed one, meaning the price increase Δp exceeds the tax t , i.e., there is tax over-shifting.

B. Tax Pass-Through for Ad Valorem Taxes

To analyze the incidence of ad valorem grocery taxes, we formalize the tax pass-through mechanism following an established two-stage approach that bridges structural microeconomic theory ([Weyl & Fabinger, 2013](#)) and reduced form empirical specifications ([Besley & Rosen, 1999](#)).

We derive the semi-log specification from a structural pricing model in which a retailer sets a pre-tax price p^* , while consumers face a tax-inclusive price $P = (1 + \tau)p^*$, where τ is the ad valorem grocery tax rate (expressed as a proportion, e.g., $\tau = 0.05$ for a 5% tax). Let $c(X)$ represent the retailer's marginal cost, which depends on observed covariates X , and let $D(P, X) = D((1 + \tau)p^*, X)$ represent demand as a function of the tax-inclusive price and non-price factors X . The retailer's profit function is then

$$\pi(p^*) = (p^* - c(X)) \cdot D((1 + \tau)p^*, X). \quad (3)$$

The first-order condition (FOC) with respect to p^* is

$$\frac{d\pi}{dp^*} = D((1 + \tau)p^*, X) + (p^* - c(X))(1 + \tau) \cdot \frac{\partial D((1 + \tau)p^*, X)}{\partial P} = 0. \quad (4)$$

Divide both sides by $D((1 + \tau)p^*, X)$ to get

$$1 + (p^* - c(X))(1 + \tau) \cdot \frac{1}{D((1 + \tau)p^*, X)} \cdot \frac{\partial D((1 + \tau)p^*, X)}{\partial P} = 0. \quad (5)$$

Then define the price elasticity of demand with respect to the tax-inclusive price as

$$\eta_D = -\frac{(1 + \tau)p^*}{D((1 + \tau)p^*, X)} \cdot \frac{\partial D((1 + \tau)p^*, X)}{\partial P}. \quad (6)$$

Substitute into the FOC and rearrange to obtain

$$\frac{p^* - c(X)}{p^*} = \frac{1}{\eta_D} \Rightarrow \frac{p^*}{c(X)} = \frac{\eta_D}{\eta_D - 1}. \quad (7)$$

Taking logarithms of both sides yields

$$\ln p^* = \ln c(X) + \ln \left(\frac{\eta_D}{\eta_D - 1} \right). \quad (8)$$

Assuming that both $\ln c(X)$ and $\ln \left(\frac{\eta_D}{\eta_D - 1} \right)$ are linear in the tax rate τ and other covariates X , we obtain the reduced-form expression

$$\ln p^* = \beta_1 \tau + \beta_2 X. \quad (9)$$

Finally, add a mean-zero stochastic error term, and one has precisely the reduced form model that [Besley & Rosen \(1999\)](#) first used to estimate the pass-through rate of ad valorem taxes to consumer prices:

$$\ln p^* = \beta_1 \tau + \beta_2 X + \epsilon, \quad (10)$$

where X includes control variables affecting demand, input costs, or both, such as county-level economic conditions, store and consumer characteristics. The error term, ϵ , satisfies $E(\epsilon|\tau, X) = 0$, implying that tax rates are exogenous conditional on X . The semi-log specification allows β_1 to represent the *semi-elasticity* of p^* with respect to τ , i.e., the percentage change in p^* for a one unit (100 percentage point, pp) increase in τ .

To link tax changes to consumer prices, we differentiate the model multiplicatively. First multiply both sides by p^* :

$$p^* \ln p^* = p^*(\beta_1 \tau + \beta_2 X), \quad (11)$$

Then totally differentiate (11) setting $dX = 0$ (i.e., holding X fixed):

$$(\ln p^* + 1) dp^* = \beta_1(p^* d\tau + \tau dp^*) + \beta_2 X dp^*. \quad (12)$$

To solve for the sensitivity of p^* to tax revenue ($\frac{dp^*}{d(p^*\tau)}$), we rearrange terms:

$$dp^*(\ln p^* + 1 - \beta_2 X) = \beta_1 p^* d\tau + \beta_1 \tau dp^* \quad (13)$$

Then take the chain rule:

$$\frac{\partial p}{\partial(\tau p^*)} = \frac{\partial p}{\partial \tau} \cdot \frac{\partial \tau}{\partial(\tau p^*)} \quad (14)$$

Write out the functional form of p and continue applying the chain rule by taking the derivative with respect to τp^* :

$$\frac{\partial p}{\partial \tau} \cdot \frac{\partial \tau}{\partial(\tau p^*)} = \left(p^* + (1 + \tau) \frac{\partial p^*}{\partial \tau} \right) \left(\frac{\partial(\tau p^*)}{\partial \tau} \right)^{-1} = \left(p^* + (1 + \tau) \frac{\partial p^*}{\partial \tau} \right) \left(p^* + \tau \frac{\partial p^*}{\partial \tau} \right)^{-1} \quad (15)$$

Using the fact that $\frac{\partial \ln p^*}{\partial \tau} = \frac{\partial \ln p^*}{\partial p^*} \cdot \frac{\partial p^*}{\partial \tau} = p^{*-1} \frac{\partial p^*}{\partial \tau}$, i.e., $\frac{\partial p^*}{\partial \tau} = \frac{\partial \ln p^*}{\partial \tau} \cdot p^* = \beta_1 p^*$, We arrive at

$$\frac{dP}{d(p^*\tau)} = 1 + \frac{dp^*}{d(p^*\tau)} = 1 + \frac{\beta_1}{1 + \beta_1 \tau} \quad (16)$$

Thus, the pass-through rate to consumers is derived by differentiating $P = p^*(1 + \tau)$:

$$\frac{dp^*}{d(p^*\tau)} = \underbrace{1}_{\text{Direct tax effect}} + \underbrace{\frac{\beta_1}{1 + \beta_1 \tau}}_{\text{Retail markup adjustment}}. \quad (17)$$

Similarly, we can denote tax revenue per unit as $t = \tau p^*$ and apply the chain rule, we differentiate $P = p^*(1 + \tau)$.⁴

From equation (17), the degree of tax pass-through reflects the underlying market structure and the elasticity of consumer demand. When the pass-through parameter β_1 is positive, retailers engage in over-shifting, raising the pre-tax price p^* by more than the grocery tax value. This is consistent with market power and convex, inelastic demand conditions, such as might be observed for perishable staples like milk. $\beta_1 = 0$ corresponds to full pass-through, typically associated with perfectly competitive markets in which tax burdens are entirely borne by consumers. Conversely, a negative β_1 implies under-shifting, where retailers absorb a portion of the tax burden in response to relatively price-elastic demand, such as the case for non-essential or highly substitutable goods or concave demand faced by a retailer with market power.

⁴Knowing $\frac{\partial P}{\partial t} = \frac{\partial P}{\partial \tau} \cdot \frac{\partial \tau}{\partial t} + \frac{\partial P}{\partial p^*} \cdot \frac{\partial p^*}{\partial t}$, and using $\frac{\partial P}{\partial \tau} = p^* + (1 + \tau) \frac{\partial p^*}{\partial \tau} = p^*[1 + \beta_1(1 + \tau)]$, $\frac{\partial \tau}{\partial t} = \frac{1}{p^* + \tau \frac{\partial p^*}{\partial \tau}} = \frac{1}{p^*(1 + \beta_1 \tau)}$, we obtain $\frac{\partial P}{\partial t} = \frac{dP}{d(p^*\tau)} = 1 + \frac{\beta_1}{1 + \beta_1 \tau}$.

Under the assumption of a small enough tax rate such that $\beta_1\tau \approx 0$, the pass-through rate simplifies to approximately $1 + \beta_1$, consistent with predictions from unit tax incidence models. For example, an estimated $\beta_1 = 0.44$ implies a pass-through rate of 144%, meaning consumers bear \$1.44 in price increases for every \$1 of tax imposed. As the tax rate increases, however, the adjustment is attenuated by the term $\frac{1}{1+\beta_1\tau}$, which captures diminishing pass-through due to reduced marginal profitability of further price increases.

3 Data

Our analysis relies on two data sets for the estimation of grocery tax pass-through rates on food prices, and then two additional data sets to explore whether grocery taxes impact factor markets.

A. State and County Grocery Taxes

We assembled data on U.S. county-level grocery tax rates from 2010 through 2019. Grocery food items refer to unprepared foods that meet USDA criteria for SNAP eligibility and consumption at home, which includes a wide range of dairy, meat, fresh produce, frozen, and packaged goods, but excludes prepared meals, hot foods, and most beverages. The total grocery tax rate in each county is the combination of the state and county-level tax rates, obtained from [Tax-Rates.org](https://www.tax-rates.org) and various websites of state Departments of Revenue. The data contains all the historical rates and the dates of tax rate changes.

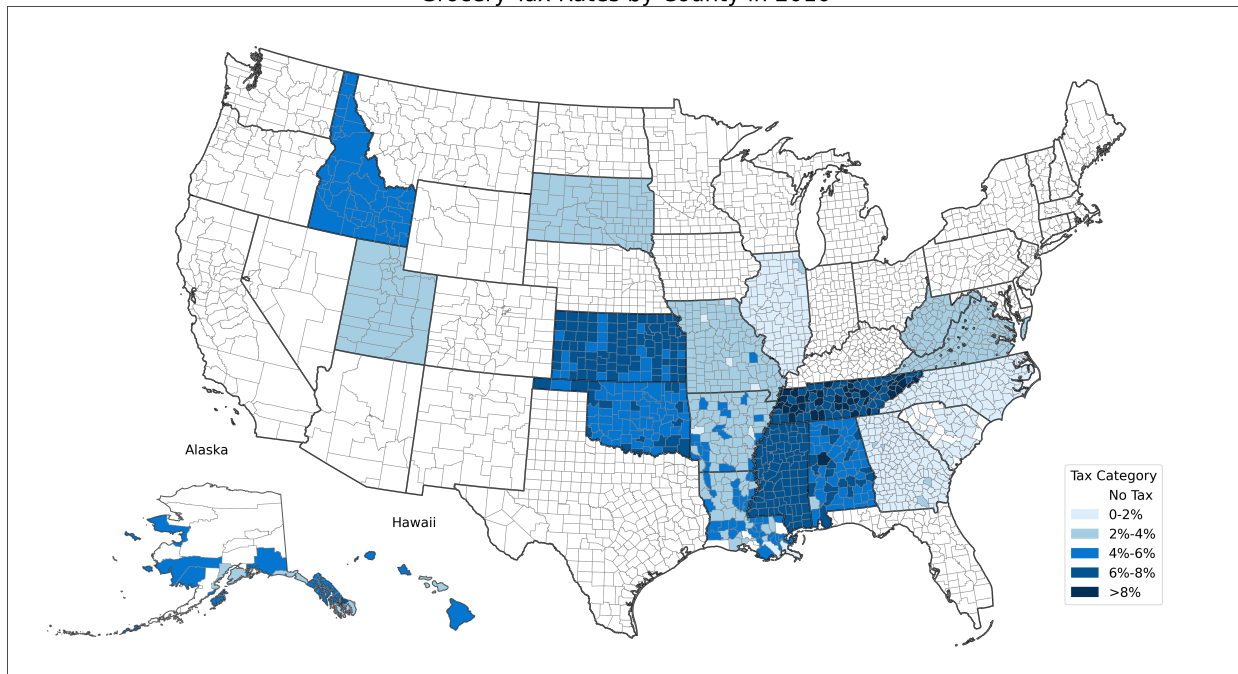
The maps in Figure 2 highlight important variations in grocery tax rates from 2010 to 2019. In 2010, the highest grocery tax rates, particularly those in the 6%-8% range and above, were concentrated in southern states such as Alabama, Mississippi, and Tennessee. These states have historically maintained 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 increased grocery tax rates between 2010 and 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. ⁵

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 imposed taxes on grocery food items at 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%).⁶ Six states collected grocery 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.

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

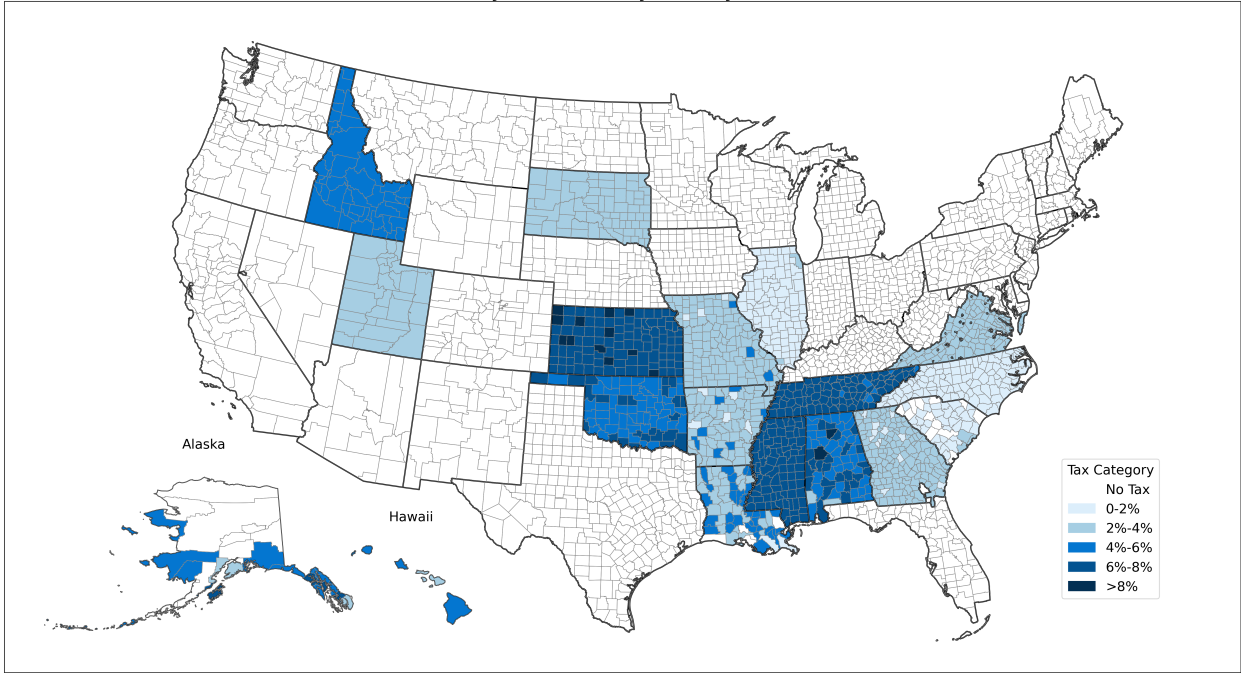
Grocery Tax Rates by County in 2010



⁵<https://www.salestaxinstitute.com/resources/west-virginia-introduces-phaseout-grocery-food-tax>

⁶Five of these states (KS, ID, TN, OK, and HI) offered a tax credit to low-income households to offset the tax costs, although it is unclear how much redemption occurs.

Grocery Tax Rates by County in 2019



Our econometric strategy (discussed below) includes county, time period, and universal product code (UPC) fixed effects. Thus, we identify estimated pass-through rates from inter-household purchase price variation within counties, time periods (months for most regressions, quarterly in the worker earnings analyses), and products, and county-level intertemporal changes in grocery sales tax rates (reported in Appendix Table A2). Over this period, the largest state-level tax change occurred in 2013 when over 30 counties in Georgia increased their grocery taxes by 3 percentage points (pp). The smallest change occurred in Kansas, when the state reduced the sales taxes on grocery food items by 0.15 pp 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.

Within-county changes in grocery tax rates are driven primarily by institutional or political processes that are plausibly exogenous to short-run changes in local food prices. For instance, in Georgia, county-level grocery tax changes often result from the expiration, renewal, or restructuring of the Special-Purpose Local Option Sales Taxes (SPLOSTs), a mech-

anism through which counties raise funds for infrastructure, school facilities, or other capital projects.⁷ These taxes must be approved by voters in county-wide referenda and are not typically framed as responses to food price dynamics nor can they be enacted swiftly. Likewise, several states - like Arkansas and Oklahoma - reformed grocery taxes through multi-year legislative processes often framed as efforts to improve tax fairness or to simplify tax codes. For example, Virginia eliminated its 1.5% state grocery tax in 2023 as part of a broader sales tax reform package. The timing and implementation of grocery tax changes thus typically reflect slow-moving institutional processes rather than rapid, reactive responses to local food price dynamics. In Alabama, rising grocery prices were cited in public debate surrounding a tax reduction bill, but the legislation itself was in development for several years. The bill was ultimately shaped by state-level fiscal politics and sustained advocacy efforts, rather than triggered by specific food price shocks.⁸ Because grocery tax rate adjustments arise primarily from slow, statewide legislative action or county fiscal calendars this should satisfy the conditional independence assumption necessary to identify the causal effects of grocery taxes on tax-exclusive retail prices. In Section 6, we nonetheless conduct a battery of robustness checks to confirm the plausibility of the conditional independence assumption.

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 takes up over 700 GB. To keep estimation computationally manageable, we used 5% bootstrapped samples, with 500 replicates.⁹ We

⁷https://ballotpedia.org/School_bond_and_tax_elections_in_Georgia

⁸<https://www.route-fifty.com/finance/2024/03/states-move-cut-grocery-taxes/394642/>

⁹We also estimated our model on a random 5% subsample without bootstrapping, yielding results nearly

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

In 2023, labor in the food value chain accounted for 54% of all US consumer expenditures on domestically produced food.¹⁰ So we test whether grocery taxes have a measurable association with grocery workers' earnings.

We obtain county-level average monthly 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 (available online at <https://qwexplorer.ces.census.gov/>). We use data from the North American Industry Classification System (NAICS) 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

Beyond labor, agricultural commodities are the other major input to the food consumers buy from retail outlets. We use farmgate fluid milk prices as an exemplar non-labor factor market for food retailers for three reasons. First, we find below that grocery tax over-shifting is highest for milk among all food products. Second, farmers receive, on average, a relatively

identical to our results with bootstrapping. Our findings appear robust to the specific sample used.

¹⁰See USDA ERS Food Dollar Series at <https://www.ers.usda.gov/data-products/food-dollar-series/quick-facts>.

large (51%) share of final consumer fluid milk expenditures.¹¹ These two points combined imply that if windfall retailer revenue from grocery tax over-shifting were to flow upstream to commodity producers, one might reasonably expect to find it most noticeably in milk sales. Third, and most practically, farmgate milk price data are available. Comparable nationwide, monthly, county-specific data for other products are generally unavailable.

We use the Class I milk price, 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 the USDA Agricultural Marketing Service.¹²

4 Estimation Strategy

In our regressions, we treat grocery tax rates as exogenous to UPC-level, individual consumer purchase prices conditional on the many controls we include. Our estimates are therefore causal under the identifying assumption that county-level grocery tax rates are independent once we control for county, purchasing household, month, and UPC-level product fixed effects as well as a host of time-varying county- and household-level controls. In Section 6 we test the assumption that the grocery tax rate is conditionally independent of the regression error term using a variety of diagnostic tests.

The main regression specification is equation (10) from the pricing model in section 2B. We expand X into its observable components and include an error term to account for unobserved heterogeneity. The reduced-form regression of pre-tax (i.e., tax-exclusive) unit prices on the grocery sales taxes is:

$$\ln(p_{uijm}) = \beta_0 + \beta_1\tau_{jm} + \eta C_{jm} + \theta X_{im} + \kappa S_{uijm} + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm} \quad (18)$$

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 . Our key

¹¹By comparison, the farm share of consumer expenditures on food overall was just 16% in 2023 ([United States Department of Agriculture Economic Research Service, 2023](#)).

¹²<https://www.ams.usda.gov/resources/price-formulas>

estimate of interest is β_1 , the coefficient on τ_{jm} , the ad-valorem tax for food groceries in county j and in month m , expressed in proportional terms (i.e., in the $[0,1]$ interval). Per [Besley & Rosen \(1999\)](#), the semi-log specification allows us to assess the degree of tax pass-through following Section 2B; a positive β_1 indicates over-shifting.¹³ We include a vector of county-level control variables, C_{jm} , to account for measurable cost-of-living differences, including median apartment rent, average commercial electricity rate, and state median wage ([Leung, 2021](#)). X_{im} is a vector of household characteristics, including income category,¹⁴ and the race and educational attainment of the household head. We include a vector of store type dummies, denoted S_{uijm} , to control for the type of retail outlet (e.g., grocery, dollar, warehouse, drug, or convenience store) at which the transaction occurred. 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 ε_{uijm} has the usual properties. Standard errors are clustered at the county level to alleviate concerns about residual serial correlation. Using product and county fixed effects, our identification comes from within-product price changes in response to within-county tax changes over time that deviate from average changes over all counties over time and are conditionally independent of cost of living changes manifest in the county-level control variables.

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 low-income households with White household heads are the baseline category) or store channels, with grocery stores as the benchmark to compare against discount stores, warehouse clubs, convenience stores,

¹³We 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](#)).

¹⁴NielsenIQ Consumer Panel data reports household income in twenty discrete brackets, which are grouped into six standard income levels. We combine the NielsenIQ income levels into our low ($< \$34k$), middle ($\$35k - \$70k$), and high income ($> \$70k$) categories to align approximately with income thresholds commonly used in USDA and ACS-based research.

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 0.446 and is significant at the one percent level. Food retailers significantly over-shift grocery taxes to retail consumers through price markups, on average. Following equation (10) – following [Besley & 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 \$1.44 across all grocery food products. If that estimate seems large, keep in mind that grocery tax rates are low. For the largest grocery tax rate increase observed in the data - three percentage points - our estimate would imply that a food product with a tax-exclusive price of \$2.30 before the tax change would be priced at \$2.40 afterwards. Small changes in monetary units can reflect significant tax over-shifting on low-priced items.

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 also estimate a specification that includes household fixed effects but omits UPC fixed effects in Column (4). The coefficient estimate is larger in magnitude than our preferred estimate, but statistically insignificant, likely because the model cannot control for induced changes in households' product choices in response to grocery tax changes, thereby conflating inter-product price variation with variation in prices in response to grocery tax changes ([Harding et al., 2012](#)). We report this result for reference, but do not rely on this misspecified regression in our main analysis.

Table 1. 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 | 0.446*** (0.119) | 0.512*** (0.126) | 0.294** (0.119) | 0.480*** (0.118) | 0.394*** (0.123) |
| Grocery Tax * Middle Income | | -0.067 (0.046) | | | -0.055 (0.046) |
| Grocery Tax * High Income | | -0.120** (0.052) | | | -0.108** (0.050) |
| Grocery Tax * Discount Stores | | | 0.332*** (0.001) | | 0.333*** (0.053) |
| Grocery Tax * Warehouse Club | | | 0.230*** (0.007) | | 0.698*** (0.104) |
| Grocery Tax * Convenience Store | | | -0.002 (0.459) | | -0.007 (0.460) |
| Grocery Tax * Dollar Store | | | 1.248*** (0.203) | | 1.254*** (0.202) |
| Grocery Tax * Drug Store | | | 0.262* (0.162) | | 0.273* (0.162) |
| Grocery Tax * Black | | | | -0.183*** (0.066) | -0.221*** (0.065) |
| Grocery Tax * Hispanics | | | | 0.107 (0.093) | 0.086 (0.093) |
| Grocery Tax * Asians | | | | -0.077 (0.171) | -0.069 (0.171) |
| Grocery Tax * Other Races | | | | -0.314*** (0.111) | -0.336*** (0.111) |
| Year Fixed Effects | Y | Y | Y | Y | Y |
| 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 Characteristics | Y | Y | Y | Y | Y |
| Store Type Dummies | Y | Y | Y | Y | Y |
| County-Level Economic Controls | Y | Y | Y | Y | Y |
| Number of Clusters | 2,804 | 2,804 | 2,804 | 2,804 | 2,804 |

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level. N=14,383,111. Household-level characteristics (income category, household head's race, and education), store type dummies (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level economic controls (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

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 (10), the national average grocery tax rate of 4.3% (conditional on having any grocery tax) is sufficiently small to approximate the pass-through rate as $1+\beta_1$. This yields an estimated pass-through rate of 1.512 for low-income households as the reference group. The highest income levels experience a statistically significant 12 percent lower grocery tax pass-through over-shifting than the lowest income households, holding everything else constant (column 2).

This result may seem counter-intuitive since the price elasticity of food demand typically declines (in absolute value) with income. Indeed, column (2)'s result masks the fact that lower-income households are much less likely than high-income households to shop at grocery stores (Appendix Table A12, panel a) and much more likely to buy food at dollar stores, which have the highest pass-through rates. When we estimate pass-through rates specific to each income group (Appendix Table A13), we find that high-income households shoulder a significantly higher rate of grocery tax over-shifting, consistent with the stylized fact that higher-income consumers exhibit more price-inelastic demand than lower-income consumers. In the income-group sub-sample regressions (Appendix Table A13), we cannot reject the null hypothesis of full grocery tax pass-through but no over-shifting onto low-income households. To better contextualize our pass through estimates, we map our household income groups to the income quintiles used in the 2019 Consumer Expenditure Survey (CES) from the U.S. Bureau of Labor Statistics (BLS), which reports annual food-at-home expenditures by income group.¹⁵ Specifically, our low-, middle-, and high-income groups are broadly aligned with the lower, middle, and upper segments of the BLS income distribution (i.e., approximately Q1–Q2, Q3, and Q4–Q5). Table A14 presents back-of-the-envelope calculations that translate our pass-through coefficient estimates into annual total grocery cost increases under a hypothetical one percentage point increase in the grocery tax. Per the CES 2019 data, households in the lower, middle, and upper income quintiles spent approximately \$2,790, \$4,422, and \$7,129 annually on food at home, respectively. Applying the pass-through es-

¹⁵<https://www.bls.gov/cex/tables/calendar-year/mean-item-share-average-standard-error/cu-income-quintiles-before-taxes-2019.pdf?>

imates from Table A13 implies additional annual grocery costs of roughly \$7.5, \$14.2, and \$42.2, respectively.¹⁶ These represent modest shares of total after-tax household income – 0.06%, 0.03% and 0.02% for the lowest, middle and highest income quintiles, respectively – but underscore the regressive incidence of grocery tax burdens. And as we show below, when aggregated across millions of grocery purchasers, the cumulative effects are considerable.

We find striking heterogeneity in grocery tax over-shifting by store type. Specifically, drug stores, discount stores, and especially dollar stores are disproportionately frequented by lower-income consumers (Appendix Table A12), and these store types (along with warehouse clubs) all over-shift grocery taxes significantly more than do grocery stores or convenience stores. The estimated tax pass-through coefficient for discount stores (column 3) is 33 percentage points higher than for grocery stores (the omitted category), drug stores' pass-through is 26 percentage points higher, 23 percentage points higher for warehouse clubs, and 125 percentage points higher for dollar stores. The dollar store pass-through point estimate may seem high. But keep in mind two facts. First, grocery tax rates are low, so high over-shifting rates do not imply large price changes for individual, low-price food items. Second, dollar stores commonly use a pricing model that eschews the continuous prices typically used by grocery stores for a small number of discrete price points. That pricing strategy can lead to large proportional price adjustments on low-cost items. For example, for a one percentage point increase in the ad valorem grocery tax rate – the modal grocery tax rate change in the data – the estimates reported in column (3) of Table 1 would be consistent with a dollar store increasing 1 out of every (roughly) 20 products' price from \$1.00 to \$1.50. This does not seem at all implausible.

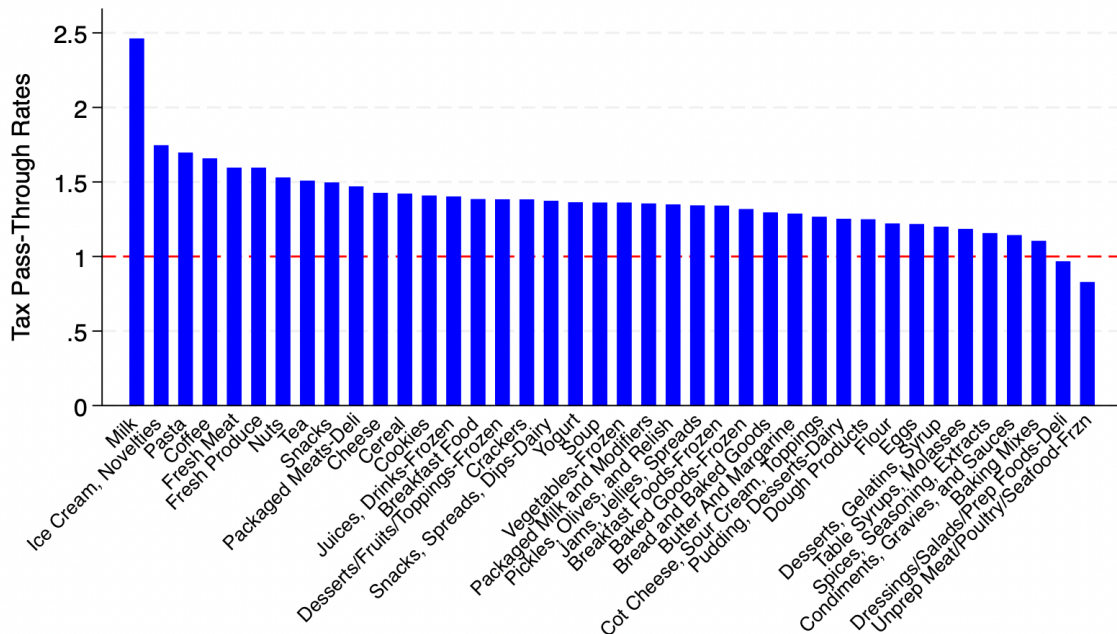
The store categories that have the highest rates of grocery tax over-shifting are disproportionately frequented by White-headed households. Indeed, we find that households with Black household heads experience only half the over-shifting rate of those with White household heads, and those with Other Race (mainly Native American) household heads face almost no statistically significant grocery tax over-shifting at all, with an estimated

¹⁶Given variation in household composition across income quintiles, this translates into per capita grocery cost increases of roughly \$4.7, \$5.7, and \$13.2 for the lowest, middle, and highest income quintile households, respectively (According to the CES, the lowest, middle, and highest income households have 1.6, 2.5, and 3.2 average numbers in consumer units, respectively).

coefficient slightly above zero ($0.166=0.480-0.314$), as shown in column 4. Once we allow for different tax rate coefficient estimates 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-headed, lower-income households (column 5).

Considerable variation in tax over-shifting exists among major product categories. Table A5 and Figure 3 (generated from column (3) of Table A5) 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 et al., 1988), -0.039 (Schmit & Kaiser, 2004), and -0.154 (Zheng & 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 \$2.46. For the modal grocery tax change of 1% that would imply an increase in the tax-exclusive price of a gallon of milk from \$3.50 to \$3.55 in response to the grocery tax change.

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 \$0.83; 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 \$0.97. 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 & 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 NielsenIQ 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 Diagnostic Checks

We subject these estimates to a range of robustness checks, all reported in the Online Appendix.

First, we assumed that grocery tax rates satisfy the conditional independence assumption, following prior studies on sales taxes (Rohlin & Thompson, 2018; Zheng et al., 2021; Zhao et al., 2022), and the random trend model assumptions (Wooldridge, 2010). Because jurisdictions tax food so as to raise fiscal revenue, political pressures that necessitate grocery tax rates changes could, in principle, arise due to other factors that likewise affect retailers' product pricing.¹⁷ The most obvious prospective source of confounding would arise from

¹⁷Note that taxes aimed at improving public health by incentivizing healthier diet choices typically target one or a small number of foods, like sugar-sweetened beverages, or are based on fat, salt, or sugar content. Such taxes are commonly implemented as excise taxes paid by producers or distributors and explicitly included in posted product prices, rather than as flat-rate sales taxes paid by consumers only at checkout.

reverse causality, i.e., states and counties change grocery tax rates in response to changing food prices. Indeed, in the past three years, Arkansas, Illinois, Kansas, Oklahoma, and Virginia all passed legislation to eliminate state-level grocery taxes, and Alabama reduced its state grocery tax rate from 4 to 3 percent, at least partly in response to rising food prices (Meadows, 2025). Note that if the controls we include do not eliminate such reverse causality, then the implied negative correlation from tax-exclusive grocery price changes to grocery tax changes would bias our estimates downward, reinforcing our qualitative findings that retailers over-shift grocery taxes onto consumers.

If indeed grocery taxes respond to tax-exclusive prices, then we should see a correlation between future grocery taxes and current food prices. We exploit the panel nature of the data to conduct that placebo test. Specifically, we add future tax rates, τ_{jm+1} , to equation (18):

$$\ln(p_{uijm}) = \beta_0 + \beta_1\tau_{jm} + \beta_2\tau_{jm+1} + \eta C_{jm} + \theta X_i + \kappa S_{uijm} + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm} \quad (19)$$

If the grocery tax rate is strictly exogenous, then prices should not be associated with future grocery tax rates once we control for current grocery tax rates, i.e., β_2 should equal zero. As shown in Table A7 column (1), the β_2 estimate is indeed statistically insignificantly different from zero, while the β_1 estimate remains substantially unchanged and statistically significant at the one percent level.

Second, one might worry that grocery tax changes are announced in advance, and thus retailers might make tax-exclusive product price changes in anticipation of the coming tax shift. We can test that hypothesis using a modified form of equation (19), by replacing τ_{jm+1} with τ_{jm-1} , the tax rate one year earlier. As shown in Table A7 column (2), the β_2 estimate is indeed statistically insignificantly different from zero, with a point estimate of just 0.002, while the β_1 estimate remains substantially unchanged and statistically significant at the one percent level.

Third, our identification relies on the assumption that pre-tax price trends would have evolved similarly across counties in the absence of tax changes. This assumption is conceptually similar to the random trend condition in staggered difference-in-differences designs

(Wooldridge, 2021). We test that hypothesis by including county-specific time trends:

$$\ln(p_{uijm}) = \beta_0 + \beta_1\tau_{jm} + \eta C_{jm} + \theta X_i + \kappa S_{uijm} + \beta_j(\delta_j * trend) + \delta_j + \varphi_m + \alpha_u + \varepsilon_{uijm} \quad (20)$$

where $\delta_j * trend$ 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.

Fourth, we use a stacked event study design to examine the dynamic effect of grocery tax changes on retail food prices. We adopt this approach given that grocery tax rates change at different times across various counties, resulting in multiple tax change events throughout our study period. Traditional event study approaches, which estimate a single event’s effect relative to a baseline period, are inappropriate in this setting because they implicitly assume homogeneity in treatment timing and effect magnitude across units (Miller, 2023). Instead, we follow recent methodological advances (Sun & Abraham, 2021) and employ a stacked event study design that accommodates multiple treatments at multiple times. Specifically, our analysis leverages county-month panel data from 2010 to 2019, where treatment events are defined as months in which counties experienced a grocery tax increase. Each tax-change event is aligned (*stacked*) by the month the tax rate change first took effect. We then estimate dynamic treatment effects within a ± 10 -month event-time window around each tax change. This stacking approach explicitly accounts for treatment heterogeneity and timing differences, providing a more accurate and interpretable depiction of the price dynamics surrounding each tax event.

To construct our stacked dataset, we first define an event-specific cohort as counties experiencing a tax increase in the same calendar month. For each event, we create an event-time index running from -10 months to +10 months, with the month in which the tax change occurs (month = 0) serving as the reference (omitted) period. We then pool all event cohorts into a single regression dataset. The equation we estimate is:

$$\ln(\text{Price}_{jct}) = \alpha_{jc} + \lambda_t + \sum_{\ell=-10, \ell \neq 0}^{10} \mu_\ell \cdot \mathbf{1}\{t - E_j = \ell\} + \epsilon_{jct} \quad (21)$$

where $\ln(\text{Price}_{jct})$ denotes the log tax-exclusive retail price of product c in county j during month t . The terms α_{jc} and λ_t represent county-product and month fixed effects, respectively. E_j is the event month (i.e., when a tax increase takes effect in county j), and μ_ℓ are the parameters of interest, capturing the average treatment effect on prices in each relative month ℓ . We cluster standard errors at the county level to account for prospective serial correlation.

Figure A2 presents our stacked event study estimates for the tax increase. Each coefficient estimate, (μ_ℓ) , represents the average log-price difference relative to the reference period ($\ell = 0$). Our results suggest a clear positive price response to grocery tax increases: prior to the event month, prices show minimal trends and are statistically indistinguishable from the reference period, supporting the parallel trends assumption required for causal interpretation. If anything, a negative pre-trend exists, which would bias downwards our estimates of grocery tax impacts. Following the tax increase (month 0), retail prices rise significantly and steadily, indicating a pronounced and persistent pass-through of grocery taxes to consumers. By the 10th month following the tax change, prices stabilize at a higher level compared to the pre-treatment period, providing robust evidence of tax over-shifting. These findings are consistent with economic theory predicting incomplete competition and pricing power among grocery retailers (Fuest et al., 2018).

We test for asymmetry between grocery tax increases and decreases by separately estimating stacked event studies each, using a consistent model specification across both samples. The effects in Figure A3 are plotted relative to the month of the tax change ($t = 0$). We observe a significant and positive price response following tax increases (Figure A3), while the price response to tax decreases is muted and statistically insignificant from zero in most post-treatment months. This asymmetric pattern suggests retailers raise prices promptly and significantly when the government increases grocery taxes, but do not similarly drop prices when taxes fall, consistent with strategic pricing behavior by retailers with market power (Loy et al., 2016).

Finally, we conduct a placebo test in which we randomize the assignment of grocery tax rates among counties, keeping the other independent variables unchanged. This mechanically breaks the hypothesized causal correlation between grocery tax rates 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 & 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 these robustness checks.

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 government grocery tax revenue increases the retail tax-inclusive price by \$1.44. 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 generate coarse estimates of the impact of grocery taxes on retailer gross revenues using the food product category-specific price elasticity of demand estimates reported by Okrent & 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, along with the budget shares of each food product category, as provided in their Table 1. Okrent & Alston (2012) relied on the Consumer Expenditure Survey and Consumer Price Indices to classify food groups, which differs from NielsenIQ’s classification. We therefore established a one-to-one correspondence between Okrent & Alston (2012)’s product categories and those of the NielsenIQ Consumer Panel (Table A10). This permits us to merge budget shares and price elasticity estimates from Okrent & Alston (2012) with our pass-through rate estimates and state-specific grocery tax rates so as to estimate the 2021 retail revenue effects of grocery taxes in each state.

For instance, in Alabama, grocery food taxes raised approximately \$500 million in 2021.¹⁸ That implies a grocery tax windfall of roughly \$80 million.¹⁹ In Mississippi, the 7% tax

¹⁸<https://wbhm.org/2021/why-alabama-lawmakers-just-wont-give-up-the-grocery-tax/>

¹⁹We calculate the retailer revenue accruing due to grocery taxes as Grocery Tax Revenue *

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.²⁰ 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 & Alston \(2012\)](#). Across all 14 states that collected statewide grocery taxes in 2021, we estimate retailers received approximately \$700 million in windfall revenue on roughly \$4.4 billion in state grocery tax revenue.

Table 2. Estimated 2021 State and Retailer Grocery Tax Revenue, \$ millions

| States | Tax Revenue | Retailer Revenue Windfall |
|------------------|-------------|---------------------------|
| AL# | 500 | 80 |
| AR | 450 | 72 |
| HI# | 270 | 43 |
| ID# | 79 | 13 |
| IL | 400 | 64 |
| KS# | 450 | 72 |
| MO | 70 | 11 |
| MS# | 267-315 | 42-50 |
| NC# | 400 | 64 |
| OK# | 300 | 48 |
| SD# | 104 | 17 |
| TN | 272 | 43 |
| UT | 200 | 32 |
| VA | 600 | 95 |
| Nationwide Total | 4,362-4,410 | 696-704 |

Notes: All tax revenue estimates come from reporting by State Departments of Revenue, tax.org, and taxfoundation.org. MS reports an interval, the other states report point estimates. # Grocery food items are taxed at the full rate as sales tax. * We omit Alaska, Georgia, Louisiana, and South Carolina because they have no state-level grocery taxes, although groceries can still be subject to county sales taxes.

$\sum [BudgetShare_i * (1 - PriceElasticity_i * TaxPassThrough_i) - 2]$, where i indexes food groups. This amounts to Grocery Tax Revenue * 0.159 on average nationwide.

²⁰<https://mississippitoday.org/2021/01/21/key-house-leader-says-mississippi-should-cut-highest-in-nation-grocery-tax/>

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 with workers and/or suppliers? The distribution of this windfall within the marketing chain is crucial to understanding the broader economic impacts of tax pass-through.

A. Earnings of Grocery Store Workers

To answer the first part of that question, we regress the average 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:

$$\ln(\text{Earnings}_{ijq}) = \beta_0 + \beta_1\tau_{jq} + \eta C_{jq} + \delta_j + \alpha_i + \gamma_q + \varepsilon_{ijq} \quad (22)$$

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.

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 ([United States Department of Agriculture Economic Research Service, 2023](#)), none of the significant revenue windfall food retailers enjoy for grocery tax over-shifting accrues to their workers. This is consistent with the observation that food retailers operate within a much broader, multi-sectoral labor market such that without external pressure to raise wages, retailers can retain the windfall revenue arising from grocery taxes.

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

| Dependent Variable: ln (Earnings) | (1) | (2) | (3) | (4) |
|--------------------------------------|-------------------|-------------------|----------------------|-----------------------|
| Grocery Tax | -0.385 (1.590) | -0.369 (0.820) | -0.421 (0.825) | 0.464 (0.593) |
| Commercial Electricity Price | | | 0.014*** (0.004) | -0.002 (0.003) |
| Median Rent | | | 0.00001 (0.00006) | 0.00006* (0.00004) |
| State Medium Wage | | | 0.000 (0.000) | 0.000** (0.000) |
| Year Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | 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 |
| <i>N</i> | 13,340,048 | 13,340,048 | 13,290,596 | 13,290,596 |

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

B. Farm 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:

$$\ln(PI_{jm}) = \beta_0 + \beta_1\tau_{jm} + \eta C_{jm} + \delta_j + \varphi_m + \varepsilon_{jm} \quad (23)$$

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 \$ 2.44 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. This is not surprising considering that milk markets are both spatially integrated and federally regulated, such that local partial equilibrium effects on retailers are unlikely to appreciably affect the broader market and thus the wholesale prices farmers receive for bulk commodity sales.

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

| | (1) | (2) | (3) | (4) |
|--|-------------------|-------------------|--------------------|-------------------|
| Dependent Variable: ln (Class 1 Milk Price) | | | | |
| Grocery Tax | -0.305 (0.320) | -0.291 (0.377) | -0.330 (0.397) | -0.309 (0.328) |
| Commercial Electricity Price | | | 0.0004 (0.004) | 0.002 (0.002) |
| Median Rent | | | -0.000 (0.0000) | -0.000 (0.000) |
| State Medium Wage | | | 0.000 (0.000) | 0.000 (0.000) |
| Year Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y |
| County Trend | N | Y | Y | N |
| Economic Controls | N | N | Y | Y |
| Number of Clusters | 2,893 | 2,893 | 2,804 | 2,804 |
| <i>N</i> | 15,889,373 | 15,889,373 | 15,729,530 | 15,729,530 |

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

8 Discussion

In this, the most comprehensive study of grocery tax pass-through in the United States, and the first in more than a quarter century, 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 (mainly Native American) households face significantly lower tax over-shifting than low-income, White-headed 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, deli items, and seafood had the lowest tax pass-through.

These findings contribute to a growing literature on the incidence of sales taxes in imperfectly competitive retail markets. For instance, [Anderson et al. \(2001\)](#) show that firms can overshift ad valorem taxes onto consumers when their own-demand curves are sufficiently curved relative to overall market demand. Consistent with this logic, we observe higher pass-through in retail formats where customers tend to buy without comparing prices across brands or nearby stores, such as dollar stores and warehouse clubs. Related theoretical work by [Cremer & Thisse \(1994\)](#) and [Fullerton & Metcalf \(2002\)](#) similarly documents the role of imperfect competition and demand curvature in shaping tax incidence.

Our findings are also consistent with empirical studies on product-specific excise taxes, which document heterogeneity in pass-through across both retail formats and product categories. [Salgado & Ng \(2019\)](#) show that Mexico's tax on non-essential, energy-dense foods (NEDF) led to higher price increases for salty snacks and sweet baked goods than for frozen meals, and that pass-through was greater in supermarkets than in small-format stores. Similarly, [Gračner et al. \(2022\)](#) find that the price effects of Mexico's NEDF tax varied substantially across both store types and products, where large-format stores exhibited stronger pass-through, and taxed items such as sugary cereals and sweet snacks experienced larger price increases than others. Although our setting involves a broad-based grocery tax rather than a more narrowly targeted excise tax, we observe comparable heterogeneity by store format. Taken together, these findings suggest that both pricing power and tax salience help explain variation in incidence across retail environments.

Although the estimated per capita consumer annual cost of excess grocery tax pass-through is just \$5-\$13, summing across consumers yields substantial aggregate windfall retailer profits from grocery tax over-shifting of perhaps \$700 million as recently as 2021. Studying the link between consumer taxes and worker and supplier earnings for the first time, we find no evidence that food retail workers or dairy farmers share in any of this windfall revenue. This disconnect suggests that higher consumer prices do not necessarily

translate into higher wages or broader farm earnings within the food sector. In concentrated retail environments, where firms often have pricing power but workers and farmers lack bargaining leverage, this dynamic may result in an uneven distribution of tax-induced revenue. Our findings suggest that grocery tax burdens fall primarily on consumers, with little evidence that benefits are passed along to labor or upstream producers in the value chain. This previously-unexplored unintended consequence of grocery taxes merits policymaker attention when (re)considering the use of grocery taxes for government finance.

The major implication of these results is that sales taxes on grocery food items appear even more regressive than previously thought. Not only does the flat (i.e., non-progressive), 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. Such considerations should be considered in any policy debate on whether to reduce or repeal grocery taxes. 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 they lowered grocery taxes.

References

- Allcott, H., Lockwood, B. B., & Taubinsky, D. (2019). Should we tax sugar-sweetened beverages? an overview of theory and evidence. Journal of Economic Perspectives, 33(3), 202–227.
- Anderson, S. P., De Palma, A., & Kreider, B. (2001). Tax incidence in differentiated product oligopoly. Journal of Public Economics, 81(2), 173–192.
- Bachmann, R. & Frings, H. (2017). Monopsonistic competition, low-wage labour markets, and minimum wages—an empirical analysis. Applied Economics, 49(51), 5268–5286.
- Barzel, Y. (1976). An alternative approach to the analysis of taxation. Journal of Political Economy, 84(6), 1177–1197.
- Berger, D., Herkenhoff, K., & Mongey, S. (2022). Labor market power. American Economic Review, 112(4), 1147–93.
- Berry, S., Gaynor, M., & Morton, F. S. (2019). Do increasing markups matter? lessons from empirical industrial organization. Journal of Economic Perspectives, 33(3), 44–68.
- Besley, T. J. & Rosen, H. S. (1999). Sales taxes and prices: an empirical analysis. National tax journal, 52(2), 157–178.
- Bleich, S. N., Lawman, H. G., LeVasseur, M. T., Yan, J., Mitra, N., Lowery, C. M., Peterhans, A., Hua, S., Gibson, L. A., & Roberto, C. A. (2020). The association of a sweetened beverage tax with changes in beverage prices and purchases at independent stores: Study compares changes in sweetened beverage prices and purchases before and twelve months after tax implementation, at small, independent stores in philadelphia. Health Affairs, 39(7), 1130–1139.
- Bonnet, C. & Réquillart, V. (2013). Impact of cost shocks on consumer prices in vertically-related markets: The case of the french soft drink market. American Journal of Agricultural Economics, 95(5), 1088–1108.

- Cawley, J. & Frisvold, D. (2023). Taxes on sugar-sweetened beverages: Political economy, and effects on prices, purchases, and consumption. Food Policy, 117, 102441.
- Cawley, J., Frisvold, D., Hill, A., & Jones, D. (2020a). The impact of the philadelphia beverage tax on prices and product availability. Journal of Policy Analysis and Management, 39(3), 605–628.
- Cawley, J., Frisvold, D., Hill, A., & Jones, D. (2020b). Oakland’s sugar-sweetened beverage tax: impacts on prices, purchases and consumption by adults and children. Economics & Human Biology, 37, 100865.
- Cawley, J., Frisvold, D., Jones, D., & Lensing, C. (2021). The pass-through of a tax on sugar-sweetened beverages in boulder, colorado. American Journal of Agricultural Economics, 103(3), 987–1005.
- Cawley, J. & Frisvold, D. E. (2017). The pass-through of taxes on sugar-sweetened beverages to retail prices: the case of berkeley, california. Journal of Policy Analysis and Management, 36(2), 303–326.
- Cawley, J., Willage, B., & Frisvold, D. (2018). Pass-through of a tax on sugar-sweetened beverages at the philadelphia international airport. Jama, 319(3), 305–306.
- Chetty, R., Looney, A., & Kroft, K. (2009). Salience and taxation: Theory and evidence. American economic review, 99(4), 1145–1177.
- Christian, P. & Barrett, C. B. (2024). Spurious regressions and panel iv estimation: revisiting the causes of conflict. Economic Journal, 134(659), 1069–1099.
- Cremer, H. & Thisse, J.-F. (1994). Commodity taxation in a differentiated oligopoly. International Economic Review, (pp. 613–633).
- Delipalla, S. & O’Donnell, O. (2001). Estimating tax incidence, market power and market conduct: The european cigarette industry. International Journal of Industrial Organization, 19(6), 885–908.

- Falbe, J., Lee, M. M., Kaplan, S., Rojas, N. A., Ortega Hinojosa, A. M., & Madsen, K. A. (2020). Higher sugar-sweetened beverage retail prices after excise taxes in oakland and san francisco. American Journal of Public Health, 110(7), 1017–1023.
- Falbe, J., Rojas, N., Grummon, A. H., & Madsen, K. A. (2015). Higher retail prices of sugar-sweetened beverages 3 months after implementation of an excise tax in berkeley, california. American journal of public health, 105(11), 2194–2201.
- Fuest, C., Peichl, A., & Siegloch, S. (2018). Do higher corporate taxes reduce wages? micro evidence from germany. American Economic Review, 108(2), 393–418.
- Fullerton, D. & Metcalf, G. E. (2002). Tax incidence. Handbook of public economics, 4, 1787–1872.
- Genakos, C. & Pagliero, M. (2022). Competition and pass-through: evidence from isolated markets. American Economic Journal: Applied Economics, 14(4), 35–57.
- Gračner, T., Kapinos, K. A., & Gertler, P. J. (2022). Associations of a national tax on non-essential high calorie foods with changes in consumer prices. Food policy, 106, 102193.
- Greenhalgh-Stanley, N., Rohlin, S., & Thompson, J. (2018). Food sales taxes and employment. Journal of Regional Science, 58(5), 1003–1016.
- Hanson, A. & Sullivan, R. (2009). The incidence of tobacco taxation: evidence from geographic micro-level data. National Tax Journal, 62(4), 677–698.
- Harberger, A. C. (1962). The incidence of the corporation income tax. Journal of Political Economy, 70(3), 215–240.
- Harding, M., Leibtag, E., & Lovenheim, M. F. (2012). The heterogeneous geographic and socioeconomic incidence of cigarette taxes: evidence from nielsen homescan data. American Economic Journal: Economic Policy, 4(4), 169–198.
- Jenkin, F. (1872). 3. on the principles which regulate the incidence of taxes. Proceedings of the Royal Society of Edinburgh, 7, 618–631.

- Jones-Smith, J. C., Walkinshaw, L. P., Oddo, V. M., Knox, M., Neuhouser, M. L., Hurvitz, P. M., Saelens, B. E., & Chan, N. (2020). Impact of a sweetened beverage tax on beverage prices in seattle, wa. Economics & Human Biology, 39, 100917.
- Kaiser, H. M., Streeter, D. H., & Liu, D. J. (1988). Welfare comparisons of us dairy policies with and without mandatory supply control. American Journal of Agricultural Economics, 70(4), 848–858.
- Kenkel, D. S. (2005). Are alcohol tax hikes fully passed through to prices? evidence from alaska. American Economic Review, 95(2), 273–277.
- Léger, P. T. & Powell, L. M. (2021). The impact of the oakland ssb tax on prices and volume sold: a study of intended and unintended consequences. Health Economics, 30(8), 1745–1771.
- Leider, J., Li, Y., & Powell, L. M. (2021). Pass-through of the oakland, california, sugar-sweetened beverage tax in food stores two years post-implementation: A difference-in-differences study. PLoS One, 16(1), e0244884.
- Leung, J. H. (2021). Minimum wage and real wage inequality: Evidence from pass-through to retail prices. Review of Economics and Statistics, 103(4), 754–769.
- Loy, J.-P., Weiss, C. R., & Glauben, T. (2016). Asymmetric cost pass-through? empirical evidence on the role of market power, search and menu costs. Journal of Economic Behavior & Organization, 123, 184–192.
- Lusk, J. L. & Tonsor, G. T. (2016). How meat demand elasticities vary with price, income, and product category. Applied Economic Perspectives and Policy, 38(4), 673–711.
- Marinello, S., Pipito, A. A., Leider, J., Pugach, O., & Powell, L. M. (2020). The impact of the oakland sugar-sweetened beverage tax on bottled soda and fountain drink prices in fast-food restaurants. Preventive Medicine Reports, 17, 101034.
- Marinello, S., Pipito, A. A., Leider, J., Pugach, O., & Powell, L. M. (2021). Longer-term

- impacts of sugar-sweetened beverage taxes on fast-food beverage prices: evidence from oakland, california, 2-year post-tax. Public Health Nutrition, 24(11), 3571–3575.
- Marion, J. & Muehlegger, E. (2011). Fuel tax incidence and supply conditions. Journal of public economics, 95(9-10), 1202–1212.
- Meadows, J. (2025). Like illinois, more states are moving to scrap sales tax at the grocery store. Harvest Public Media.
- Miller, D. L. (2023). An introductory guide to event study models. Journal of Economic Perspectives, 37(2), 203–230.
- Okrent, A. & Alston, J. (2012). The demand for disaggregated food-away-from-home and food-at-home products in the united states. USDA-ERS Economic Research Report, (139).
- Pless, J. & Van Benthem, A. A. (2019). Pass-through as a test for market power: An application to solar subsidies. American Economic Journal: Applied Economics, 11(4), 367–401.
- Politi, R. B. & Mattos, E. (2011). Ad-valorem tax incidence and after-tax price adjustments: evidence from brazilian basic basket food. Canadian Journal of Economics/Revue canadienne d'économique, 44(4), 1438–1470.
- Powell, L. M. & Leider, J. (2020). Evaluation of changes in beverage prices and volume sold following the implementation and repeal of a sweetened beverage tax in cook county, illinois. JAMA network open, 3(12), e2031083–e2031083.
- Powell, L. M., Leider, J., & Léger, P. T. (2020). The impact of the cook county, il, sweetened beverage tax on beverage prices. Economics & Human Biology, 37, 100855.
- Powell, L. M., Marinello, S., & Leider, J. (2021). A review and meta-analysis of tax passthrough of local sugar-sweetened beverage taxes in the united states. Chicago, IL.
- Roberto, C. A., Lawman, H. G., LeVasseur, M. T., Mitra, N., Peterhans, A., Herring, B., & Bleich, S. N. (2019). Association of a beverage tax on sugar-sweetened and artificially

- sweetened beverages with changes in beverage prices and sales at chain retailers in a large urban setting. Jama, 321(18), 1799–1810.
- Rohlin, S. M. & Thompson, J. P. (2018). Local sales taxes, employment, and tax competition. Regional Science and Urban Economics, 70, 373–383.
- Rojas, C. & Wang, E. (2021). Do taxes on soda and sugary drinks work? scanner data evidence from berkeley and washington state. Economic Inquiry, 59(1), 95–118.
- Saelens, B., Rowland, M., Qu, P., Walkinshaw, L., Oddo, V., Knox, M., Chan, N., & Jones-Smith, J. (2020). Twelve month report: Store audits & child cohort—the evaluation of seattle’s sweetened beverage tax. Public Health-Seattle King Cty, (pp. 20–24).
- Salgado, J. C. & Ng, S. W. (2019). Understanding heterogeneity in price changes and firm responses to a national unhealthy food tax in mexico. Food policy, 89, 101783.
- Schmit, T. M. & Kaiser, H. M. (2004). Decomposing the variation in generic advertising response over time. American Journal of Agricultural Economics, (pp. 139–153).
- Seiler, S., Tuchman, A., & Yao, S. (2021). The impact of soda taxes: Pass-through, tax avoidance, and nutritional effects. Journal of Marketing Research, 58(1), 22–49.
- Silver, L. D., Ng, S. W., Ryan-Ibarra, S., Taillie, L. S., Induni, M., Miles, D. R., Poti, J. M., & Popkin, B. M. (2017). Changes in prices, sales, consumer spending, and beverage consumption one year after a tax on sugar-sweetened beverages in berkeley, california, us: a before-and-after study. PLoS medicine, 14(4), e1002283.
- Stern, D., Robinson, W. R., Ng, S. W., Gordon-Larsen, P., & Popkin, B. M. (2015). Us household food shopping patterns: dynamic shifts since 2000 and socioeconomic predictors. Health Affairs, 34(11), 1840–1848.
- Stolper, S. (2016). Competition and incidence: Automotive fuel tax pass-through at state borders. Technical report, Working paper.
- Sullivan, R. S. & Dutkowsky, D. H. (2012). The effect of cigarette taxation on prices: an empirical analysis using local-level data. Public Finance Review, 40(6), 687–711.

- Sun, L. & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of econometrics, 225(2), 175–199.
- United States Department of Agriculture Economic Research Service (2023). Food Dollar Series. <https://www.ers.usda.gov/data-products/food-dollar-series/download-the-data/>. Data downloaded on December 21, 2023.
- Weyl, E. G. & Fabinger, M. (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. Journal of political economy, 121(3), 528–583.
- Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT press.
- Wooldridge, J. M. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. Available at SSRN 3906345.
- Zhang, Y. & Palma, M. A. (2021). Revisiting sugar taxes and sugary drink consumption. Journal of Agricultural and Resource Economics, 46(1), 37–55.
- Zhao, J. J., Kaiser, H. M., & Zheng, Y. (2022). Do grocery food taxes incentivize participation in snap? Regional Science and Urban Economics, 95, 103736.
- Zheng, Y. & Kaiser, H. M. (2008). Advertising and us nonalcoholic beverage demand. Agricultural and Resource Economics Review, 37(2), 147–159.
- Zheng, Y., Zhao, J. J., Buck, S., Burney, S., Kaiser, H. M., & Wilson, N. L. (2021). Putting grocery food taxes on the table: Evidence for food security policy-makers. Food Policy, 101, 102098.

9 Online Appendix

Figure A1. Transactions by NielsenIQ Department

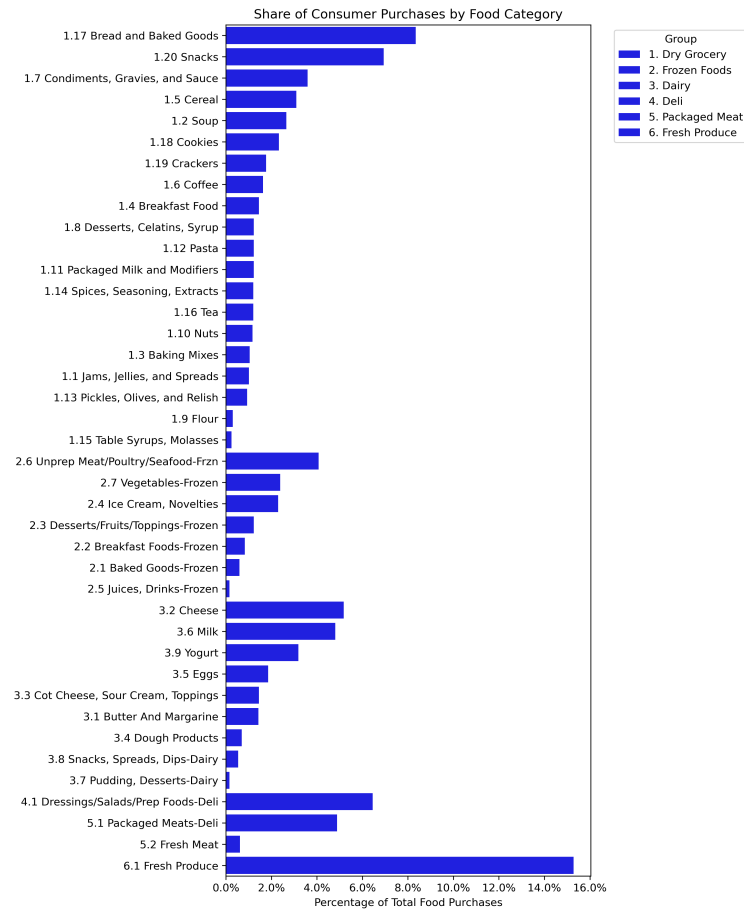
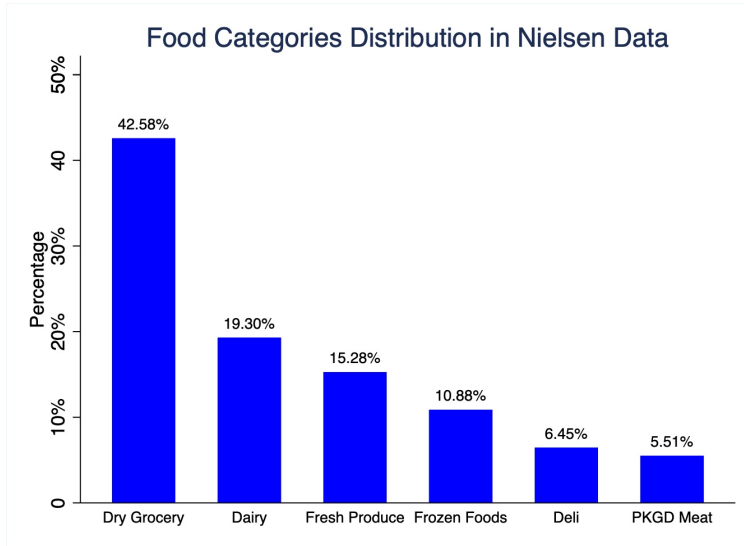


Figure A2. Stacked Event Study Estimates for Grocery Tax Increase

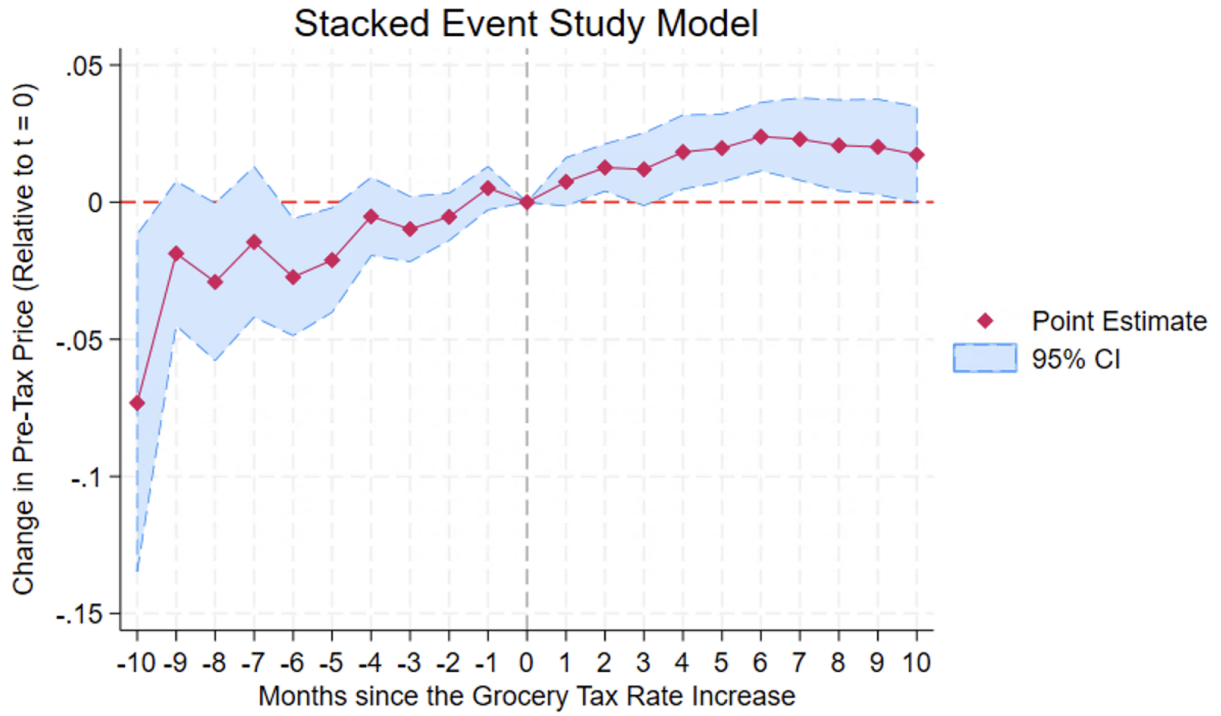


Figure A3. Stacked Event Study of Grocery Tax Increase vs Decrease

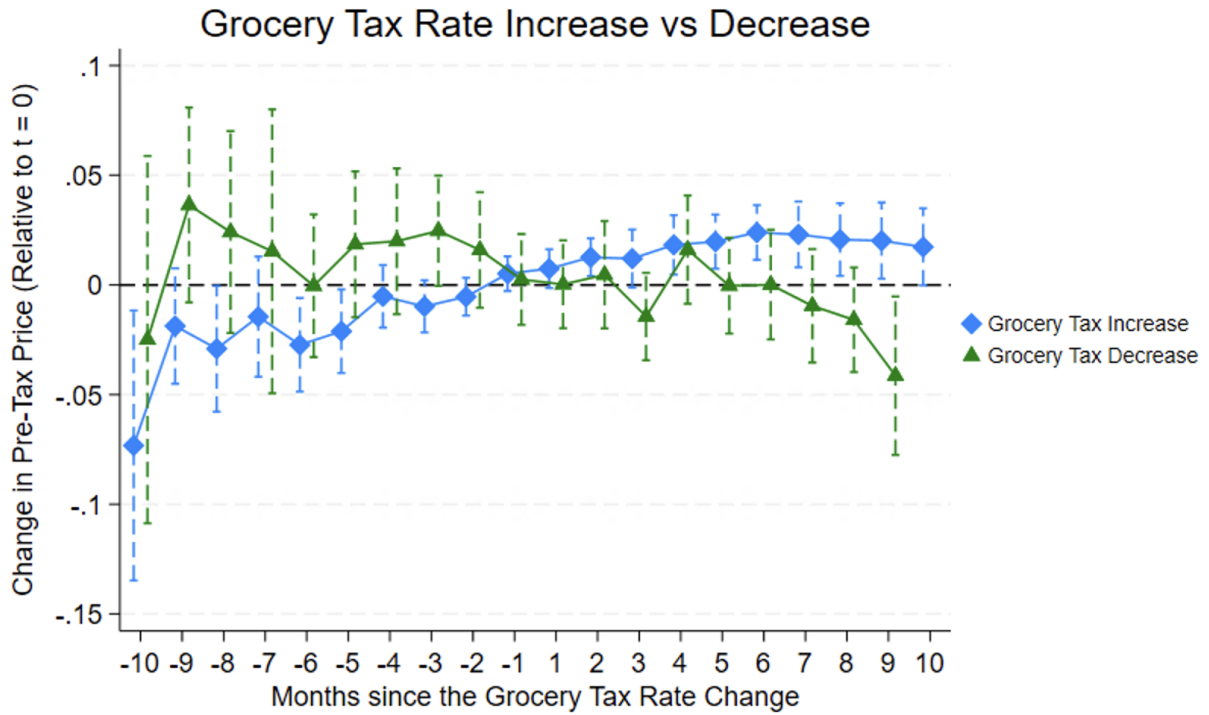


Figure A4. Distribution of Placebo Test Coefficient Estimates

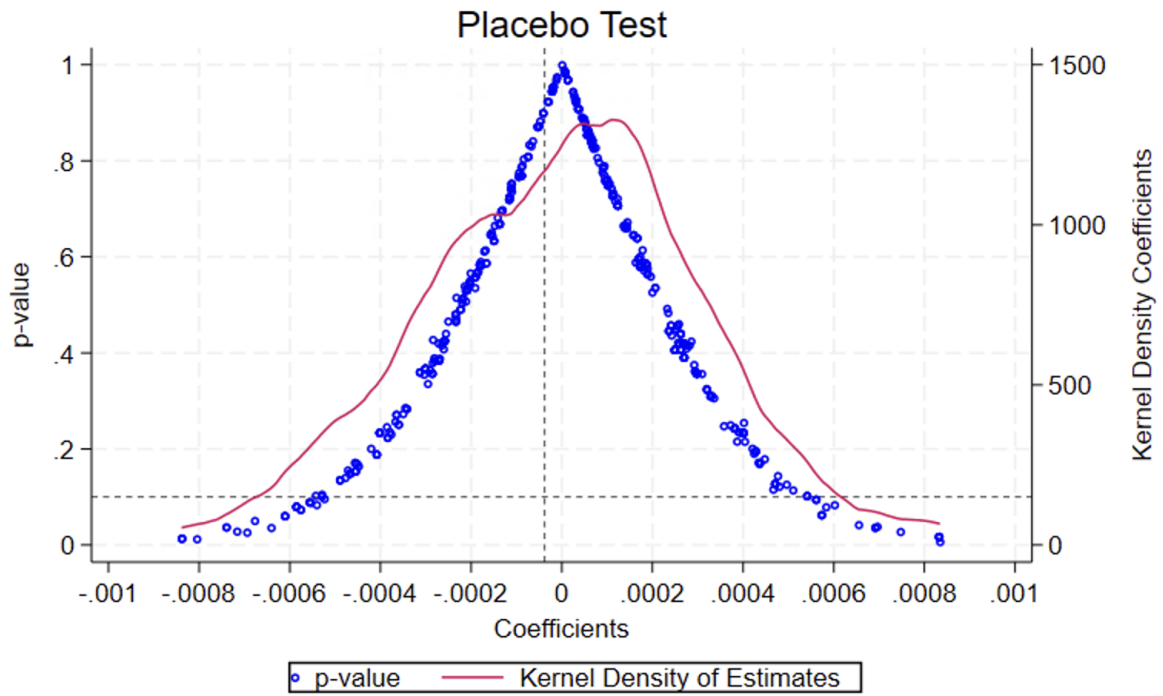


Table A1. States With Grocery Taxes in 2019

| State | Min Grocery Tax Rate | Max Grocery Tax Rate | Mean Grocery Tax Rate | # Counties with Grocery Taxes | # Counties with NO Grocery Tax | Mean General Sales Tax Rate | Tax Groceries at Reduced Rate | Counties with 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 grocery taxes from 2010 to 2019.

Table A2. States with Grocery 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 | <i>n/a</i> | 1% | 3 | 3 | 15 |
| AR | -1% | 2% | 75 | 137 | <i>n/a</i> |
| GA | <i>n/a</i> | 3% | 185 | 257 | 1 |
| IL | <i>n/a</i> | 1.25% | 6 | 6 | 96 |
| KS | -0.15% | 2% | 105 | 327 | <i>n/a</i> |
| LA | -1.55% | 1% | 11 | 11 | 49 |
| MO | <i>n/a</i> | 2.5% | 87 | 148 | 27 |
| OK | <i>n/a</i> | 1.25% | 44 | 60 | 33 |
| SC | <i>n/a</i> | 1% | 3 | 3 | 31 |
| TN | -1% | 0.5% | 95 | 284 | <i>n/a</i> |
| WV | -1% | <i>n/a</i> | 55 | 110 | <i>n/a</i> |

Notes: 1. % means the ad valorem tax rate, i.e., percentage points.

2. The other states did not change grocery sales tax rates from 2010 to 2019.

3. “n/a” means there is no increase or decrease in our studied period.

Table A3. Descriptive Statistics

| Variable | # Observations | Mean | SD |
|-----------------------------|----------------|----------|----------|
| Total Grocery Taxes | | 0.009 | 0.019 |
| Household Income | | | |
| < \$ 35,000 | | 0.175 | 0.379 |
| \$35,000-\$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 | | | |
| Grocery Store | | 0.626 | 0.484 |
| Discount Store | | 0.190 | 0.392 |
| Warehouse Club | | 0.044 | 0.205 |
| Convenience Store | | 0.004 | 0.060 |
| Dollar Store | | 0.017 | 0.128 |
| Drug Store | | 0.009 | 0.091 |
| Market Concentration | | | |
| 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 | (3) Household FE + Demographics | (4) Household FE No UPC FE |
|--|--|------------------------|---------------------------------------|----------------------------------|
| Grocery Tax | 0.396*** (0.114) | 0.283** (0.112) | 0.265** (0.117) | 0.444 (0.384) |
| Year Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y |
| UPC Fixed Effects | Y | Y | Y | N |
| Household Fixed Effects | N | Y | Y | Y |
| Household Characteristics | N | N | Y | N |
| Store Type Dummies | N | N | Y | N |
| Number of Clusters | 2,894 | 2,894 | 2,894 | 2,894 |
| <i>N</i> | 15,825,274 | 15,824,881 | 14,382,738 | 15,920,206 |

Notes: 1. *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

2. Household-level controls (income category, household head's race, and household head's education), store type controls (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level cost-of-living differences (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

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** (0.126) | 0.319*** (0.129) | 0.347*** (0.131) | 0.307** (0.139) |
| Grocery Tax * Product Category (Baseline Product = Jams, Jellies, Spreads) | | | | |
| 1. Dry Grocery | | | | |
| 1.2 Soup | 0.007 (0.071) | 0.007 (0.071) | 0.020 (0.075) | -0.027 (0.077) |
| 1.3 Baking Mixes | -0.213*** (0.071) | -0.209*** (0.071) | -0.242*** (0.073) | -0.290*** (0.075) |
| 1.4 Breakfast Food | 0.045 (0.085) | 0.044 (0.085) | 0.044 (0.094) | -0.022 (0.094) |
| 1.5 Cereal | 0.048 (0.077) | 0.047 (0.077) | 0.083 (0.083) | 0.0008 (0.088) |
| 1.6 Coffee | 0.293** (0.124) | 0.312** (0.123) | 0.330** (0.135) | 0.336** (0.144) |
| 1.7 Condiments, Gravies, and Sauces | -0.183*** (0.069) | -0.176** (0.070) | -0.203*** (0.073) | -0.205*** (0.077) |
| 1.8 Desserts, Gelatins, Syrup | -0.147** (0.073) | -0.142** (0.074) | -0.145* (0.077) | -0.181** (0.083) |
| 1.9 Flour | -0.165* (0.092) | -0.163* (0.093) | -0.124 (0.092) | -0.168* (0.101) |
| 1.10 Nuts | 0.180** (0.078) | 0.193** (0.078) | 0.195* (0.081) | 0.163** (0.081) |
| 1.11 Packaged Milk and Modifiers | 0.034 (0.075) | 0.025 (0.074) | 0.014 (0.077) | -0.066 (0.077) |
| 1.12 Pasta | 0.374*** (0.086) | 0.371*** (0.086) | 0.371*** (0.093) | 0.340*** (0.103) |
| 1.13 Pickles, Olives, and Relish | 0.041 (0.077) | 0.046 (0.077) | 0.007 (0.076) | 0.002 (0.080) |
| 1.14 Spices, Seasoning, Extracts | -0.168** (0.073) | -0.165** (0.074) | -0.189*** (0.073) | -0.210*** (0.079) |
| 1.15 Table Syrups, Molasses | -0.132 (0.089) | -0.136 (0.090) | -0.161* (0.088) | -0.219** (0.094) |
| 1.16 Tea | 0.137* (0.072) | 0.139* (0.072) | 0.173** (0.076) | 0.120 (0.081) |
| 1.17 Bread and Baked Goods | -0.053 (0.077) | -0.044 (0.077) | -0.048 (0.082) | -0.080 (0.084) |
| 1.18 Cookies | 0.042 (0.076) | 0.040 (0.075) | 0.069 (0.078) | 0.007 (0.079) |
| 1.19 Crackers | 0.017 (0.080) | 0.018 (0.081) | 0.042 (0.086) | -0.003 (0.089) |
| 1.20 Snacks | 0.131* (0.074) | 0.137* (0.073) | 0.160** (0.078) | 0.082 (0.078) |

| Dependent Variable: ln (Pre-Tax Unit Price) | (1) No Trend or Controls | (2) County Trend | (3) Controls | (4) Trend + Controls |
|--|--------------------------------|----------------------|----------------------|----------------------------|
| 2. Frozen Foods | | | | |
| 2.1 Baked Goods-Frozen | -0.006 (0.079) | 0.0009 (0.080) | -0.025 (0.084) | -0.100 (0.092) |
| 2.2 Breakfast Foods-Frozen | -0.019 (0.075) | -0.007 (0.076) | -0.001 (0.081) | -0.002 (0.085) |
| 2.3 Desserts/Fruits/Toppings-Frozen | 0.042 (0.083) | 0.048 (0.084) | 0.043 (0.087) | 0.009 (0.093) |
| 2.4 Ice Cream, Novelties | 0.389*** (0.078) | 0.397*** (0.079) | 0.424*** (0.082) | 0.365*** (0.087) |
| 2.5 Juices, Drinks-Frozen | 0.073 (0.129) | 0.098 (0.130) | 0.063 (0.143) | 0.145 (0.153) |
| 2.6 Unprep Meat/Poultry/Seafood-Frzn | -0.543*** (0.114) | -0.518*** (0.112) | -0.517*** (0.122) | -0.529*** (0.124) |
| 2.7 Vegetables-Frozen | 0.001 (0.065) | 0.004 (0.066) | 0.020 (0.068) | -0.004 (0.073) |
| 3. Dairy | | | | |
| 3.1 Butter And Margarine | -0.062 (0.070) | -0.050 (0.073) | -0.056 (0.074) | -0.085 (0.082) |
| 3.2 Cheese | 0.073 (0.068) | 0.087 (0.068) | 0.088 (0.072) | 0.100 (0.075) |
| 3.3 Cot Cheese, Sour Cream, Toppings | -0.048 (0.071) | -0.051 (0.072) | -0.078 (0.072) | -0.094 (0.074) |
| 3.4 Dough Products | -0.107 (0.085) | -0.106 (0.087) | -0.095 (0.092) | -0.161* (0.096) |
| 3.5 Eggs | -0.113 (0.099) | -0.104 (0.098) | -0.128 (0.105) | -0.182* (0.109) |
| 3.6 Milk | 1.102*** (0.130) | 1.106*** (0.123) | 1.213*** (0.140) | 1.107*** (0.130) |
| 3.7 Pudding, Desserts-Dairy | -0.071 (0.139) | -0.074 (0.139) | -0.091 (0.157) | -0.055 (0.171) |
| 3.8 Snacks, Spreads, Dips-Dairy | 0.110 (0.107) | 0.117 (0.109) | 0.033 (0.109) | -0.044 (0.117) |
| 3.9 Yogurt | 0.207*** (0.072) | 0.211*** (0.071) | 0.222*** (0.077) | 0.208*** (0.079) |
| 4. Deli | | | | |
| 4.1 Dressings/Salads/Prep Foods-Deli | -0.417*** (0.135) | -0.389*** (0.137) | -0.379*** (0.147) | -0.476*** (0.157) |
| 5. Packaged Meat | | | | |
| 5.1 Packaged Meats-Deli | 0.111 (0.076) | 0.126 (0.073) | 0.133* (0.079) | 0.123 (0.080) |
| 5.2 Fresh Meat | 0.220*** (0.085) | 0.239*** (0.083) | 0.265*** (0.070) | 0.214*** (0.092) |
| 6. Fresh Produce | | | | |
| 6.1 Fresh Produce | 0.199 (0.157) | 0.203 (0.133) | 0.265 (0.173) | 0.139 (0.139) |

| Dependent Variable: ln (Pre-Tax Unit Price) | (1) No Trend or Controls | (2) County Trend | (3) Controls | (4) Trend + Controls |
|--|--------------------------------|---------------------|-----------------|----------------------------|
| Year Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y |
| UPC Fixed Effects | Y | Y | Y | Y |
| Household Characteristics | Y | Y | Y | Y |
| Store Type Dummies | Y | Y | Y | Y |
| County Trends | N | Y | N | Y |
| Economic Controls | N | N | Y | Y |
| Number Of Clusters | 2,894 | 2,894 | 2,804 | 2,804 |
| <i>N</i> | 15,822,571 | 15,820,365 | 15,612,350 | 15,236,650 |

Notes: 1. *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

2. Household-level controls (income category, household head's race, and household head's education), store type controls (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level cost-of-living differences (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

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 | 0.511*** (0.122) | 0.383** (0.202) | 0.517*** (0.166) | 0.034 (0.678) | 0.399** (0.225) | -0.241 (0.245) |
| Year Fixed Effects | Y | Y | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y | Y | Y |
| County Fixed Effects | Y | Y | Y | Y | Y | Y |
| UPC Fixed Effects | Y | Y | Y | Y | Y | Y |
| Household Characteristics | Y | Y | Y | Y | Y | Y |
| Store Type Dummies | N | N | N | N | N | N |
| County-Level Economic Controls | Y | Y | Y | Y | Y | Y |
| Number of Clusters | 2,802 | 2,760 | 2,794 | 2,710 | 2,752 | 2,832 |
| N | 6,888,878 | 1,631,199 | 3,011,521 | 935,960 | 880,685 | 2,263,792 |

Notes: 1. *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

2. Household-level controls (income category, household head's race, and household head's education), store type controls (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level cost-of-living differences (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

Table A7. Strict Exogeneity Test

| | (1) | (2) |
|--|---------------------|---------------------|
| Dependent Variable: ln (Pre-tax Unit Price) | | |
| Grocery Tax in the current year | 0.445*** (0.119) | 0.447*** (0.119) |
| Grocery Tax in one year later | 0.176 (0.110) | |
| Grocery Tax in one year before | | 0.002 (0.006) |
| Year Fixed Effects | Y | Y |
| Month Fixed Effects | Y | Y |
| County Fixed Effects | Y | Y |
| UPC Fixed Effects | Y | Y |
| Household Characteristics | Y | Y |
| Store Type Dummies | Y | Y |
| County-Level Economic Controls | Y | Y |
| Number of Clusters | 2,804 | 2,804 |
| <i>N</i> | 15,606,621 | 15,606,641 |

Notes: 1. *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

2. Household-level controls (income category, household head's race, and household head's education), store type controls (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level cost-of-living differences (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

Table A8. County Group Specific Trends

| Dependent Variable: n (Pre-tax Unit Price) | (1) County Linear Trend by Year | (2) County Linear Trend by quarter | (3) County Linear Trend by month |
|---|--|---|---|
| Grocery Tax | 0.420** (0.178) | 0.402** (0.179) | 0.404** (0.179) |
| Year Fixed Effects | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y |
| County Fixed Effects | Y | Y | Y |
| UPC Fixed Effects | Y | Y | Y |
| Household Characteristics | Y | Y | Y |
| Store Type Dummies | Y | Y | Y |
| Number of Clusters | 2,894 | 2,894 | 2,894 |
| <i>N</i> | 15,822,571 | 15,822,571 | 15,822,571 |

Notes: 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the county level.

2. Household-level controls (income category, household head's race, and household head's education), store type controls (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level cost-of-living differences (median apartment rent, average commercial electricity rate, and state median wage) are included in all regressions but omitted from the table for brevity.

Table A9. Placebo Test based on Shuffling Taxes

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

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are clustered at the county level.

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

| NielsenIQ | 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 | -0.772 (1.532) | -0.066 (0.793) | 1.410 (0.995) | 0.822 (1.025) |
| Commercial Electricity Price | -0.0003 (0.008) | -0.007 (0.005) | -0.001 (0.007) | 0.003 (0.005) |
| Median Rent | 0.0001 (0.00009) | 0.00003 (0.00007) | 0.00004 (0.00006) | 0.0001 (0.00008) |
| Minimum Wage | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) | 0.000 (0.000) |
| Year Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y |
| County Fixed Effects | 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 |
| <i>N</i> | 3,080,438 | 3,482,403 | 3,216,275 | 3,278,861 |

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the county level.

Table A12. Purchase Shares by Household Income Group, Store and Product

(a) By Store Types

| Store Types (%) | Low Income | Middle Income | High Income |
|--------------------|------------|---------------|-------------|
| Grocery Stores | 16.64 | 41.59 | 41.77 |
| Discount Stores | 19.89 | 45.62 | 34.49 |
| Warehouse Clubs | 9.14 | 35.90 | 54.96 |
| Convenience Stores | 25.94 | 42.40 | 31.65 |
| Dollar Stores | 34.74 | 44.13 | 21.12 |
| Drug Stores | 23.13 | 43.59 | 33.28 |

(b) By Product Categories

| Product Categories (%) | Low Income | Middle Income | High Income |
|------------------------|------------|---------------|-------------|
| Dry Groceries | 18.42 | 42.96 | 38.62 |
| Frozen Foods | 17.92 | 42.72 | 39.36 |
| Dairy | 17.09 | 42.06 | 40.85 |
| Deli | 17.31 | 41.55 | 41.14 |
| Packaged Meat | 18.32 | 43.16 | 38.51 |
| Fresh Produce | 14.75 | 40.27 | 44.98 |

Table A13. Regressions Specific to Each Household Income Subsample

| Dependent Variable: ln (Pre-tax Unit Price) | (1) Low Income | (2) Middle Income | (3) High Income |
|--|-------------------|----------------------|---------------------|
| Grocery Tax | 0.268 (0.251) | 0.321** (0.143) | 0.602*** (0.210) |
| Year Fixed Effects | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y |
| County Fixed Effects | Y | Y | Y |
| UPC Fixed Effects | Y | Y | Y |
| Household Characteristics | Y | Y | Y |
| Store Type Dummies | Y | Y | Y |
| County-Level Economic Controls | Y | Y | Y |
| Number of Clusters | 2,543 | 2,694 | 2,432 |
| <i>N</i> | 2,662,174 | 6,537,193 | 6,248,674 |

Notes: 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the county level. Controls include household-level characteristics (income category, household head's race, and household head's education), store type dummies (discount stores, warehouse clubs, convenience stores, dollar stores, and drug stores), and county-level economic controls (median apartment rent, average commercial electricity rate, and state median wage) which we omit from the table for brevity.

2. Although the pass-through estimate is statistically significant for middle-income households but not for low-income households, a formal test indicates that the two are not statistically significantly different ($p = 0.127$).

Table A14. Estimated Annual Grocery Cost Increases from a One Percentage Point Grocery Tax Increase

| Income Group | Food-at-Home Expenditure in 2019 (in USD \$) | Estimated Over-Shifting Rate (%) | Implied Annual Extra Cost (in USD \$) |
|---------------|--|----------------------------------|---------------------------------------|
| Low-income | 2,790 | 0.268 | 7.48 |
| Middle-income | 4,422 | 0.321 | 14.20 |
| High-income | 7,129 | 0.602 | 42.18 |

Notes: Food-at-home expenditure data are from the 2019 Consumer Expenditure Survey (BLS). Estimated pass-through coefficients are taken from Table A13. Our income groups, constructed from Nielsen income brackets, are approximately aligned with the BLS income quintiles as follows: low-income with Q1–Q2, middle-income with Q3, and high-income with Q4–Q5.