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How Are Grocery Taxes Passed Through to Retail Food Prices?

Evidence from Nielsen Homescan Data

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Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

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Jason Zhao, Yuqing Zheng, Harry M. Kaiser, and Christopher Barrett

05/18/2022

Approximately one-third of all U.S. counties have a sales tax on grocery food. These taxes are among the most regressive in the United States having their most severe impact on low-income households more likely to suffer food insecurity (Gundersen & Ziliak, 2018; Zheng et al., 2021). A central policy question concerning the regressive nature of grocery food taxes is therefore how grocery taxes are passed through to consumers. Additionally, the poor who work in the food retail industry are also disproportionately to be impacted by grocery taxes through the impact on their wages. Interestingly, there have been few studies that have addressed the economic burden of grocery food taxes, which is the focus and contribution of this study.

Standard welfare theory shows that the tax incidence between consumers and retailers under perfect competition depends on the relative price elasticities of demand and supply with whichever party is less price responsive bearing more of the tax burden (Harberger, 1962). However, previous empirical studies of taxes on cigarettes (e.g., Barzel (1976), Coats (1995), Hanson and Sullivan (2009), Harris (1987), Johnson (1978), Keeler et al. (1996), Sullivan and Dutkowsky (2012)) and alcohol (e.g., Barzel (1976), Kenkel (2005), Young and Bielinska-Kwapisz (2002)) find that taxes are often over-shifted, i.e., retail tax-inclusive prices rise by more than the amount of the tax. Since over-shifting should not occur in equilibrium under perfect competition, one needs a model of imperfect competition to allow for this type of market behavior (see, for example, Dutkowsky and Sullivan (2014), Fullerton and Metcalf (2002), Hanson and Sullivan (2009), Sullivan and Dutkowsky (2012), and Young and Bielinska-Kwapisz (2002)).

Tax over-shifting has been observed in earlier empirical studies (e.g., Besley and Rosen 1999, Delipalla and O'Donnell 2001, Kenkel 2005). According to microeconomic theory, the presence of tax over-shifting reveals important features within a market, including market power of sellers and the

dynamics between the supply and demand curves. More specifically, over-shifting can occur within an imperfectly competitive market if the demand curve is sufficiently convex (Seade 1985, Weyl and Fabinger 2013). In a recent study, Pless and Van Benthem (2019) demonstrate the theory of over-shifting in the market for residential solar systems in California, under the presence of market power. The research shows over-shifting is achieved by sufficiently convex demand, and the authors propose a simple test for market power to demonstrate how estimating demand convexity can corroborate this conclusion.

There are two research issues addressed in the current study. First, we examine tax pass-through for all food items (defined by Nielsen food department) in the United States to determine the incidence of grocery food taxes. Our analysis is based on a unique panel dataset of U.S. grocery food tax rates collected at the state and county level, that we combined with AC Nielsen Homescan household food purchase data over the period 2010-2019. These panel data are used to estimate the extent to which consumer retail prices increase due to grocery taxes. Our tax data comprise a comprehensive set of all county-level grocery food tax rates in the contiguous United States from 2010 through 2019, while the Homescan data for grocery food provides a rich set of information on products purchased and prices at the Universal Product Code (UPC) level as well as detailed demographic data on approximately 40,000-60,000 households for the same time-period. Together, these data enable us to examine tax pass through using individual household-level observations on specific food products at the UPC-level. Our results show significant over-shifting of grocery taxes by food retailers.

Second, given that over-shifting of taxes is prevalent, we address whether retailers are the primary beneficiary of the over-shifting revenue wind fall, or is some of it passed onto their workers? Using county level earnings data in the grocery sector, we assemble a similar time series-county panel data set to determine if earnings are positively impacted by the grocery tax. The results demonstrate no relationship between the grocery food tax and the average earning of grocery store workers within a county. This suggests that the revenue windfall due to tax over-shifting accrues to grocery retailers rather than their workers.

This research makes four contributions to the tax and public policy literature. First, while there are many studies that have measured tax pass through on “sin items” such as cigarettes (e.g., Barzel (1976), Johnson (1978), Harris (1987), Coats (1995), Harding, Leibtag, and Lovenheim (2019), Keeler et al. (1996), Hanson and Sullivan (2009), Sullivan and Dutkowsky (2012)), alcohol (e.g., Barzel (1976), Young and Bielinska-Kwapisz (2002), Kenkel (2005)), and unhealthy foods like sugar-sweetened beverages (e.g., Cawley et al., 2020, 2021), there are very few studies that have estimated the grocery food tax pass-through for food items. Our study adds to this literature by extending the analysis to all grocery food items for the entire United States. This information is important for public policy discussions especially in municipalities considering implementing or eliminating grocery food taxes. For example, West Virginia removed their state-wide grocery taxes in 2012. More recently, Alabama considered removing their 4% state grocery taxes, while New Mexico was considering reinstating a statewide tax on groceries. The results of this study therefore fill a gap in the literature on tax pass through.

Second, we examine whether grocery food tax incidence differs by consumers demographic characteristics and by retail outlets. Specifically, we measure how tax pass-through varies by consumers’ income, education, and race. Tax incidence may differ among distinct types of consumers because of different shopping behaviors. For example, wealthier consumers may have more price inelastic demand for food and therefore the tax pass through may be greater for them than for less-wealthy consumers. We also test whether tax pass through varies by retail outlet (e.g., national mass merchandisers vs. regional grocery stores vs. other retail outlets). We hypothesize that large national retailers such as Walmart have more market power than smaller retail outlets, which could allow the large outlet stores to pass through or over-shift grocery taxes more fully to consumers.

Third, in addition to estimating the overall impact of grocery taxes on retail food prices, we also estimate tax incidence individually for 48 specific food categories defined by Nielsen data. This enables us to test whether different food groups have different degrees of pass through. Our hypothesis is that the

foods for which demand is most price inelastic (e.g., milk and eggs) will have higher degrees of pass through while items exhibit more price elastic demand (e.g., steak) will have lower pass through.

Finally, since our results show that food retailers over-shift the grocery food tax on most food items, we examine whether any of this retail revenue windfall trickles down to grocery store workers in locations with grocery taxes, or whether it is retained by business owners instead. We find no empirical evidence that workers receive any of the windfall of revenue due to tax over-shifting, in the form of increased earnings.

The remainder of this paper is organized as follows. The next section reviews the pertinent literature on tax incidence studies in products such as tobacco and sugar-sweetened beverages. Next, we present the data and estimation strategy. We finally propose a conceptual model for estimating the degree of tax pass-through on retail prices, which is followed by a presentation of results. The paper concludes with a discussion and implications section.

Background and Literature Review

There is a rich empirical literature on tax incidence, with most papers estimating pass-through rates bounded between 0 and 100 percent (Doyle and Samphantharak 2008; Nakamura and Zerom 2010; Harding et al., 2012; and Goldberg and Hellerstein 2013). That is often observed in the studies of sugar-sweetened beverage tax. However, if the market is imperfectly competitive, taxes can be over shifted when oligopolists reduce the output and charge higher prices based on the consumers' demand curve (Anderson, de Palma, and Kreider 2001; Bonnet and Réquillart 2013). As the consequence, studies have also documented over 100 percent of the taxes are passed through to consumers, on products such as cigarettes and gasoline.

There is a larger literature on the incidence of sugar sweetened beverages (SSB) taxes in the United States, as well as its health outcomes. Six U.S. cities have levied taxes on sugar-sweetened beverages, including Berkeley, CA, in 2015; Philadelphia, Boulder, and Oakland in 2017; and San

Francisco and Seattle in 2018 (Cawley et al., 2021). Most studies have found the incidence of these taxes have been shared by consumers and retailers. For example, based on data on retail prices in Berkeley and San Francisco, Falbe et al. (2015) and Cawley and Frasad (2017) estimate that 43%-47% of the SSB tax is passed on to consumers. Similarly, Cawley, Willage, and Frisvold (2018) find 55% of the SSB tax was passed on to consumers based on data from stores in the Philadelphia airport terminal, where the concern of cross-border shopping is alleviated since the passengers would not leave the airport for lower prices. In terms of store heterogeneity, Cawley et al. (2020) find the pass-through rates are greater among stores that are in higher-poverty neighborhoods, and that are located farther from the untaxed stores outside Philadelphia. In Boulder, Cawley et al. (2021) estimated the pass-through of SSB taxes based on posted (pre-tax) prices is 51.2%; while the pass-through of SSB taxes based on register (tax-inclusive) prices is 79.3%. In Seattle, Jones-Smith et al. (2020) estimate pass-through at 90%, whereas Powell and Leider (2020) found pass-through of 59% using scanner data. This difference may be due to scanner data excluding prices from smaller store types, as well as the tax avoidance in the form of cross-border shopping. In contrast to other studies, Bleich et al. (2020) observed over-shifting, which estimated a 121% pass-through rate if consumers buy from small, independent stores in Philadelphia.

The literature on the responsiveness of retail prices to cigarette excise taxes is small due to limited accurate data on retail cigarette prices (Harding, Leibtag, and Lovenheim, 2012), but most studies have found tax over-shifting. For instance, Hanson and Sullivan (2009) conducted a phone survey of cigarette retailers for a generic product and a brand product and found a one cent increase in cigarette taxes increased prices by between 1.13 and 1.18 cents. Similarly, DeCicca, Kenkel, and Liu (2010) estimated tax pass through based on consumer-reported prices from the 2003 and 2006–2007 CPS Tobacco Use Supplements. The authors found the tax was almost fully shifted to consumers. Using Nielsen HomeScan data, Harding et al. (2012) found that only one-half of the cigarette tax was passed on to customers living close to lower-tax state borders (due to cross-border shopping), while the tax impact was more significant for the consumers in interior counties. In addition, tax avoidance may significantly

impact the responsiveness to cigarette taxes by influencing customer search, prices paid, and purchases (Lovenheim 2008). Similar results are presented by Chiou and Muehlegger (2012), who used store-level scanner data in the Chicago metropolitan area. They estimate a tax pass-through rate of about 80%, which may be driven by the fact that all parts of Chicago are near at least one lower-tax border.

We are aware of only three previous studies that have examined tax pass through to consumers on food items. In the earliest study, Besley and Rosen (1999) examined sales tax pass through for select food and non-food products based on data from the 155 largest cities in the United States. They found over-shifting of sales taxes for most of the food items considered in the study including bananas, bread, milk, eggs, Crisco, and Coke. A second study (Politi and Mattos, 2011) examined pass through of ad-valorem taxes on retail prices for ten food products in Brazil's 16 states between 1994 and 2008, including beans, beef, bread, butter, coffee, flour, milk, rice, soybean oil, and sugar. Their results showed full tax shifting occurred for three out of these ten goods (beans, butter, and flour), while tax over-shifting occurred for only one good (sugar). Finally, Gračner et al. (2022) examined tax pass through for energy-dense food in Mexico between 2012 and 2016. The authors found tax over-shifting to retail prices for cookies, candies, and packaged pastry, while prices of cakes, and savory snacks were under-shifted. Price increases were also larger in supermarkets than in mini-markets and convenience stores. 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 main focus here.

Our research contributes to the literature of tax incidence by examining grocery tax pass-through for all food items in the United States. Food items are often considered as necessities and are usually price inelastic. Thus, we expect a significant rate of tax shifting on food items.

Conceptual Framework of Tax Pass-Through

Why Tax Over Shifting Occurs?

Let t , p , and P denote a tax expressed in per-unit format, tax exclusive price, and tax inclusive price, respectively. Canonical economic theory posits that under perfect competition, the pass-through of tax to consumers vs. producers depends on the price elasticities of demand and supply (ε_D and ε_S denote the absolute values of the two elasticities), and thus is bounded between zero and one (Jenkin, 1872):

$$(1) \quad \frac{dP}{dt} = \frac{1}{1 + \varepsilon_D / \varepsilon_S} = \frac{\varepsilon_S}{\varepsilon_S + \varepsilon_D}$$

Chetty, Looney, and Kroft (2009) show that consumers may underreact to a tax that is not salient, such as a sales tax added at the register, but not reflected in the shelf price. Let η represent the degree of under-reaction (or inattention) to the tax, where $\eta = 0$ and $\eta = 1$ mean consumers either completely ignore or pay full attention to the tax, respectively. The tax pass-through becomes (Pless and van Benthem, 2019):

$$(2) \quad \frac{dP}{dt} = \frac{\varepsilon_S + (1 - \eta)\varepsilon_D}{\varepsilon_S + \varepsilon_D} = \frac{1 + (1 - \eta)\varepsilon_D / \varepsilon_S}{1 + \varepsilon_D / \varepsilon_S}$$

To illustrate, let the price elasticities of demand and supply be of equal size at -0.5 and 0.5. Chetty, Looney, and Kroft (2009) provide the only empirical estimate of η we know of in the literature at 0.35. In this case, the tax pass-through will increase from 0.5 to 0.825 solely due to under-reaction to the tax. However, while salience can contribute to shifting more of the tax burden to consumers, salience alone cannot explain over-shifting in a competitive market because equation (2) also has an upper limit of one when η equals zero.

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

$$(3) \quad \frac{dP}{dt} = \frac{1}{1 + \frac{\varepsilon_D - 1}{\varepsilon_S} + \frac{1}{\varepsilon_{ms}}}$$

$$(4) \quad \frac{dP}{dt} = \frac{1}{1 + \frac{\theta}{\varepsilon_\theta} + \frac{\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}$$

Where $\varepsilon_{ms} = -p'P$ is the elasticity of the inverse marginal surplus function measuring the logarithm demand function curvature, which shows by how much the consumers pay when the quantity expands. θ

is the market conduct parameter ranging from zero (perfect competition) and one (pure monopoly), which is invariant to the changes of P . Finally, since $1/\varepsilon_\theta = 0$ for many standard models of imperfect competition, the value of equation (4) exceeds the unity for a sufficiently convex demand function ($\varepsilon_{ms} < 0$), and hence tax over shifting can occur.

Pless and van Benthem (2019) also contemplate other potential reasons for tax over shifting, including Giffen behavior, tax/subsidy manipulation (tax evasion by firms), decreasing marginal costs, and nominal pricing rigidities. Those do not seem to fit with the characteristics of the U.S. food retail industry. As a result, we also can interpret our finding of tax over shifting as evidence of market power in the food retail industry.

Tax Pass-Through Formula for Sales Taxes

Since sales tax is an ad valorem tax (t), we build on Besley and Rosen (1998) to illustrate how to derive a unit-tax equivalent measure of sales tax pass-through. We start with the following model where the logarithm of a tax exclusive price is regressed on sales tax τ and controls X

$$(5) \quad \ln p = \beta_1 \tau + \beta_2 X.$$

Multiplying both sides of the equation by p yields

$$(6) \quad p \ln p = p(\beta_1 \tau + \beta_2 X).$$

Differentiating equation (6) leads to

$$(7) \quad dp \ln p + dp = \beta_1 d(p\tau) + \beta_2 X dp, \text{ or equivalently}$$

$$(8) \quad \frac{dp}{d(p\tau)} = \frac{\beta_1}{1 + \ln p - \beta_2 X} = \frac{\beta_1}{1 + \beta_1 \tau}.$$

Using the fact that $P = p(1 + \tau)$, we finally have

$$(9) \quad \frac{dP}{d(p\tau)} = 1 + \frac{dp}{d(p\tau)} = 1 + \frac{\beta_1}{1 + \beta_1 \tau}.$$

Equation (9) shows given an increase in tax revenue $d(p\tau)$ resulting from an increase in the ad valorem tax rate, by how much the tax inclusive price P increases, which is comparable to the tax pass-through in the previous sub-section focusing on a unit tax (t).

Data

State and County Food Sales Taxes- We assembled a large, historical data set of food sales tax rates in the U.S. over a 10-year period (2010-2019). The total grocery tax rate in each county is the combination of the state and county-level tax rates, which are obtained from *Tax-Rates.org* and various websites of State Departments of Revenue.

In 2019, a total of 18 states in the U.S. collected food sales taxes at the state, county, or municipal levels, with a combined rate as high as 9% in some cities of Alabama, shown in Figure 1 (Zheng et al, 2021). Over this period, the largest state-level tax change occurred in 2017 when the West Virginia Senate decided to reinstate its food tax to 3.5%, having eliminated the sales tax on groceries in the July of 2013. The smallest change occurred in Kansas, when the state reduced the food sales tax by 0.15% in early 2014. In general, we observed greater tax magnitudes at the state level, while our dataset captured more variations at the county levels.

The average combined (state and county levels) grocery tax rate was 4.3% in 2019, and the states with the highest grocery tax rates were generally located in the southern part the US, which often face higher rates of food insecurity comparing to the national average. At the state level, eight states impose taxes on food with the same rate that the general sales are taxed. These states include Alabama with a combined tax rate of 8%, Mississippi having 7%, South Dakota with 4.5%, Tennessee with 5%, Oklahoma with 4.5%, Kansas having 6.5%, Idaho having 6%, and Hawaii having 4%. Five states collected food sales taxes at the reduced rate comparing to general sales taxes, which include Arkansas with 1.50%, Illinois with 1%, Missouri with 1.225%, Utah with 3%, and Virginia with 2.5%. The purpose of exempting or reducing taxes on groceries is to reduce the cost of food, thus protecting low-income consumers food security. Finally, five states do not impose grocery sale taxes at the state level, but they allow local governments to collect grocery taxes if they deem so, which states include Colorado, Georgia, South Carolina, North Carolina, and Louisiana.

Some states have debated eliminating grocery taxes or exempting low-income residents from it, but often the exemptions are not made because of a lack of alternative taxes sources. In states, such as

Alabama, lawmakers have debated whether to include food sales in the list of taxation products or to exempt them (Greenhalgh, 2018). Most recently, a bill was introduced in the 2022 Alabama legislative, which plans to exempt the sales of grocery food from sales taxes. However, eliminating the grocery tax would reduce the State's education budget by more than \$500 million, and it is difficult to find an alternative tax source for this lost revenue.¹ Local governments impose or increase the tax rates on food and drinks as a stable resource of tax revenue, particularly in bad economic times. However, for low-income households, food sales taxes can be a significant cost relative to their food budget, so the regressive nature of the tax will lead to a worsening of household food security (Gundersen & Ziliak, 2018; Zheng et al., 2021).

Nielsen Consumer Panel- We use the food purchases and household demographic from Nielsen Homescan panel data (NHCP) from January 1, 2010, through December 31, 2019. Nielsen data represents a longitudinal panel of approximately 40,000 to 60,000 U.S. households in a year, which is well-known to provide market intelligence to retailers by constructing a nationally representative panel of consumer purchases (Harding et al., 2012). It provides demographic details about the households and information of transactions such as products purchased, product size, and when and where the purchases were made. The products tracked include both food and non-food items, but our research only considers transactions of food items regarding the pass-through of grocery food taxes. For each transaction, Nielsen records socioeconomic characteristics as well as the types of stores the purchase was made. Appendix 1 presents the average and standard deviation of this data for 2010-2019.

The Nielsen Company uses a random stratified sampling method for the NHCP. This design involves the recruitment and maintenance of a panel household that matches a selected group of demographic characteristics. The households are randomly recruited to join the panel via direct mail, using a variety of targeted and general industry name lists (Kilts Center for Marketing, 2014). Though

¹ <https://www.wbrc.com/2022/02/06/new-bills-would-get-rid-state-grocery-tax/>

households may rotate in and out of the program, over 80% of the households stay every year. These households continually provide information to Nielsen about what products they buy, as well as when and where the purchase occurs. Due to the limitation of our desktop, we randomly draw 5% sample households from the total observations, which covers a total of 18,023,768 transactions made by 145,794 households in all the 50 states plus the District of Columbia.

The advantage of using the NHCP is that it 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, socioeconomic characteristics such as the household residence, education, income, type of employment, and other attributes are included. Overall, the dataset provides an excellent set of purchase characteristics that allow one to identify whether the pass-through of sales taxes on food groceries without making assumptions about the market structure.

Since our focus is the pre-tax retail prices of food groceries, our sample only covers the transactions of food items defined by Nielsen product Departments, including Dry Grocery, Frozen Foods, Dairy, Deli, Packaged Meat, and Fresh Produced. The distribution of each category is shown in Figure 2. Around half of the observed transactions are dry grocery products (e.g., cereal, breakfast food, crackers, and cookies, etc.). The next two major categories are dairy products (fluid milk, cheese, etc.), and fresh produce (vegetables and fresh fruits). The other categories include frozen foods, deli, and packaged meat.

Labor Market Data- To test whether the grocery store workers benefit from this increased retail revenue in terms of wage, we use the county-level average earning data of grocery store workers from the Quarterly Workforce Indicators (QWI) dataset, through 2010 to 2019. The QWI is labor market data released every quarter under the Longitudinal Employer-Household Dynamics (LEHD) program of the United States Census Bureau. This dataset is useful to track both firm characteristics (industry, size, age, and ownership) and worker demographics (sex, age, education, race, and ethnicity) over time, which enables analyses such as a longitudinal look at wages by various groups across counties. Since QWI is

based on the Unemployment Insurance (UI) wage records through a data sharing agreement between the Census Bureau/State partnership, it provides more reliable information for individual small counties, comparing to other surveys (Thompson and Rohlin, 2012). By 2019, the dataset covers all the 51 states, including the District of Columbia.

Since our grocery food tax data is available only available annually, we only take the average earning data of the first quarter for each year. Our sample only covers the workers' wages of food retailers as the focus of this study is the pre-tax retail prices of food groceries. These store types include grocery and merchant wholesalers, grocery stores, specialty food stores, and warehouse clubs.

Empirical Model

We employ a fixed effects model to evaluate the extent to which pre-tax retail prices respond to grocery taxes. Specifically, our baseline model estimates a transaction-level, reduced-form regression of pre-tax unit prices on the grocery sales tax that allows us to identify the rate of pass-through. The empirical model is:

$$\ln(p_{uijt}) = \beta_0 + \beta_1\tau_{jt} + \eta C_{jt} + \theta X_i + \delta_j + \varphi_t + \alpha_u + \gamma_m + \varepsilon \quad (10)$$

Where $\ln(p_{uijt})$ is the natural logarithm of the pre-tax price paid for food products per amount, for UPC u by household i in county j in year t . The log format specification gives the interpretation of β_1 as the elasticity of food sales taxes with respect to the growth rate of individual food prices. The variable τ_{jt} is the ad-valorem tax for food groceries in county j and in year t , which is our key variable of interest.

Following Besley and Rosen (1999), we include the vector C_{jt} to account for measurable differences in cost-of-living in county j and year t , which include the median rent of an apartment, the average rate of commercial electricity, and state minimum wage (Leung 2021, the minimum wage impacts both labor costs and product demand, especially in low-income neighborhoods). X_i is the vector of household demographics, including the household income, and the race and education of the household heads. We also include a set of fixed effects to control for time-invariant mean differences in prices across

county, UPC, month (seasonality), and year. The standard errors are clustered at the county level to alleviate concerns about residual serial correlation within each county and adjusted for heteroskedasticity by using robust standard errors.

One of the major benefits of our data is that we observe the UPC code of each product purchased. These codes provide extremely fine product descriptions for each good. The UPC codes allow us to include UPC fixed effects in equation (10), α_u , which avoids the potential measurement error related to the product size. Our use of UPC fixed effects allows us to focus on the price per size by examining within-UPC changes in prices when taxes increase. Additionally, by taking grocery stores as the benchmark, we examine the heterogenous price responses across store channels, including discount stores (e.g., Wal-Mart, Target), Warehouse Clubs (like BJ's and Sam's Club), convenience stores, Dollar Stores, and drug stores.

To present a preliminary pattern between the growth rate of the pre-tax price and total grocery taxes, we employed the Binscatter plot to visualize the relationship. Since our sample size is very big (over 18 million transactions are observed), we divide the region into 30 bins, and allocate the scatters into different bins in each region. Stata takes the average within every unit and shows only one scatter for each bin. As shown in Figure 3, we observed a strong positive correlation between the grocery tax rates and the log format of the pre-tax unit prices of food.

Results

Table 1 presents results from estimation of equation (10) using the NHCP data. This is a Fixed Effects model with single log format on the left-hand-side. The estimation was carried out in Stata 16 using the REGHDFE command, which is suitable for a linear model with high-dimensional fixed effects. We first estimate the model with fixed effects for year, month (seasonality), county, and UPC under several specifications to provide a check on how robust the results are for the grocery tax coefficient. Table 1 displays the main baseline results for the model estimated with: (1) no household fixed effect and no

household or demographic control variables, (2) household fixed effects with no demographic controls, (3) demographic and other control variables, but no household fixed effects, and (4) demographic and other control variables with household fixed effects. The estimated coefficient on the grocery tax variable is positive and statistically significant for all four specifications and quite similar in magnitude ranging from a low of 0.281 (Model 2) to 0.393 (Model 2). The results therefore appear to be quite robust. Our preferred specification is Model 3 that includes household demographic controls with a tax coefficient of 0.393.

Given the statistical significance of the grocery tax coefficient, the results indicate that retail outlets in positive grocery tax locations over-shift the tax to the tax-inclusive retail price. To put the results into perspective, it is useful to use equation (9) in the framework section to convert the estimated coefficient into a measure of how much the tax-inclusive retail price increases in response to a tax increase (expressed in tax revenue since the grocery tax is ad valorem). For our preferred model, an increase in the ad valorem tax rate necessary to raise one dollar of revenue increases the retail tax-inclusive price by \$1.28, on average, for all grocery foods. Thus, retailers in locations that have grocery taxes are increasing their prices by more than the amount of the tax.

To better understand whether demographics play a role in tax-shifting, the model was re-estimated with various demographic variables interacted with the grocery tax. Table 2 shows the results in terms of income, race, and head of household's education level interacted with the grocery tax. With respect to income level, the results show that the highest income levels have a lower degree of tax-shifting than the lowest income level households. Specifically, the highest income households experience tax over-shifting that is almost 25% lower than the poorest households. This result at first seems counter-intuitive since higher income people tend to have a more price inelastic demand for food than lower income people and one might expect the opposite to occur. However, one plausible explanation for this result is that lower income households do not have as much flexibility to travel to alternative locations in response to the grocery tax as wealthier households have, and therefore face a higher degree of tax pass through. A second possibility is that low-income household participating in SNAP are shielded from the

tax in groceries purchased with SNAP benefits and consequentially may be protected from the higher greater pass-through.

The results indicate that the race-tax interaction coefficient is significant for several categories. For instance, we find African Americans experience significantly lower over-shifting than White households. Specifically, the tax over-shifting for Black households' is almost 19% lower than that for White households. Similarly, we find that the Other Races category, which is predominantly Native American households, face an even lower degree of tax pass through (28.6% lower) than White households. The results are plausible as both African Americans and Hispanic Americans consume less than the recommended levels of dairy foods (Bailey et al., 2013), and we observed the biggest rate of over-shifting in dairy products. The less consumption of dairy foods can significantly bring down the coefficients of the African and Hispanic Americans group, where the perceived or actual lactose intolerance can be a primary reason for their limiting or avoiding dairy intake.

In terms of education, we find that the education level of the head of the household does not have a statistically significant interaction with the grocery tax. Hence, it appears that tax pass through does not vary with consumers educational levels.

The results indicate a huge variation in tax pass through by type of retailer. Taking grocery stores as the benchmark, Discount stores (e.g., Wal-Mart, Target), warehouse clubs (e.g., Sam's Club, BJ's), and Dollar Stores all have a significantly higher degree of over-shifting than the regular grocery stores. The estimated pass through for warehouse stores (Table 2 Column (6)) is almost 2.5 times higher than grocery stores. The estimated pass through for discount stores is over 1.25 times higher than grocery stores. Pass through for Dollar Stores is even higher at almost 5 times that of grocery stores. These results are likely due to two possibilities. First, large retailers like Walmart may be exploiting their market power and over-shift the grocery tax more than smaller retail outlets. Second, people living in locations that tax groceries have to pay the tax regardless of where they shop (within their location) and may turn to large retailers that offer lower pre-tax prices even when these retailers over-shift more than their competitors since taxes are not perfectly salient. Somewhat surprisingly, we find Dollar Stores, which are often located in rural

locations without a lot of competitors, have the highest pass through of all retailers. For residents who live in areas where there are no other grocery stores and supermarkets within their travel radius, the Dollar Store is the only source of food available to them, making they have no more options for grocery shopping.

There is a lot more variation in tax shifting among major product categories. Table 3 shows the interaction of the grocery tax with various product categories (we omit the product group of spreads, jellies, and jams) based on four model specifications: (1) no county trends and no control variables, (2) county trend, but no control variables, (3) both county trends and control variables, and (4) control variables with no county trends. Model (4) is our preferred model, and the other three offer a robustness check (the results are consistent across the four specifications).

Not surprisingly, milk products have the highest over-shifting because these products tend to be among the most price inelastic of all grocery items. For example, estimated price elasticities for milk products have included -0.045 (Kaiser, Streeter, and Liu, 1988), -0.039 (Schmit and Kaiser, 2004), and -0.154 (Zheng and Kaiser, 2008). For milk products, an increase in the ad valorem tax rate equivalent to one dollar of tax revenue increases the retail tax-inclusive price for milk relative to spreads by \$1.59. At the opposite extreme, our findings indicate that unprepared meat and seafood have the lowest tax incidence for consumers. Here a tax increase equivalent to one dollar raises the tax-inclusive price for poultry products by \$0.70. A similar, but not as large, result holds for salads and deli, where one dollar raises the tax-inclusive price for their products by \$0.77. These two results are likely due to both product categories being significantly more price elastic than the others. For instance, recent estimates of demand elasticities for deli ham range from -1.3 to -1.6 (Lusk and Tonsor, 2016) and for produce range from -0.57 (apples) to -1.11 (citrus) (Orkent and Alston, 2011). The remaining product categories exhibit over-shifting of the grocery food tax. The results of pass-through rates by categories are displayed in Figure 4.

Robustness and Model Diagnostic Checks

These results depend upon our assumption that the grocery tax is exogenous, which may or may not be the case. It is possible that grocery taxes are related to the economic and political composition of the county, which could also influence tax pass through. However, it is difficult to find a good instrumental variable for the grocery tax and there is not much guidance from past studies on good instruments. Instead, we perform the following strict exogeneity test. Exploiting the panel nature of the dataset, the following model is estimated based on Wooldridge (2002, p.255):

$$\ln(p_{uijt}) = \beta_0 + \beta_1\tau_{jt+1} + \beta_2\tau_{jt-1} + \eta C_{jt} + \theta X_i + \delta_j + \varphi_t + \alpha_u + \gamma_m + \varepsilon. \quad (11)$$

This model is identical to equation (10) except the grocery tax in the future year is appended. The strict exogeneity test requires that β_1 not be statistically significant, while β_2 remains statistically significant. The results of this test indicate that $\beta_1=0.176$, but it not statistically significant at the 10% confidence level, while $\beta_2=0.387$ and remains significant at better than the 1% confidence level. Hence, these results alleviate the concern of endogeneity of the grocery tax.

Next, we address our model assumption that a common trend holds for counties that tax and do not tax groceries. This assumption is crucial to assure that the estimated tax pass through we measure is due to the tax and not to other potentially important unobservable variables. To test whether the assumption of a parallel trend holds across counties, we modify equation (10) to include county-specific time trends on the right-hand side (Hansen et al., 2017; Wing et al., 2018). In practice, this approach corresponds to an outcome regression of treatment variables (food sales taxes), group effects, and time-period effects, with each group effect interacting with a linear or quadratic trend term. We estimate the following model:

$$\ln(p_{uijt}) = \beta_0 + \beta_1\tau_{jt} + \eta C_{jt} + \theta X_i + \beta_j(\tau_{jt} * t) + \delta_j + \varphi_t + \alpha_u + \gamma_m + \varepsilon \quad (12)$$

This equation is identical to equation (1), except that county-specific trends $\beta_j(\tau_{jt} * t)$ are added to capture any unobservable variables impacting the pre-tax prices of food in the baseline regression. More specifically, we include county, UPC, year, and month (seasonality) fixed effects in both models. The

standard errors are clustered at the county level to allow for the possibility that the error terms might be correlated for counties across times.

Since grocery tax policy varies at the county level, we include the trend for three different combinations including: (1) county trend times year; (2) county trend times quarter; and (3) county trend times month. The results are reported in Table 4.

From Table 4, we observed that our main coefficient remains statistically significant at the 5% confidence level or better after controlling for county linear trends by year, quarter, and month. These results imply that the county-specific trends do not absorb important variables that are unobservable in our main regression, and that the parallel trend assumption is therefore not violated.

Finally, we conduct two placebo tests on the model to check for spurious regression results. To do this, one creates a counterfactual dependent variable (instead of the pre-tax retail food price) to see if the grocery food tax is also significantly associated with the counterfactual dependent variable. If the grocery tax is significantly associated with the counterfactual dependent variable, this indicates a spurious regression result, which may suggest that tax pass through is also spuriously correlated with retail food prices.

For the first placebo test, the retail price of food products is replaced with the retail price for tobacco and alcohol products (p_{uijt}), which performs as a counterfactual dependent variable in the regression. We include the full set of covariates and full sample used in the main regression. The following model is estimated:

$$\ln(p_{uijt}) = \beta_0 + \beta_1 \tau_{jt} + \eta C_{jt} + \theta X_i + \delta_j + \varphi_t + \alpha_u + \gamma_m + \varepsilon \quad (13)$$

This is identical to the main regression except for replacing the prices of food items with tobacco and alcohol products. Given that food sales taxes cannot be collected on the tobacco and alcohol products, we should not see a statistically significant tax effect. This is indeed the case in each of the placebos we run for both outcome variables of interest. These results provide confidence that the pre-tax prices of food yields credibly causal effects of the tax shock in our sample.

In addition, we re-run the regression within the counties that have grocery taxes in the given years, reflecting the spirit of the Average Treatment Effect of the Treated (ATT). The coefficient of the ATT group is slightly greater but remain statistically insignificant. That is consistent to show that the grocery tax is an exogenous shock. The results are reported in the Appendix 1.

In the second placebo test, we follow the analog of Christian and Barrett (2021) and randomly assign the value of total grocery taxes across counties. With applying randomization, we introduce randomness into the endogenous explanatory variable of interest of Equation (10) but keep the other variable on the LHS unchanged. This is to break the causal correlation between grocery taxes and pre-tax prices in each county. As shown in App. 1 Column (5), the coefficient of the new tax variable remains insignificant after the randomization, which means that there are no unobserved variables in addition to our regression coefficients.

Conclusion and Discussion

The purpose of this research was to measure grocery tax pass-through for all food items in the United States. The analysis used a unique panel dataset of U.S. grocery food tax rates collected at the state and county level that was combined with AC Nielsen Homescan household food purchase data over the period 2011-2019. These panel data were used to estimate the extent to which consumer retail prices increase due to grocery taxes.

The main finding of this study is that retailers are significantly over-shifting grocery taxes to consumers. For all food items, on average, the results indicate that an ad valorem tax sufficient to raise one dollar of revenue increases the retail tax-inclusive price by \$1.28. This finding indicates that existence of grocery food taxes creates a significant revenue windfall for retailers located in positive tax states. An important question that remains is do retailers keep all this wind fall, or is some of it passed onto their workers?

To shed some light on this question, we regress earnings by grocery store employees on the grocery food tax and the same set of co-variates used as control variables in the retail food price

regression model. Specifically, we slightly modified the main regression equation (10) by replacing the left-hand side of the equation with the logarithm of the average earnings of employees in the food stores in a county. The identification is the following:

$$\ln(Earnings_{uijt}) = \beta_0 + \beta_1\tau_{jt} + \eta C_{jt} + \theta X_i + \delta_j + \varphi_t + \alpha_u + \gamma_m + \varepsilon \quad (11)$$

Where the variable τ_{jt} is the ad-valorem tax for food groceries, C_{jt} is a vector of cost variables, and X_i is the vector of household demographics. We include county, UPC, year, and month (seasonality) fixed effects. The standard errors are clustered at the county level. The rest setup is identical to Equation (10). The results of the earnings model are reported in Table 5 under the same four specifications as in Table 1. The finding is that the grocery food tax has no impact in grocery worker earnings. We also ran this regression by the food store types, including the Grocery and Merchant Wholesalers, conventional grocery stores, specialty food stores, and warehouse clubs. The results are presented in Table 6. The results indicate no linkage between the grocery food tax and the average earning of grocery store workers within a county. This suggests that the significant revenue windfall due to tax over-shifting accrues to grocery retailers rather than their workers.

The results also showed evidence of heterogeneous tax pass through based on consumer demographics as well as type of retail outlet. Specifically, African American and Other Race (i.e., Native American) household had significantly lower tax over-shifting than White households. While we find no difference in tax shifting by education level, the highest income households had significantly lower tax-over-shifting than poorer households. Large retailers like Walmart, Costco, Target, and Sam's Club had substantially higher over-shifting than regular grocery stores. And, the Dollar Store had almost 5 times higher over-shifting than grocery stores.

In addition, tax pass-through also varied extensively across food product categories. Highly price inelastic product categories like milk had the greatest over-shifting while more price elastic products like unprepared meat and seafood had the lowest tax pass through.

A major implication of these results is that when factoring in tax pass through, the use of sales taxes on grocery foods is even more regressive than previously thought. Not only does the flat rate feature of the sales tax harm the poor relative to higher income households, but its impact on the tax-inclusive price is, in effect, even higher than the tax rate itself. This amplifies the regressive nature of the grocery sales tax, and this should be considered in any policy debate on whether or not to reduce or repeal their usage by local governments. Policy makers should look at ways to lessen the burden of this tax on lower income households. Lowering or eliminating the grocery tax would be one way to deal with this problem. However, doing so would reduce tax revenue, and government officials would need to look at alternative revenue generating options if it lowered grocery taxes.

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Figure 2. Transactions by Nielsen Department

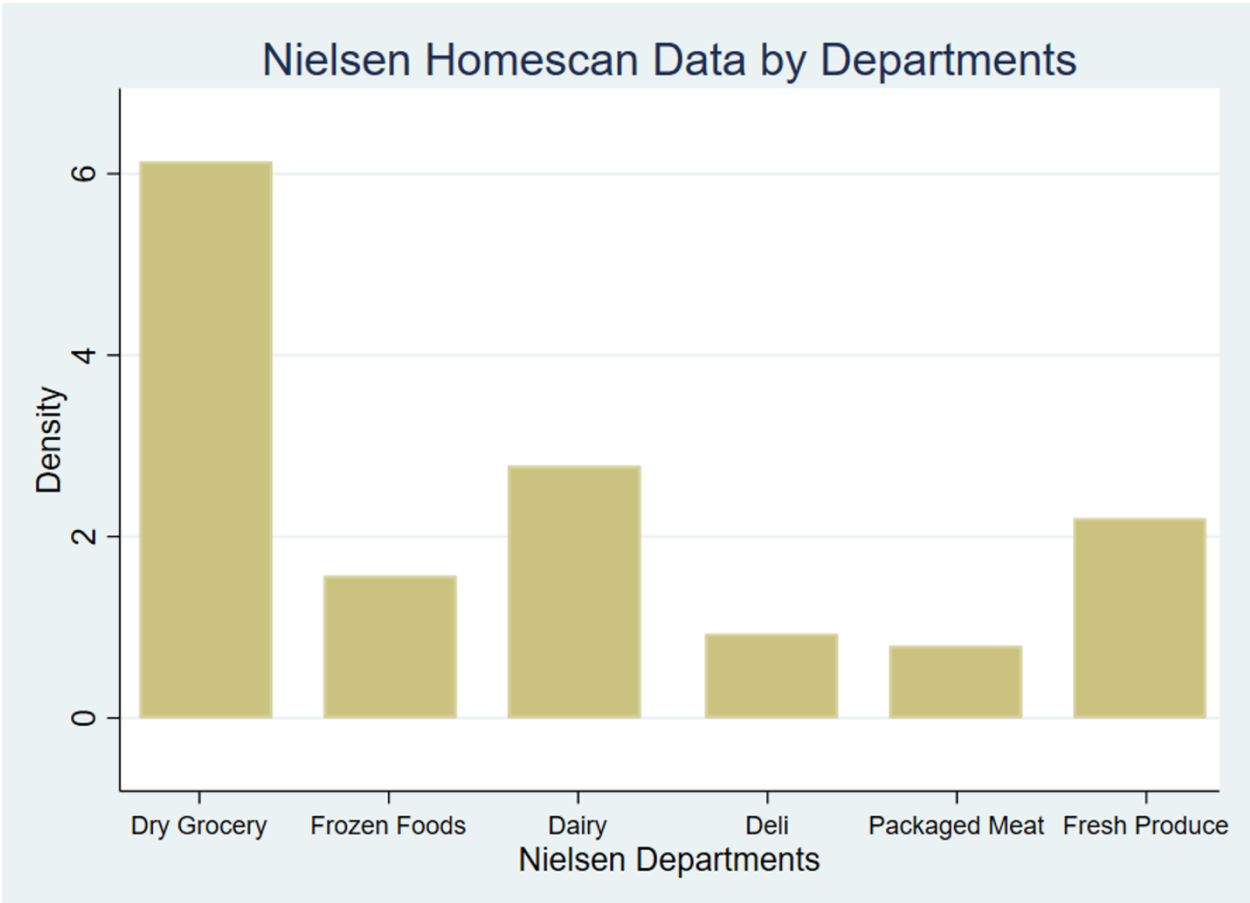


Figure 3. BinScatter Plot

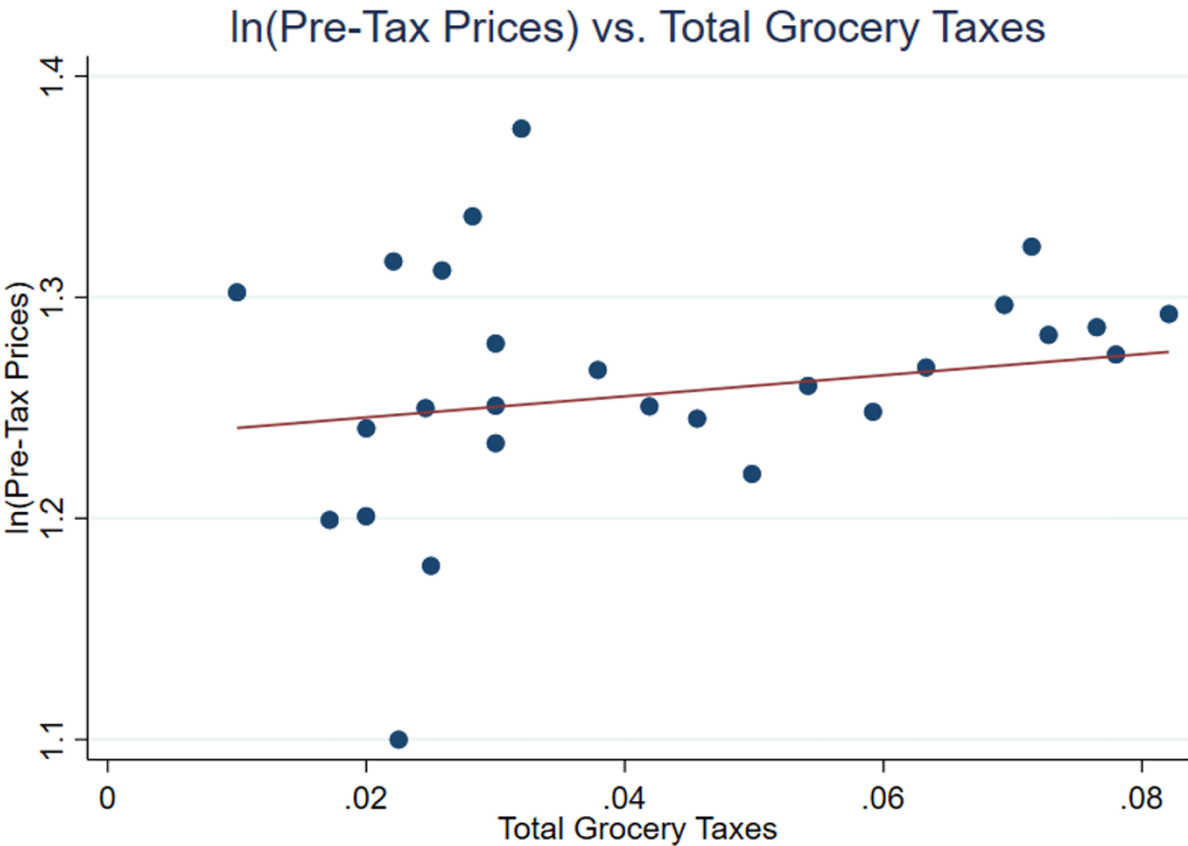


Figure 4. Pass-Through Rates by Categories

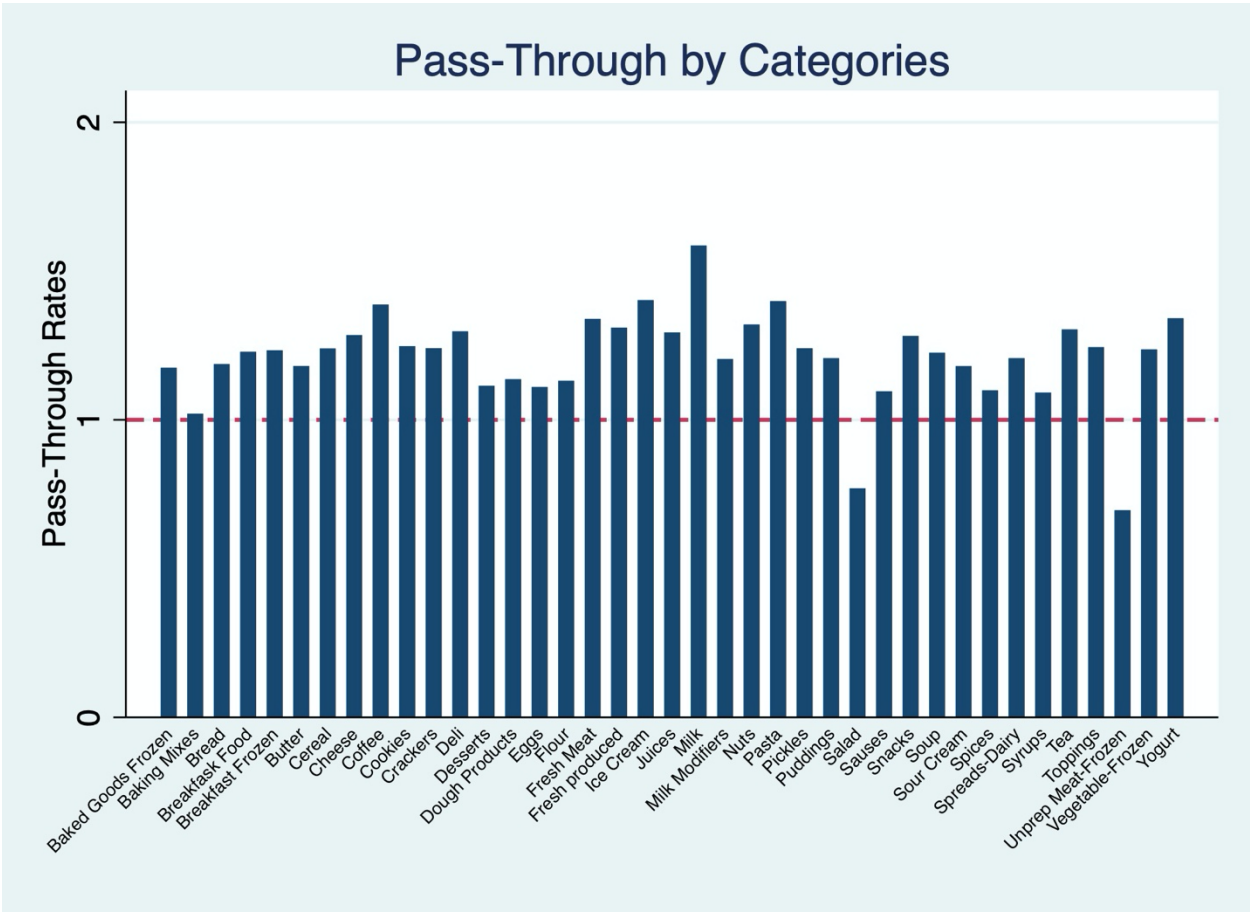


Table 1. Baseline Regression Results on Tax Pass-through

Dependent Variable: ln (Pre-tax Unit Price)	(1) No Household or Demographics	(2) Household Fixed Effects	(3) Demographics	(4) Household Fixed Effects+ Demographics
Grocery Tax	0.396*** (0.114)	0.281** (0.112)	0.393*** (0.112)	0.294*** (0.111)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y
Household FE	N	Y	N	Y
Demographics	N	N	Y	Y
Store Channels	N	N	Y	Y
Number of Clusters	2,894	2,894	2,894	2,894
<i>N</i>	15,822,571	15,822,177	15,822,571	15,822,177

Note: standard errors are clustered at the county level.

Table 2. Tax Pass-through by Household Demographics and Store Channels

Dependent Variable: ln (Pre-tax Unit Price)	(1) By Income	(2) By Race	(3) By Head Education	(4) By Store Types
Grocery Tax	0.451*** (0.214)	0.144 (0.157)	0.257* (0.149)	0.251** (0.113)
Grocery Tax * Median Income	-0.053 (0.043)			
Grocery Tax * High Income	-0.111** (0.050)			
Grocery Tax * Black		-0.189*** (0.063)		
Grocery Tax * Hispanics		0.022 (0.086)		
Grocery Tax * Asians		-0.068 (0.169)		
Grocery Tax * Other Races		-0.286*** (0.106)		
Grocery Tax * High School			0.165 (0.111)	
Grocery Tax * Some College or Above			0.344 (0.112)	
Grocery Tax * Discount Stores				0.318*** (0.050)
Grocery Tax * Warehouse Club				0.599*** (0.105)
Grocery Tax * Convenience Store				-0.065 (0.401)
Grocery Tax * Dollar Store				1.225*** (0.199)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y
Household FE	N	N	N	N
Demographics	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y
Number of Clusters	2,894	2,894	2,894	2,894
<i>N</i>	15,822,571	15,822,571	15,822,571	15,822,571

Note: standard errors are clustered at the county level.

Table 3. Interactions by Categories (Total Coefficient= Total Grocery Tax+ Interaction, Model 4 is preferred.)

Dependent Variable: ln (Pre-tax Unit Price)	(1) By Product* Grocery Tax	(2) By Product* Grocery Tax	(3) By Product* Grocery Tax	(4) By Product* Grocery Tax
Total Grocery Tax	0.321** (0.126)	0.319*** (0.129)	0.307** (0.139)	0.314** (0.148)
BASELINE PRODUCT: JAMs, JELLIES, SPREADS				
1. DRY GROCERY				
1.2 SOUP	0.007 (0.071)	0.007 (0.071)	-0.027 (0.077)	-0.023 (0.076)
1.3 BAKING MIXES	-0.213*** (0.071)	-0.209*** (0.071)	-0.290*** (0.075)	-0.293*** (0.075)
1.4 BREAKFAST FOOD	0.045 (0.085)	0.044 (0.085)	-0.022 (0.094)	-0.018 (0.094)
1.5 CEREAL	0.048 (0.077)	0.047 (0.077)	0.0008 (0.088)	0.001 (0.087)
1.6 COFFEE	0.293** (0.124)	0.312** (0.123)	0.336** (0.144)	0.318** (0.147)
1.7 CONDIMENTS, GRAVIES, AND SAUCES	-0.183*** (0.069)	-0.176** (0.070)	-0.205*** (0.077)	-0.208*** (0.076)
1.8 DESSERTS, GELATINS, SYRUP	-0.147** (0.073)	-0.142** (0.074)	-0.181** (0.083)	-0.185** (0.082)
1.9 FLOUR	-0.165* (0.092)	-0.163* (0.093)	-0.168* (0.101)	-0.163 (0.100)
1.10 NUTS	0.180** (0.078)	0.193** (0.078)	0.163** (0.081)	0.157* (0.082)
1.11 PACKAGED MILK AND MODIFIERS	0.034 (0.075)	0.025 (0.074)	-0.066 (0.077)	-0.057 (0.078)
1.12 PASTA	0.374*** (0.086)	0.371*** (0.086)	0.340*** (0.103)	0.349*** (0.102)
1.13 PICKLES, OLIVES, AND RELISH	0.041 (0.077)	0.046 (0.077)	0.002 (0.080)	0.002 (0.078)
1.14 SPICES, SEASONING, EXTRACTS	-0.168** (0.073)	-0.165** (0.074)	-0.210*** (0.079)	-0.204*** (0.079)
1.15 TABLE SYRUPS, MOLASSES	-0.132 (0.089)	-0.136 (0.090)	-0.219** (0.094)	-0.213** (0.093)
1.16 TEA	0.137* (0.072)	0.139* (0.072)	0.120 (0.081)	0.122 (0.082)
1.17 BREAD AND BAKED GOODS	-0.053 (0.077)	-0.044 (0.077)	-0.080 (0.084)	-0.084 (0.086)
1.18 COOKIES	0.042 (0.076)	0.040 (0.075)	0.007 (0.079)	0.015 (0.081)
1.19 CRACKERS	0.017 (0.008)	0.018 (0.081)	-0.003 (0.089)	0.003 (0.091)
1.20 SNACKS	0.131* (0.074)	0.137* (0.072)	0.082 (0.078)	0.079 (0.081)

2. FROZEN FOODS

2.1 BAKED GOODS-FROZEN	-0.006 (0.079)	0.0009 (0.080)	-0.100 (0.092)	-0.102 (0.091)
2.2 BREAKFAST FOODS-FROZEN	-0.019 (0.075)	-0.007 (0.076)	-0.002 (0.085)	-0.009 (0.084)
2.3 DESSERTS/FRUITS/TOPPINGS-FROZEN	0.042 (0.083)	0.048 (0.084)	0.009 (0.093)	0.009 (0.092)
2.4 ICE CREAM, NOVELTIES	0.389*** (0.078)	0.397*** (0.079)	0.365*** (0.087)	0.359*** (0.086)
2.5 JUICES, DRINKS-FROZEN	0.073 (0.129)	0.098 (0.130)	0.145 (0.153)	0.102 (0.152)
2.6 UNPREP MEAT/POULTRY/SEAFOOD-FRZN	-0.543*** (0.114)	-0.518*** (0.112)	-0.529*** (0.124)	-0.547*** (0.128)
2.7 VEGETABLES-FROZEN	0.001 (0.065)	0.004 (0.066)	-0.004 (0.073)	-0.004 (0.072)

3. DAIRY

3.1 BUTTER AND MARGARINE	-0.062 (0.070)	-0.050 (0.073)	-0.085 (0.082)	-0.093 (0.079)
3.2 CHEESE	0.073 (0.068)	0.087 (0.068)	0.100 (0.075)	0.084 (0.078)
3.3 COT CHEESE, SOUR CREAM, TOPPINGS	-0.048 (0.071)	-0.051 (0.072)	-0.094 (0.074)	-0.094 (0.074)
3.4 DOUGH PRODUCTS	-0.107 (0.085)	-0.106 (0.087)	-0.161* (0.096)	-0.156* (0.095)
3.5 EGGS	-0.113 (0.099)	-0.104 (0.098)	-0.182* (0.109)	-0.190* (0.111)
3.6 MILK	1.102*** (0.130)	1.106*** (0.123)	1.107*** (0.130)	1.100*** (0.142)
3.7 PUDDING, DESSERTS-DAIRY	-0.071 (0.139)	-0.074 (0.139)	-0.055 (0.171)	-0.053 (0.171)
3.8 SNACKS, SPREADS, DIPS-DAIRY	0.110 (0.107)	0.117 (0.109)	-0.044 (0.117)	-0.053 (0.115)
3.9 YOGURT	0.207*** (0.072)	0.211*** (0.071)	0.208*** (0.079)	0.204** (0.080)

4. DELI

4.1 DRESSINGS/SALADS/PREP FOODS-DELI	-0.417*** (0.135)	-0.389*** (0.137)	-0.476*** (0.157)	-0.501*** (0.154)
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5. PACKAGED MEAT

5.1 PACKAGED MEATS-DELI	0.111 (0.076)	0.126 (0.073)	0.123 (0.080)	0.109 (0.086)
5.2 FRESH MEAT	0.220*** (0.066)	0.239*** (0.066)	0.214*** (0.074)	0.199*** (0.075)

6. FRESH PRODUCE

6.1 FRESH PRODUCE	0.199 (0.157)	0.203 (0.133)	0.139 (0.139)	0.135 (0.178)
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Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
County Trends	N	Y	Y	N
Economic Controls	N	N	Y	Y
Number of Clusters	2,894	2,894	2,693	2,693
<i>N</i>	15,822,571	15,820,365	13,236,650	13,239,830

Note: Standard errors are clustered at the county level.

Table 4. County Group Specific Trends

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

Note: Standard errors are clustered at the county level.

Table 5. The Average Earnings Model

	(1)	(2)	(3)	(4)
Dependent Variable: ln (Earnings)				
Grocery Tax	-0.658 (1.022)	-0.557 (0.643)	-0.225 (0.638)	0.107 (0.682)
Commercial Electricity Price			-0.007** (0.003)	-0.001 (0.003)
Median Rent			0.0005*** (0.00005)	0.0009*** (0.00005)
Minimum Wage			0.004 (0.003)	0.008** (0.004)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	N	Y	Y	N
Economic Controls	N	N	Y	Y
Number of Clusters	2,693	2,693	2,693	2,693
<i>N</i>	13,429,160	13,428,025	13,427,946	13,429,081

Note: Standard errors are clustered at the county level.

Table 6. The Average Earnings Model by Industry

Dependent Variable: ln (Earnings)	(1) Grocery and Merchant Wholesalers	(2) Grocery Stores	(3) Specialty Food Stores	(4) Warehouse Clubs
Grocery Tax	-0.759 (1.551)	-0.215 (0.798)	1.115 (0.978)	0.748 (1.063)
Commercial Electricity Price	-0.0003 (0.008)	-0.007 (0.005)	0.003 (0.007)	0.004 (0.005)
Median Rent	0.0001 (0.00009)	0.00003 (0.00007)	0.00008 (0.00006)	0.0001 (0.00008)
Minimum Wage	0.004 (0.006)	0.002 (0.005)	-0.001 (0.006)	-0.004 (0.004)
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	N	N	N	N
Economic Controls	Y	Y	Y	Y
Number of Clusters	2,180	2,664	1,998	2,615
<i>N</i>	3,161,207	3,582,541	3,310,320	3,374,869

Appendix.

App. 1. Descriptive Statistics of Analysis Variables

Variable	# Observations	Mean	SD
Total Grocery Taxes		0.009	0.019
Household Income	18,033,103		
< \$30,000		0.175	0.379
\$30,000-\$69,999		0.422	0.494
≥ \$70,000		0.403	0.491
Race	18,033,103		
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	18,023,768		
Less than HS		0.021	0.142
HS Graduate		0.246	0.431
Some College		0.305	0.460
BA+		0.429	0.495
Store Channels	19,039,294		
Grocery Store		0.626	0.484
Discount Store		0.190	0.392
Warehouse Clue		0.044	0.205
Convenience Store		0.004	0.060
Dollar Store		0.017	0.128

Drug Store		0.009	0.091
# Transactions	18,023,768		
# Households	145,794		
# UPC Codes	329,678		

App. 2. Placebo Test

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: ln (pre-tax prices)	Tobacco	Alcohol	Tobacco	Alcohol	Randomization
Total Food Sales Tax	0.741 (0.133)	0.547 (0.643)	0.522 (0.317)	0.478 (0.635)	0.00005 (0.0003)
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
County Trend	N	N	N	N	N
Economic Controls	Y	Y	Y	Y	Y
Include only Counties with Food Tax?	N	N	Y	Y	Y
Number of Clusters	2,866	2,866	2,866	2,866	2,866
<i>N</i>	1,941,699	2,382,320	893,217	893,217	893,217

App. 3. Strict Exogeneity Test

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