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Do taxes on groceries increase body weight and restaurant food expenditures? Theory and evidence from the PSID data

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A B S T R A C T

We examine the impacts of grocery food sales taxes on body weight, grocery food expenditures, and restaurant food expenditures from both a theoretical and empirical perspective. Theoretically, grocery taxes affect food expenditure allocations by changing the prices of grocery foods relative to restaurant foods consequently influencing body weight because restaurant foods are generally higher in calories and less healthy. This theory is tested empirically using six waves of Panel Study Income Dynamics (PSID) panel data conducted from 2007 through 2017. We find that increases in grocery taxes relative to restaurant taxes incentivize low-income households to substitute restaurant foods in place of grocery foods. The results indicate that a one-percentage-point increase in the grocery tax rate relative to the restaurant tax rate leads to an increase in the body mass index (BMI) of 0.061, which translates to a weight gain of about 0.361 lb. This result is largely driven by overweight individuals and low-income individuals who do not participate in the Supplemental Nutrition Assistance Program. These are the two most vulnerable cohorts of the general population to grocery taxes.

1. Introduction

Grocery sales taxes exist in about one third of U.S. counties in the form of a state and/or county and/or city sales tax (Cawley, 2012, Zheng, et al., 2021). However, in the past several decades, there has been a policy trend (with several exceptions such as Kansas) of eliminating or reducing grocery taxes. These tax reducing policies serve the purpose of promoting a more progressive tax system since people with lower incomes spend a disproportionately larger share of income on food (Banks, et al., 1997). Meanwhile, grocery taxes change the relative after-tax price of grocery foods and restaurant foods. This could affect individuals' body weights by changing the consumer's budget allocation between grocery foods and restaurant foods because restaurant foods are generally higher in calories and less healthy than store-bought foods. The causal impacts of grocery taxes especially on health outcomes such as obesity have been overlooked in policy debates and remain little known in the literature. This is the focus of the research reported here.

Local governments have utilized food policies such as taxes and subsidies to offset increasing food-related health risks. Such policies change the relative price of certain food types (Powell and Chriqui, 2011), such as soda (Fletcher et al., 2010a; Goryakin et al., 2017; Paarlberg et al., 2017), and thus influence food consumption. Soda taxes significantly increase soda prices and decrease consumption (Seiler, et al., 2021), but their health impacts are weak (Restrepo and Cantor, 2020) due to cross-border shopping and substitution avoidance (Zhang, et al., 2021). Despite the mixed evidence of the impacts of soda taxes on reducing obesity (Fletcher et al., 2010b; Phonsuk et al., 2021; Zhang et al., 2021), there seems to be a consensus that food and beverage tax policies can affect health outcomes through influencing food and beverage consumption (Finkelstein, et al., 2013, Powell and Chaloupka, 2009). Since the World Health Organization officially recognized soda taxes as a strategic approach to reduce soda consumption and curb the epidemic of obesity and diabetes (Le Bodo, et al., 2022), more jurisdictions from Europe, North and South America and Asia have proposed, adopted or modified soda taxation strategies (Cornelsen and Smith, 2018). Unlike a tax on a specific food item or type, grocery taxes apply to all grocery items and could exacerbate the obesity problem by encouraging consumption of more calorie dense, less healthy restaurant foods (Wang, et al., 2021). The poorest segment of the U.S. population could be especially vulnerable to grocery taxes because of their limited budgets. As grocery foods become more expensive, they are primarily substituted by fast restaurant foods (French, 2003) which are more easily accessible (Powell, et al., 2007, Rydell, et al., 2008) and affordable (Khan, et al., 2012) for poorer households. There are also higher

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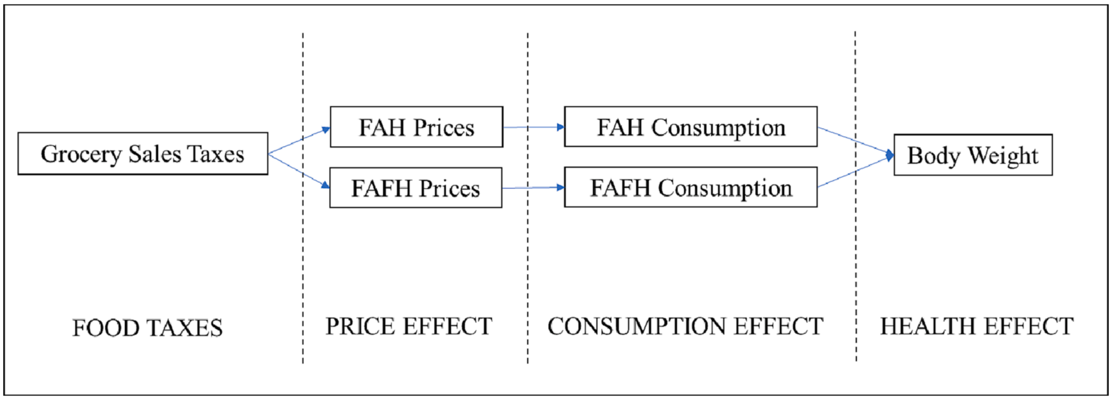

Fig. 1. How grocery sales taxes affect body weight notes: FAH represents food at home, while FAFH represents food away from home.

health risks of consuming fast restaurant foods rather than store-bought foods in the long term (Powell, 2009). Regularly consuming fast restaurant foods can directly and indirectly cause obesity, diabetes, and other chronic cardiovascular diseases (Chou, et al., 2004).

There are several challenges to identify the causal impacts of grocery taxes. First, grocery taxes are added at the register and are not completely salient (Chetty, et al., 2009, Zheng, et al., 2012). In fact, more than one-third of customers surveyed in New York State did not know the actual tax status of groceries (Zheng, et al., 2012). Therefore, a portion of consumers may optimize their budget allocation ignoring the taxes. Second, the price elasticities of many grocery food items are inelastic (Andreyeva, et al., 2010), making the tax impact even harder to discern. Third, the tax impact on health outcomes could take some time to take effect (Gračner, 2021), highlighting the importance of using longitudinal data. Fourth, there are other causes of obesity, including physical inactivity (Pietiläinen, et al., 2008) and a toxic food environment (Barrera, et al., 2016). Individuals who live in food deserts and food swamps have a difficult time gaining access to healthy food, may be more prone towards obesity (Cooksey-Stowers, et al., 2017, Ghosh-Dastidar, et al., 2014). Without controlling these causes of obesity may result in inaccurate estimates of grocery tax impacts. Finally, genetics, gender, race, income etc. all contribute to heterogeneous health impacts. For instance, low-socioeconomic status (SES) households are eligible for the Supplemental Nutrition Assistance Program (SNAP), and SNAP purchases are sheltered from sales taxes. Researchers have also found that black, female and low-SES populations are more sensitive to food tax rate changes (Goryakin, et al., 2017, Yaniv, et al., 2009). Therefore, it is important to control these factors in the empirical design.

The purpose of this study reported here is to examine whether grocery sales taxes affect body weight through changing people's food budget allocation between at-home and away-from-home consumption. We first develop a model based on previous economic analyses of obesity, in which the tax impacts on food consumption and body weight are theoretically analyzed. This theory is tested empirically by merging county-level grocery tax data with the individual longitudinal data from the Panel Study Income Dynamics (PSID). Specifically, the causal impact of grocery sales taxes on family food expenditures and individual body mass index (BMI) are estimated over a twelve-year window, with the use of a variety of individual/family covariates and fixed effects. The PSID data, which trace the body weight of individuals during a long period, have been widely used in policy evaluation analyses (Hoynes and Schanzenbach, 2009). The tax impacts on individuals and families with different characteristics are estimated as well. Overall, we find that a one-percentage-point increase in the grocery tax rate relative to the restaurant tax rate leads to a rise in BMI by 0.061, which translates to a body weight gain of about 0.361 lb. These results are driven by the overweight population (whose BMI is between 25 and 30). As for the heterogeneous effects, low-income households are the most vulnerable cohort of the population to grocery taxes.

There are two main contributions of this study. First, while there is a considerable amount of literature about how soda taxes and other sin taxes affect health outcomes such as obesity and diabetes, this is the first attempt to estimate the causal impact of grocery food taxes on health outcomes. Our novel tax data for both grocery and restaurant foods capture food sales tax rate variations at the county and state levels over 12 years, largely reflecting the actual tax environment faced by consumers. We examine whether grocery taxes affect body weight through these mechanisms from both theoretical and empirical perspectives. Second, it is important to learn which population, if any, is affected the most by the grocery tax. Our heterogeneous analysis finds that the non-SNAP participating, low-income population is harmed the most from grocery sales taxes. The impacts of grocery sales taxes on individual body weight are over three times higher for the non-SNAP low-income population than the average population.

2. Literature on food and beverage taxes

In this section, we review studies on food and beverage taxes and summarize the tax impacts on corresponding food and beverage consumption and obesity. Although there is not a federal food and beverage tax in the United States, local governments have levied food and beverage taxes to collect tax revenue since the end of the Great Depression (Creighton, 2010). There are two major food and beverage taxes, grocery taxes and sin taxes on products such as alcohol, with the latter receiving the bulk of studies. These two taxes may affect body weight through similar paths depicted in Fig. 1: a change in relative after-tax prices leads to a change in consumption and subsequently to a change in body weight (Powell and Chaloupka, 2009).

2.1. Fat and soda taxes

Sin taxes have usually been levied on addictive products such as tobacco and alcohol to overcome health externalities. Today, they are applied to a broader category of goods that are satisfying to consume, but lead to health risks (O'Donoghue and Rabin, 2006) such as fat and sugar intensive food and beverages (Allcott, et al., 2019) or energy-dense foods (Cawley, 2015). Denmark introduced a tax on high fat foods in 2011, but was quickly abandoned in 2012 (Bødker, et al., 2015). The tax largely increased the after-tax prices of food rich in saturated fat such as butter, butter blends, margarine, and oil. As a result, the estimated consumption of fat sharply declined by an estimated 41.8 g/week per person (Jensen and Smed, 2013). However, since the implemented period was short, no significant health impact was found. Other countries implementing such taxes obtained similar results. The junk food tax in Hungary significantly decreased the consumption of "unhealthy food" among the poorest households (Bíró, 2015); Mexico's tax on high calorie packaged foods reduced purchases of non-essential energy-dense food (Hernández-F, et al., 2019); a tax on fast food in the Kerala state of India showed little effect on curbing obesity in its first phase (Krishnamoorthy, et al., 2020).

Inspired by the Danish fat tax, researchers from other high-income countries estimated demand system models to calculate the price, consumption, and health effects of hypothetical fat taxes. For example, employing consumer expenditure surveys from Norway, researchers found that Norwegian consumers limited their purchases of the taxed items, resulting in a small body weight change (Gustavsen and Rickertsen, 2013). In contrast, a French study using a simulation model found that fat taxes had little impact on building healthy diets for households in France due to the price inelastic demand for high fat products in France (Allais, et al., 2010). In other studies of fat taxes, researchers have found similar results (Hyseni, et al., 2017). Based on simulation studies, fat taxes reduce the consumption of the taxed food, but the health effect is small because of inelastic food consumption to price changes (Tiffin and Arnoult, 2011).[1] Another major sin tax that is frequently studied is the soda tax, a tax that exists in over 50 countries and jurisdictions.. Most studies focus on the U.S. and Mexico. Some studies directly estimate how the soda tax affects body weight outcomes using reduced-form equations with self-reported data from national cross-sectional surveys. For example, by employing the Behavioral Risk Factor Surveillance System survey data, Fletcher et al. (2010a) found that state-level soda taxes had a significant but small impact on adult weight. No impact was found for children or adolescents as they can easily substitute with other high-calorie drinks (Fletcher et al., 2010b). Other researchers employed scanner data in a location or aggregate national data and found soda taxes reduced soda consumption (Cawley, et al., 2019, Colchero, et al., 2016, Debnam, 2017, Zheng and Kaiser, 2008). Based on the consumption reduction, some researchers have further calculated the decline in calorie intake and the resulting weight loss (Zhen et al., 2014). Most of these studies find that soda taxes have significant impacts on soda prices and consumption, but it is uncertain how large the tax effects are reflected in weight loss (Paarlberg, et al., 2017, Teng, et al., 2019) due to the increased compensated consumption from untaxed categories (Aguilar, et al., 2021). In general, the weight-loss impact estimated from the reduced-form analyses is smaller than that obtained from simulation studies (Barrientos-Gutierrez, et al., 2017, Harding and Lovenheim, 2017). Recently, more research has explored the policy impacts of soda taxes in European, South American and Asian countries. In South American and Asian countries, results are similar as Mexico and the U.S. For instance, researchers found soda taxes in Chile reduced soda consumption significantly for high socioeconomic groups who have higher education, income, asset and well-reputed occupation according to Chilean SES classification, but the effect on reducing bodyweight was unclear (Nakamura, et al., 2018); the soda tax in Saudi Arabia increased soda prices by 67% compared to the announced 55% tax rate, and soda purchases were reduced by 58% (Alsukait, et al., 2019). For European countries, the effects of soda taxes are mixed. One study compared soda consumption in six European countries before and after they adopted soda taxes and found reductions in the soda consumption for Latvia, Finland, Belgium and Portugal, but not for Hungary and France (Chatelan, et al., 2022). Another study simulated potential impacts of soda taxes in the U.K. and found that the tax only had limited effects on diminishing soda consumption (Tiffin, et al., 2015).

2.2. Grocery food sales taxes

There is not a large body of literature on economic impacts of grocery food taxes, which is likely due to the lack of a comprehensive database of tax data at a fine level over years. Only one study examined how grocery tax changed consumers' grocery demand (Srithongrung, 2017). This study found that for Kansas counties, a 1% increase in grocery tax difference was associated with a large decrease in grocery food consumption. Based on a unique dataset on county-level grocery tax rates over years, a group of researchers have examined various effects of grocery taxes. These researchers found that grocery taxes could induce people to consume more food away from home (Dong, et al., 2020, Zheng, et al., 2019), that grocery taxes increased food insecurity among the lower-SES population (Wilson, et al., 2016, Zheng, et al., 2021), and that grocery taxes incentivized SNAP participation (Zhao, et al., 2021).

The most relevant study to ours was conducted by Wang, et al. (2021), who investigated how grocery taxes are associated with county-level obesity and diabetes prevalence. Their study found that a one-percentage-point increase in grocery tax rate was associated with 0.588 and 0.215 percentage point increases, respectively, in county-level obesity and diabetes rates. However, the authors' research design, which utilized county-level obesity and diabetes rates with grocery tax rates, did not claim to show causality, but rather association.

All the above grocery tax studies either employed cross sectional household survey data (Wilson, et al., 2016, Zheng, et al., 2019), panel data (i.e., the Current Population Survey Food Security Supplement) where only a very small portion of households are observed over a long period (Zheng, et al., 2021), or county-level aggregate data (Wang, et al., 2021, Zhao, et al., 2021). In comparison, the PSID is a true panel that has continuously surveyed families since 1968. It is the world's longest running household panel survey (McGonagle, et al., 2012) and also contains information of food expenditure and health outcomes at the levels of households and individuals. The PSID data allow us to examine the impacts of grocery taxes on health outcomes as well as the mechanism through which it occurs.

3. Theoretical model of grocery taxes impacts

The model developed here illustrates how changes in grocery tax rates affect body weight, and it is based on three previous theoretical models (Kalamov, 2020, Schroeter, et al., 2008, Yaniv, et al., 2009). In their models, individuals maximize their utility by choosing inter-substitutable foods that induce different body weight gains. Several assumptions and limitations of the three studies are worth noting. Yaniv, et al. (2009) assumed a scenario specific consumption function and did not consider products other than food. Schroeter et al. (2008) assumed that there was an ideal body weight for each individual such that being underweight or overweight decreased utility. Their results largely depend on the price, income, and weight elasticities. Kalamov (2020) assumed a constant elasticity of substitution (CES) consumption function and considered other non-food commodities. However, his model neither penalized being underweight nor included an essential basal metabolic rate (BMR) constraint, which ensures that people need to eat at a BMR to sustain their lives.

Similar to the setup of Kalamov's (2020) model, our model uses a general form of a consumption function and includes products other than foods. We also include a BMR constraint similar to Yaniv's (2009) and the assumption that people gain weight by consuming restaurant foods and not by consuming grocery foods. This assumption allows us to focus on the substitution between grocery and restaurant foods without the need to model substitution within the grocery foods. This is clearly a simplifying assumption, but it is necessary to solve Yaniv's (2009) and our theoretical model. Therefore, the two propositions derived from this theory should be taken with this simplifying assumption in mind. Specifically, we note that the two propositions from the theoretical model should be viewed as hypotheses to be tested with the empirical model, which does not rely on this assumption. It is also worth noting that while this assumption is restrictive, there is empirical evidence that is consistent with it, namely that food-away-from-home (FAFH) have higher calories than food-at-home (FAH). For instance, one recent study found that meals away-from home averaged 200 calories more than home-cooked meals (Nguyen and Powell, 2014). Another study found

[1] We are not aware of any empirical econometric studies of fat taxes.

that eating one meal away from home each week translates to roughly two extra pounds each year (Todd et al., 2010). Hence, while our assumption that FAH does not lead to weight change is restrictive, there is empirical evidence that consumption of FAFH leads to more weight gain than grocery foods.

Compared with the study by Yaniv (2009) that focuses on the time trade-offs among exercise time, time of preparing food and leisure, we instead focus more on the trade-off between consuming FAFH vs. FAH.[2] The empirical literature has generally found positive cross-price elasticities between FAFH and FAH. For example, Nayga et al. (1992) found the compensated cross price elasticity of FAFH with respect to FAH to be 0.127, and the cross price elasticity of FAH with respect to FAFH to be 0.052. Okrent and Alston (2012) used a much more disaggregated model in terms of both FAH and FAFH products. They find the following cross price elasticities of FAFH (and alcohol) with respect to the following FAH categories: cereals and bakery (0.16), meat and eggs (0.17), dairy (0.23), fruits and vegetables (0.24), and other FAH (0.45). Lusk (2017) found a wide dispersion in the cross-price elasticities of demand for FAH and FAFH, with the two goods being substitutes for 92% of the consumer clusters and compliments for the other 8%. Piggott (2003) estimated cross-price elasticities of demand for FAH with respect to the price of FAFH ranged from 0.16 to 0.43, implying that they are gross substitutes. Huffman (2011) developed a productive household model and found that the FAH and "food away from home" (FAFH) are substitutes. These studies indicate that FAH and FAFH are substitutes. The magnitudes are not large, but neither are the magnitudes of the own price elasticities, which is common for food elasticities for the U.S.

3.1. The individual's weight-gain problem

People gain weight when their caloric intake exceeds burned calories. The literature shows that restaurant foods, especially fast foods are highly related with weight gain (Currie, et al., 2010, Dunn, 2010). Let R and S denote the consumption of restaurant foods and (the degree of) weight gain respectively for an individual. Assuming a linear relationship, we express the weight gain as:

1) $S = \delta R$

where δ is the excess calorie intake per restaurant food meal and $\delta \geq 0$. The weight gain is defined as the difference between the caloric intake from consuming restaurant and grocery foods (R and G), and the calorie loss from BMR: $S = \vartheta R + \varepsilon G - BMR$, where ϑ is the calorie intake per restaurant meal, and ε is the calorie intake per grocery food meal. We assume that BMR is deducted by grocery food consumption and some restaurant consumption, $BMR = (\vartheta - \delta)R + \varepsilon G$. Therefore, $S = \vartheta R + \varepsilon G - BMR$ could be rewritten as $S = \delta R$.

We assume that the individual consumes three types of goods (grocery foods, restaurant foods, and other goods [Z]) and the food industry is competitive. The before-tax prices of restaurant foods and grocery foods are consistent with their respective marginal cost of production, p_R and p_G. Denoting restaurant and grocery sales taxes as τ_R and τ_G, we then have after-tax prices of restaurant foods and grocery foods as $P_R = p_R(1+\tau_R)$ and $P_G = p_G(1+\tau_G)$, respectively. The budget constraint of the individual is:

2) $P_R R + P_G G + Z = I$

where I is the individual's income, and the price of the other good is normalized to one. Therefore, through this general form of budget constraint and the later utility function, both the substitution and income effects (at these three category levels) associated with a tax change is being modeled here.

Suppose the individual consumes both grocery foods and restaurant foods so that the food consumption function can be written as:

3) $C = C(G, R)$,

where the marginal consumption of grocery (or restaurant) foods increases at a decreasing rate: $C_{GG} \leq 0$ and $C_{RR} \leq 0$. When C_{GG} and C_{RR} are both zero, equation (3) reduces to the case where food consumption is the sum of grocery and restaurant food purchases. When either C_{GG} or C_{RR} is negative, this accounts for the possibility of food waste. We assume a substitution relation between the two foods, and the change in the marginal consumption of restaurant food given marginal consumption of other goods (Z) will decrease as individuals consume more grocery foods. A typical example is CES functional form, where $C_{RG} < 0$.

We also assume the utility of the individual is composed of consumption of food and the other good:

4) $U = U(C, Z)$.

According to the Law of Marginal Utility, the marginal utilities of consumption increase at a decreasing rate, that is, $U_C = \partial U / \partial C > 0$, $U_z > 0$, $U_{CC} < 0$, and $U_{zz} < 0$. Since the marginal utility of food consumption does not decrease as we consume more the other good, we have $U_{cz} \geq 0$.

For a weight-conscious individual whose utility decreases linearly with weight gain, the linear penalty of gaining weight is b, $b > 0$. Therefore, the individual chooses optimal consumption of grocery and restaurant foods to solve the net utility constrained maximization problem:

5) $\underset{G,R}{\text{Max}} NetU = U(C, Z) - bS(R)$,

subject to the budget constraint specified in equation (2), where U and $S(R)$ were defined in equations (4) and (1).

3.2. Solution and propositions

The first order conditions for this constrained maximization problem are:

6) $V_G(G^*, R^*, P_G, P_R) = \frac{\partial NetU}{\partial G} = U_C \frac{\partial C}{\partial G} + U_z \frac{\partial Z}{\partial G} = U_C C_G - P_G U_z = 0$ and

7) $V_R(G^*, R^*, P_G, P_R) = \frac{\partial NetU}{\partial R} = U_C \frac{\partial C}{\partial R} + U_Z \frac{\partial Z}{\partial R} - b\delta = U_C C_R - P_R U_z - b\delta = 0$,

where superscript asterisk denotes the optimal level. The first order condition for grocery foods implies that eating grocery foods affects the individual's net utility in two ways. First, it increases the total food consumption, thus increasing the utility through $U_C C_G$. Second, it reduces the budget to buy the other good, so that the net utility decreases through $P_G U_z$. In addition to the two mechanisms above, a penalty to utility through $b\delta$ is imposed to account for the extra body weight gain caused by consuming restaurant foods.

Using systems of implicit functions (Simon and Blume, 1994) with the first order conditions, we derive

$$\frac{dS^*}{d\tau_G} = \frac{dS^*}{dP_G} {*} p_G = \frac{\partial S}{\partial R} \frac{\partial R^*}{\partial P_G} {*} p_G = \delta p_G \frac{-U_Z V_{RG}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}$$

and

[2] Considering travel to and waiting in restaurants and the development of kitchen appliances (e.g., air fryer), it is not necessary that restaurant meals always save time.

Table 1
Summary statistics (Mean).

Variable	Unit	Description	All	With Grocery Tax	Without Grocery Tax	Difference
County-Level Variables						
Grocery Tax	%	Grocery tax rate	1.309	3.750	0	3.750***
Restaurant Tax	%	Restaurant tax rate	6.466	6.806	6.284	0.522***
Tax Difference	%	Grocery tax rate – Restaurant tax rate	−5.157	−3.056	−6.284	3.228***
Infant Mortality Rate	NA	Deaths per 1000 live births	6.462	7.462	5.925	1.537***
Family-Level Variables						
Grocery Food Expenditure	$	Grocery food expenditure per week	123.744	112.364	130.128	−17.764***
Restaurant Food Expenditure	$	Restaurant food expenditure per week	77.907	68.066	83.401	−15.335***
Delivery Food Expenditure	$	Delivery food expenditure per week	4.304	3.274	4.881	−1.607***
Family Income	$	Annual family income	78,042.63	66,719.56	84,114.14	−17,394.58***
Family Size	NA	Numbers of family members	2.657	2.643	2.664	−0.019
SNAP	NA	Whether participating in SNAP (Yes = 1)	0.151	0.181	0.135	0.045***
SNAP Value	$	Annual SNAP benefits	6,339.250	7,453.992	5,715.374	1,738.618***
TANF	NA	Whether participating in TANF (Yes = 1)	0.009	0.006	0.012	−0.006***
Health Insurance	NA	Whether having insurance	0.833	0.798	0.853	−0.054***
Female Head	NA	Whether household head is female	0.300	0.331	0.283	0.048***
Individual-Level Variables						
BMI	NA	Body mass index	27.494	28.121	27.158	0.963***
Weight	Pound	Body weight	181.110	185.113	179.055	6.058***
Age	Year	Age	45.238	44.537	45.614	−1.077***
Female	NA	Whether is female	0.551	0.562	0.544	0.017***
White	NA	Whether is white	0.502	0.394	0.559	−0.165***
Hispanic	NA	Whether is Hispanic	0.027	0.010	0.036	−0.025***
Married	NA	Whether is married	0.673	0.636	0.693	−0.058***
Have Child(ren)	NA	Whether having child(ren)	0.445	0.456	0.439	0.016***
Education Years	Year	Years of education	15.151	15.011	15.226	−0.215***
Housework	Hours/week	Weekly hours of housework	11.885	11.681	11.994	−0.313***
Health Insurance	NA	Whether has health insurance	0.834	0.798	0.853	−0.054***
Cigarettes Per Day	Number	Daily cigarettes smoking	3.788	4.320	3.502	0.819***
Drinking Alcohol	NA	Whether drinking alcohol	0.614	0.539	0.654	−0.115***
Physical Activity	Hours/week	Weekly hours of physical activity	2.149	2.062	2.196	−0.134***

Notes: *** denotes 1% significance.

$$\frac{dG^*}{d\tau_G} = \frac{dG^*}{dP_G}{*}p_G = \frac{\partial G^*}{\partial P_G}{*}p_G = \frac{\begin{vmatrix} U_Z & V_{GR} \\ 0 & V_{RR} \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}{*}p_G = \frac{p_G U_Z V_{RR}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}$$

$$\frac{dR^*}{d\tau_G} = \frac{\partial R^*}{\partial P_G}{*}p_G = \frac{\begin{vmatrix} V_{GG} & U_Z \\ V_{RG} & 0 \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}{*}p_G = \frac{-p_G U_Z V_{RG}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}$$

Since $\begin{pmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{pmatrix}$ is a Hessian Matrix, the second order condition implies $\left|\begin{matrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{matrix}\right| \rangle 0$. In addition, we assume $U_z > 0$, as well as deriving $V_{RG} < 0$ and $V_{RR} < 0$. Based on the solution to this maximization problem, the following two propositions can be derived (full proofs are provided in the Appendix A):

Proposition 1. *Increasing (decreasing) grocery taxes leads to a weight gain (loss) (i.e.,* $\frac{dS^*}{d\tau_G} > 0$*).*

Proposition 2. *Increasing (decreasing) grocery taxes decreases (increases) grocery food consumption and increases (decreases) restaurant food consumption (i.e.,* $\frac{dG^*}{d\tau_G} < 0, \frac{dR^*}{d\tau_G} > 0$*). We next turn to testing these two theoretical propositions empirically.*

4. Econometric identification

4.1. Econometric models

The first proposition is tested empirically by estimating the impacts of grocery taxes on individuals' BMIs, i.e.:

$$BMI_{ict} = \beta_0 + \beta_1 TaxDif_{ct-1} + \boldsymbol{\theta W_{it}} + \sigma_c + \psi_t + \lambda_c t + e_{ict} \tag{8}$$

where BMI_{ict} is the body mass index of individual i residing in county c in year t, and $TaxDif_{ct-1}$ is the difference in the grocery sales tax rate and restaurant sales tax rate of county c in year $t-1$. Similar to the bulk of the aforementioned tax literature, we use a reduced form equation to directly estimate the impact of the tax on each health outcome (the full mechanism, as discussed in (Fletcher et al., 2010b), is through the tax impact on prices). Both taxes are measured at the state and county combined level. The tax difference reflects the relative taxes faced by consumers when making a choice as to where to eat. We allow one year for a tax change to take effect since it would likely take some time for consumers to adjust their consumption habits in response to a tax change[3]. We also find the optimal lag-length is one period using sequential tests (Gujarati, et al., 2012). Additionally, we argue that the previous decision of tax changes is much less likely to be endogenous, an issue we will discuss further later. This equation is also estimated separately with body weight as the dependent variable. The vector $\boldsymbol{W_{it}}$ includes individual-level demographic characteristics following a large literature on factors influencing weight (Cohen, et al., 2013, Kanter and Caballero, 2012, McLaren, 2007, Pickett, et al., 2005, Wolf, et al., 1993). These factors include whether individual i is the household head (the respondent person of the survey), age, gender, race, marital status, having child(ren), years of education, types of industry where working, family income, SNAP participation status, Temporary Assistance for Needy Families (TANF) participation status, time spent on housework, whether the individual has health insurance, whether the individual smokes cigarettes, whether the individual consumes alcohol, and frequency of physical activity. We report summary statistics of these

[3] Since PSID interviews happened between March and November, we apply a one-year lag of the tax difference to avoid regressing current health outcomes on future rates. For example, if a tax rate change happened in the same year but after the PSID survey time, using current tax differences would be problematic since it would not have an impact on previous health outcomes.

variables in the section of individual-level variables in Table 1. We also control the infant mortality rate at the county level. Finally, the equation is estimated using a fixed effect approach[4]. σ_c is the county fixed effect controlling for the time-invariant unobserved county variables. We use county fixed effects instead of individual/family fixed effects because the main independent variable of interest, the tax difference, primarily varies at the county level (Hoynes, et al., 2016), and the panel time-series is relatively short. The within-county variation for the tax difference is less than 40% of the between-county variation, and the within-individual or -family variation is smaller. ψ_t is the yearly fixed effect controlling for the annual time shock, $\lambda_c t$ represents a county-specific time trend, and e_{it} is an error term. Standard errors are clustered at county-level[5], which is the tax implementation level (Cameron and Miller, 2015).

Our main parameter of interest, β_1, indicates how the difference of the grocery tax rate and restaurant tax rate in the previous year affect the BMIs of individuals on average holding other variables constant. A positive and statistically significant β_1 would suggest that increasing the grocery tax rate relative to the restaurant tax rate would induce weight gain and confirm our theoretical Proposition 1 on body weight.

The second proposition is tested empirically by estimating how the tax affects grocery and restaurant food consumption, separately, using the following equation (this equation is estimated separately for grocery food and restaurant consumption):

$$9)\ FoodExp_{hct} = \alpha_0 + \alpha_1 TaxDif_{ct-1} + \zeta \boldsymbol{X}_{ht} + \sigma_c + \psi_t + \lambda_c t + \epsilon_{hct}$$

where $FoodExp_{hct}$ is the average weekly grocery (or restaurant) food expenditures of household h residing at county c in year t. [6] The vector $\boldsymbol{X}_{ht}$ contains household characteristics including family income, number of children, health insurance status, employment status and gender of the household head, delivery food expenditure, annual SNAP benefits and participation in TNAF. We report summary statistics of these variables in the section of family-level variables in Table 1. Since the unit of research is the household, we adopt the family weight created by PSID to reduce the bias from oversampling low-income households. These specifications largely resemble the one developed by Hoynes and Schanzenbach (2009) to examine the impact of SNAP introduction on food expenditures, using the same data. We follow them and use a large number of individual or household socio-demographic variables (mostly time-varying) as control variables instead of individual or household fixed effects.

Our main parameter of interest, α_1, indicates how the difference of the grocery tax rate and restaurant tax rate in the previous year affect grocery food and restaurant food consumption, measured by food expenditures on each. For the grocery food expenditures equation, a negative and statistically significant α_1 suggests that increasing the grocery tax rate relative to the restaurant tax rate decreases grocery food consumption, while for the restaurant food expenditures equation, a positive and statistically significant α_1 suggests that increasing the grocery tax rate relative to the restaurant tax rate increases restaurant food consumption.

4.2. Empirical challenges/issues

There are two primary empirical challenges pertaining to estimating the impact of grocery taxes on BMI and food expenditures that should be acknowledged. First, and like soda taxes, grocery taxes should affect body weight and food expenditures through their impact on prices. Hence, knowledge of the pass-through of grocery taxes to retail tax-inclusive prices is important. From a theoretical perspective, as Pless and van Benthem (2019) show, a tax pass through depends largely on the absolute values of demand elasticity (decreasing in) and supply elasticity (increasing in), and the degree of under-reaction or inattention to the tax (increasing in inattention cause consumers to bear more burden because they ignore the tax). Unfortunately, there have been few studies that have estimated grocery tax pass through to retail prices. One potential reason is that the price elasticities of demand and supply for grocery foods could differ greatly across food products. One earlier study on selected city level grocery taxes shows that the taxes are over-shifted to retail prices for several grocery items such as bananas (Besley and Rosen, 1999). However, this study only included six grocery food products. Consequently, in this study, we examine the direct impact of taxes using a reduced-form approach that assumes that at least part of the taxes is passed through consumers (Fletcher et al., 2010b).

Second, it is possible that grocery and restaurant taxes are endogenous. That is, grocery taxes could be related to current local economic conditions, which could in turn influence obesity rates. Unfortunately, there is little guidance from past studies on what variables determined grocery taxes thus providing little guidance on choice of an instrumental variable. Instead, we address the possibility of grocery/restaurant taxes being endogenous in several ways in the absence of valid instruments and strictly exogenous natural experiments. First, we conduct a direct test of endogeneity of grocery taxes using a procedure based on (Wooldridge, 2010), utilizing the panel nature of the data. The intuition is that if grocery taxes are exogeneous, then the future taxes should not affect the outcome variable. The result of this test is endogeneity of the grocery tax with body weight is rejected thus providing evidence of exogeneity. Second, we follow Zhao, et al. (2021) and use county fixed effects and county-specific trends while treating grocery taxes as exogenous. The county fixed effects and county-specific trends should be able control for many unobserved local economic conditions that may or may not change over time, thus further mitigating the endogeneity concern. Third, we use one-year lagged taxes instead of current taxes, which lessens the possibility of endogeneity in our key variable of interest in this study.

Finally, we conduct two separate robustness checks to compare against the original model results. In the first robustness check, we use only the bordering counties between states and apply a general border method estimation. By adding pair-by-year fixed effects, we control the time-variant unobservable among the counties that share similar environmental, cultural, and economic factors. As a result, we can obtain the Local Average Treatment Effect (LATE) of grocery sales tax rates on the BMI and body weight of individuals. For the second robustness check, we focus on counties with just one tax change over the data period and conduct an event study. The event study is useful because it enables testing of the parallel trend assumption in the spirit of a difference-in-difference methodology. The assumption is that if the pre-trends of the outcomes are parallel between the control (i.e., un-taxed) and treatment (i.e., taxed) group, the trend of the counterfactual outcome of the treatment group is expected to be parallel to the outcome trend of the control group in the post period. Hence, we can claim causal treatment effects on the treated (ATT) based on the difference-in-difference design (Cunningham, 2021).

5. Data

The tax data include sales tax rates of grocery and restaurant foods

[4] We also tried IV estimation where the current tax difference is instrumented with the lagged tax difference. The IV estimates are larger in magnitude, but the signs and significance levels are consistent with the baseline results.

[5] Standard errors become smaller when they are clustered at the household level.

[6] We also estimate the two equations simultaneously using seemingly unrelated regression (SUR) to account for possible shocks common to both types of food consumption. Results remain robust.

from 2006 to 2017 at both the state and county levels.[7] The data were obtained from Bridging the Gap, Tax-Rates.org, and various local Departments of Revenue. This is the most comprehensive grocery/restaurant tax dataset covering the longest duration to our knowledge. The grocery tax data were used by Zhao, et al. (2021) and Zheng, et al. (2021), but the restaurant tax data have not yet been utilized in any analysis. The tax data are a balanced panel of 3,101 counties for all states over 12 years. The twelve-year tax change is illustrated with four maps (Appendix Fig. A1).

The individual-level and family-level data for body weight and other covariates were obtained from the PSID. The PSID is a longitudinal family survey conducted every other year by the University of Michigan. The entire PSID data consist of more than 18,000 individuals from over 5,000 households. The survey contains family-level questions such as family income and food expenditures, which are stored in family-level datasets. In addition, the survey also reports individual-level questions such as self-reported individual weight and height of the family head and spouse (Sastry, et al., 2018), which are stored in individual-level datasets. We merged individual-level datasets with family-level datasets based on the family interview id and the individual id. During our research period from 2006 to 2017, the survey was conducted six times, in 2007, 2009, 2011, 2013, 2015 and 2017. We matched the PSID data to our tax data in the years of 2006, 2008, 2010, 2012, 2014 and 2016, examining how the tax in the previous year affected body weights. In this research, we only focus on the adult sample over the study window.

The original weight outcome variable, body weight (measured in pounds), was collected from the PSID family data. The reference individuals in the family who responded to the family survey reported both their own and their spouses' body weights. We calculated the BMI as:

$$10)\ BMI = \frac{Weight}{Height^2}$$

where weight and height are measured in kilogram and meter respectively. We then matched the weight with the control variables from both the PSID individual and family dataset. Individual characteristics, such as age and frequency of physical activity, were obtained from the individual dataset. Family characteristics, including family income as well as participation in SNAP and TANF, were collected from the family dataset.

Specifically, the food expenditure data are collected based on two questions in the PSID family file code books: 1) For the food at home, "How much do you spend on that food in an average week? - AMOUNT". 2) For the food away from home, "About how much do you (and everyone else in your family) spend eating out in an average week? - AMOUNT".

After merging the PSID data with the tax data by the Federal Information Processing Standards (FIPS) codes, our dataset has 19,432 individuals from 13,949 families.[8] During the merge, we dropped residents in unmatched cities, which account for 1.7% of the observations. At last, there were 9,145 men and 10,287 women from 1,468 counties, resulting in 78,872 observations for individuals by year and 57,475 observations for family by year over the 6 years. Among the households that reported their food expenditure, all of them had positive expenditures on FAFH. Table 1 presents the mean values for the variables used, also broken down by grocery tax status. The summary statistics show that the BMI is higher in places with grocery taxes, suggesting a potential positive association between grocery taxes and obesity. The average weight of individuals residing in counties with grocery taxes is 6.06 lb higher than of those in counties without taxes.

Table 2
Impacts of relative grocery sales tax rate on individual BMI and body weight.

Variables	(1) BMI	(2) BMI	(3) BMI	(4) BMI	(5) BMI	(6) Weight (pound)
Panel A: Entire Sample						
Tax Difference	0.066*	0.078**	0.050*	0.061**	0.046*	0.361**
	(0.035)	(0.035)	(0.029)	(0.028)	(0.027)	(0.171)
Observations	78,872	78,872	78,872	78,872	78,872	78,872
R-squared	0.001	0.003	0.124	0.169	0.348	0.354
Panel B: Counties with Grocery Sales Taxes						
Tax Difference	−0.076	−0.056	0.073	0.092*	0.077*	0.585*
	(0.068)	(0.07)	(0.052)	(0.050)	(0.043)	(0.289)
Observations	27,530	27,530	27,530	27,530	27,530	27,530
R-squared	0.001	0.003	0.136	0.190	0.373	0.339
Year FE	N	Y	Y	Y	Y	Y
County FE	N	N	Y	Y	Y	Y
County Trend	N	N	Y	Y	Y	Y
Individual covariates	N	N	N	Y	Y	Y
Gene/Family FE	N	N	N	N	Y	N

Note: Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

6. Results

6.1. Main BMI and weight results

Table 2 reports the impacts of relative grocery tax on body weights based on equation (8) for several specifications. The first column is estimated without any fixed effect or individual-level covariates. In the next three columns, we gradually add yearly fixed effects, then county fixed effects and county trend, and then the covariates. Focusing on the full specification, which is our preferred specification with all the controls in column (4), the estimated tax coefficient is 0.061 and statistically significant at the 5% default level. If the tax difference (grocery minus restaurant tax rate) increases by one percentage point, the result indicates that BMI, on average, increases by 0.061, holding other factors constant. The estimate remains largely consistent and robust for the first three columns where less controls are used. Applying the full specification to body weight, we find that a one-percentage-point increase in the tax rate difference leads to a weight gain of 0.361 lb on average, as reported in column (6). These results are consistent with our proposition on weight gain from the theoretical model.

To put these results into more perspective, consider two similar individuals, one living in a county that has a 7% tax on restaurant foods and no tax on grocery foods, and the other living in a county that taxes both restaurant and grocery foods at 7%. Applying the average point estimates from above to this example, the person living in the grocery tax exempt county would have a predicted BMI that is 0.43 (=0.061*7) less, and weigh 2.53 (=0.361*7) pounds less than the individual living in the 7% grocery tax county.

We also estimate the average treatment effect by only including the counties with grocery taxes. In this case, the magnitude of the tax difference impact becomes larger at 0.092 for BMI and 0.585 lb for weight (Table 2, Panel B, both statistically significant at the 10% level), implying that increasing the relative tax has a larger effect on individuals from counties with grocery taxes. Applying the point estimates from this model to the example above implies that the person living in the grocery tax exempt county would have a predicted BMI that is 0.64 (=0.092*7) less, and weigh 4.1 (=0.585*7) pounds less than the individual living in the 7% grocery tax county.

[7] The sales tax rate of restaurant foods is identical to the general sales tax rate in most cases.

[8] We obtain the PSID Geographic Information data based on the contract for use of restricted data from the University of Michigan.

Table 3
Impacts of relative grocery sales tax rate on household food expenditure.

	(1) Full Sample	(2) SNAP	(3) Non-SNAP Low-Income	(4) Mid-Income	(5) High-Income
Dependent Variable: Grocery Food Cash Expenditure per Week					
Tax Difference	−6.765	−6.337**	−4.990*	−9.889	−5.844
	(5.211)	(2.486)	(2.955)	(6.558)	(17.745)
R-squared	0.227	0.351	0.652	0.393	0.315
Dependent Variable: Restaurant Food Expenditure per Week					
Tax Difference	1.403	4.138***	2.837*	−3.856	15.278
	(3.724)	(1.747)	(1.715)	(3.511)	(17.678)
R-square	0.178	0.661	0.858	0.184	0.393
Year FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
County Trend	Y	Y	Y	Y	Y
Household covariates	Y	Y	Y	Y	Y
Observations	57,475	9,064	8,567	29,660	10,184

Note: The non-SNAP low-income group includes SNAP eligible non-participants with household income below the 165% FPL. The mid-income households have incomes above 165% FPL but no greater than twice of the state median income. The high-income households have incomes exceeding twice of the state median income. Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

Table 4
Heterogeneous impacts on individual BMI and weight by SNAP and Income.

	(1) SNAP	(2) Non-SNAP Low-Income	(3) Mid-Income	(4) High-Income
Dependent Variable: BMI				
Tax Difference	0.092	0.238**	0.031	−0.030
	(0.132)	(0.105)	(0.044)	(0.060)
R-squared	0.263	0.279	0.2	0.336
Dependent Variable: Body Weight (Pound)				
Tax Difference	0.451	1.315*	0.243	−0.305
	(0.809)	(0.696)	(0.274)	(0.426)
R-square	0.348	0.420	0.385	0.586
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	Y	Y	Y	Y
Individual covariates	Y	Y	Y	Y
Observations	10,612	10,264	40,927	17,069

Note: The non-SNAP low-income group includes SNAP eligible non-participants with household income below the 165% FPL. The mid-income households have incomes above 165% FPL but no greater than twice of the state median income. The high-income households have incomes exceeding twice of the state median income. Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

6.2. Heterogeneous impacts by SNAP and income

Table 3 presents the results of the tax difference on food expenditures, which corresponds to equation (9), and is estimated with the full model specification including household covariates. For the full sample, the impact of the tax difference is negative, but not statistically significant (see column (1)). We conduct a subsample analysis by household's participation status in SNAP and income level. Column (2) measures the impact of the tax difference on grocery food cash or out-pocket expenditures (i.e., total grocery food expenditure minus SNAP benefits amount) and that on restaurant food expenditure for SNAP participating households. We divide the remaining observations into three subsamples. The first includes SNAP eligible non-participants with household income below the 165% Federal Poverty Line (FPL).[9] The second includes mid-income households with income above 165% FPL but no greater than twice of the state median income .[10] Those households with income exceeding twice the state median are denoted as high-income group.

The results indicate that the tax difference affected the low-income population, whether they participated in SNAP or not. In particular, a one-percentage-point increase in the relative grocery tax rate led to a $6.34 per-week decrease in grocery food cash expenditure and a $4.14 per-week increase in restaurant food expenditure for SNAP participating households. For SNAP eligible non-participating households, the magnitudes are smaller at $4.99 and $2.84, respectively and are statistically significant at the 10% level. The estimates are consistent with Proposition 2 on food grocery vs. restaurant food consumption and highlight the subsample that could be most affected by the relative grocery tax.

We also conduct a placebo test by using the SNAP benefit amount as the dependent variable. Though grocery taxes could incentivize SNAP participation (Zhao, et al., 2021), the benefit amount depends on factors such as income and family size, and should not vary with grocery taxes. The placebo test result, based on the SNAP receiving households in the data, is consistent with our expectation, i.e., we do not find any impact of the tax on SNAP benefit.

The heterogeneous impacts of the relative grocery tax on the body weight by SNAP and income level are presented in Table 4. The results show statistically significant impacts (0.217 for BMI and 1.269 lb for body weight with the latter being significant at the 10% level) only for the low-income SNAP non-participants. Compared with our main results in columns 4 and 6 of Table 2 (average effect), the tax effects on low-income SNAP non-participants are much larger.

To put the results into perspective, consider the following example that utilizes the empirical estimates reported in Table 3 (i.e., column 2). For SNAP households, our data show that SNAP benefits, on average, cover 40% of grocery food expenditures. Suppose a SNAP household spends $40 of their SNAP benefits and $60 cash on groceries, and $50 on restaurants each week. Contrast this with a SNAP eligible non-participant who spends the same amount: $100 cash on groceries and $50 on restaurants. First suppose that these two households face a 10% restaurant tax, but no grocery tax. In this case, both household's food purchasing power (food expenditures excluding taxes) would be $145.45 (= $40+$60+$50/1.1), specifically because the $50 restaurant spending was discounted by the 10% tax.

Now suppose that both households face a 10% restaurant and grocery tax. In this case, the grocery and restaurant food purchasing power for the SNAP household becomes $88.8 and $49.22, respectively

[9] We also include the 130% to 165% of the FPL to cover the categorical SNAP-eligible households. E.g., elderly and disabled households, households with all members receiving TANF, Supplemental Security Income or in some cases other general assistance Aussenberg, R.A., and G. Falk. 2019. "The Supplemental Nutrition Assistance Program (SNAP): Categorical Eligibility." *Congressional Research Service Reports.*

[10] There are various definitions of the threshold between the low-income and the mid-income. Some researchers and organizations (U.S. Department of Education) propose 150% of the FPL while others use 2/3 of the state-level median income (Social and Trends, 2012). In this paper, we propose 165% of the FPL which is in the middle of both. By defining this way, our observations are fully split, and there are no overlapped and omitted observations.

Table 5
Impacts of Grocery Sales Taxes on Individual BMI and Body Weight by Weight.

	(1) Underweight	(2) Normal	(3) Overweight	(4) Obese
Dependent Variable: BMI				
Tax Difference	−0.040	0.012	0.039**	0.047
	(0.083)	(0.021)	(0.017)	(0.050)
R-squared	0.475	0.21	0.149	0.215
Dependent Variable: Body Weight (Pound)				
Tax Difference	−0.436	0.066	0.268**	0.241
	(0.631)	(0.140)	(0.119)	(0.326)
R-square	0.855	0.797	0.869	0.508
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	Y	Y	Y	Y
Individual covariates	Y	Y	Y	Y
Observations	1,861	28,125	26,807	22,079

Note: Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

Table 6
The local average treatment effect (LATE) of grocery sales taxes on BMI and body weight.

	(1) BMI	(2) Body Weight (Pound)
Tax Difference	0.064***	0.382***
	(0.015)	(0.091)
R-squared	0.162	0.346
Pair-by-Year FE	Y	Y
County FE	Y	Y
County Trend	Y	Y
Individual covariates	Y	Y
Observations	59,695	59,695

Note: Standard errors are in parentheses and clustered at the pair level; *** denotes 1% significance level.

(column 4 of Appendix Table A1),[11] and \$86.37 and \$48.03 for the SNAP eligible non-participating household. As the last column of this table illustrates, both households experienced a similar decrease in the total food expenditure (from \$150 to around \$147.8); however, the decrease in purchasing power is less pronounced for the SNAP household (decrease of \$7.45 vs. \$11, or \$387.40 vs. \$572 on an annual basis), largely driven by a less severe impact of grocery expenditure. As a result, the share of grocery food purchasing power is slightly higher for the SNAP household compared with the non-participating household. This is precisely because SNAP provides a partial shield protecting participating low-SES households from being affected by the grocery tax on the SNAP benefit grocery purchases, which bridges some of the gap in the findings of Tables 2 and 3.

Finally, we examine the potential heterogeneous tax impact by four weight categories: underweight, normal, overweight, and obese (Flegal, et al., 1998). We find that the weight gain result, whether it is measure by BMI or body weight, is largely driven by the impact on the overweight population (BMI is between 25 and 30). In particular, one percentage point increase in the relative grocery sales tax rate leads to an increase in BMI by 0.039 and a gain in body weight by 0.268 lb for the overweight population on average. These results are shown in Table 5.

6.3. Gene/family confounder

One of the endogeneity concerns comes from the gene or family confounder. Since the PSID expands their panel by adding the households whose parents are also in the PSID sample, this leads to the case where a person's children, parents, grandparents, and siblings could all be in the sample. These people share the same family gene pool and perhaps similar life patterns that affect BMI (and even places to live). Omitting the gene/family confounder could lead to biased estimates. Since families from the same family tree share the same interview number dating back to the year 1968, we added a gene/family fixed effect based on this interview number and report the results in the column (5) of Table 2. This gene/family fixed effect allows us to link a person to the right family tree and controls for the gene/family confounder. The tax coefficient decreases slightly to 0.051 but remains robust at the 10% significance level. The drawback of the gene fixed effect is that it also counts spouses (who do not have connections in genes with their parents-in-law) into the family tree. In this sense, we use the gene fixed effect as a robustness check.

7. Robustness checks

We conduct two robustness checks using two subsamples. For the first robustness check, we select only the bordering counties between states, while for the second robustness check, we select counties that only experience one tax change during our study window. While both of these approaches produce local rather than national estimated effects, they also imply more causal impacts of grocery sales taxes on BMI and body weight, and hence provide useful further empirical evidence.

7.1. The LATE for bordering counties

We explore the nature of the state border and apply general border method in the spirit of Barwick, et al. (2021) and Zhao, et al. (2021). Counties along the state border share similar environmental, cultural, social and economic factors which are usually time-variant and unobserved; yet there is the sharp discontinuity of grocery sales tax rates among the paired neighboring counties. Paired neighboring counties are defined as adjacent counties from different states along the state borders. Thus, we utilize the discontinuity in the grocery sales tax rates and the continuity in the unobserved time-variant factors across state borders by adding the pair-by-year fixed effects (δ_{pt}) into our main identification:

$$11)\ BMI_{icpt} = \gamma_0 + \gamma_1 TaxDif_{ct-1} + \Theta Z_{it} + \sigma_c + \psi_t + \lambda_c t + \delta_{pt} + e_{icpt},$$

The estimate of γ_1 is the LATE of relative grocery sales taxes on the BMI of individuals.

There are finally 880 pairs of 553 bordering counties in the PSID dataset. Because each county may have more than one paired county, the individual observations can repeatedly exist in different pairs. Therefore, the observation numbers in the general border regression are more than those in the main identification. Overall, we use 6,949 individuals and 59,695 observations in the regression of general border method.

The results of LATE presented in Table 6 are virtually identical with our main identification, which provides further evidence that the assumption of exogeneity of grocery sales taxes is not violated. On average, a one-percentage point increase in relative grocery sales tax rates causes increases in BMI by 0.064 and body weight by 0.382 lb for

[11] Based on Table 3, the grocery food cash expenditure will be \$60 – \$6.337= \$53.66, where −6.337 is the impact of relative tax impact found on grocery expenditures for SNAP households reported in Table 3. Dividing this number by 1.1 leads a worth of \$48.8. The restaurant food expenditure excluding tax will be (\$50+\$4.138)/1.1 = \$49.2, where 4.138 is the impact of relative tax impact found on restaurant expenditures for SNAP households reported in Table 3. For the non-SNAP participant, we replace 6.337 and 4.138 with the estimates of 4.99 and 2.837, respectively.

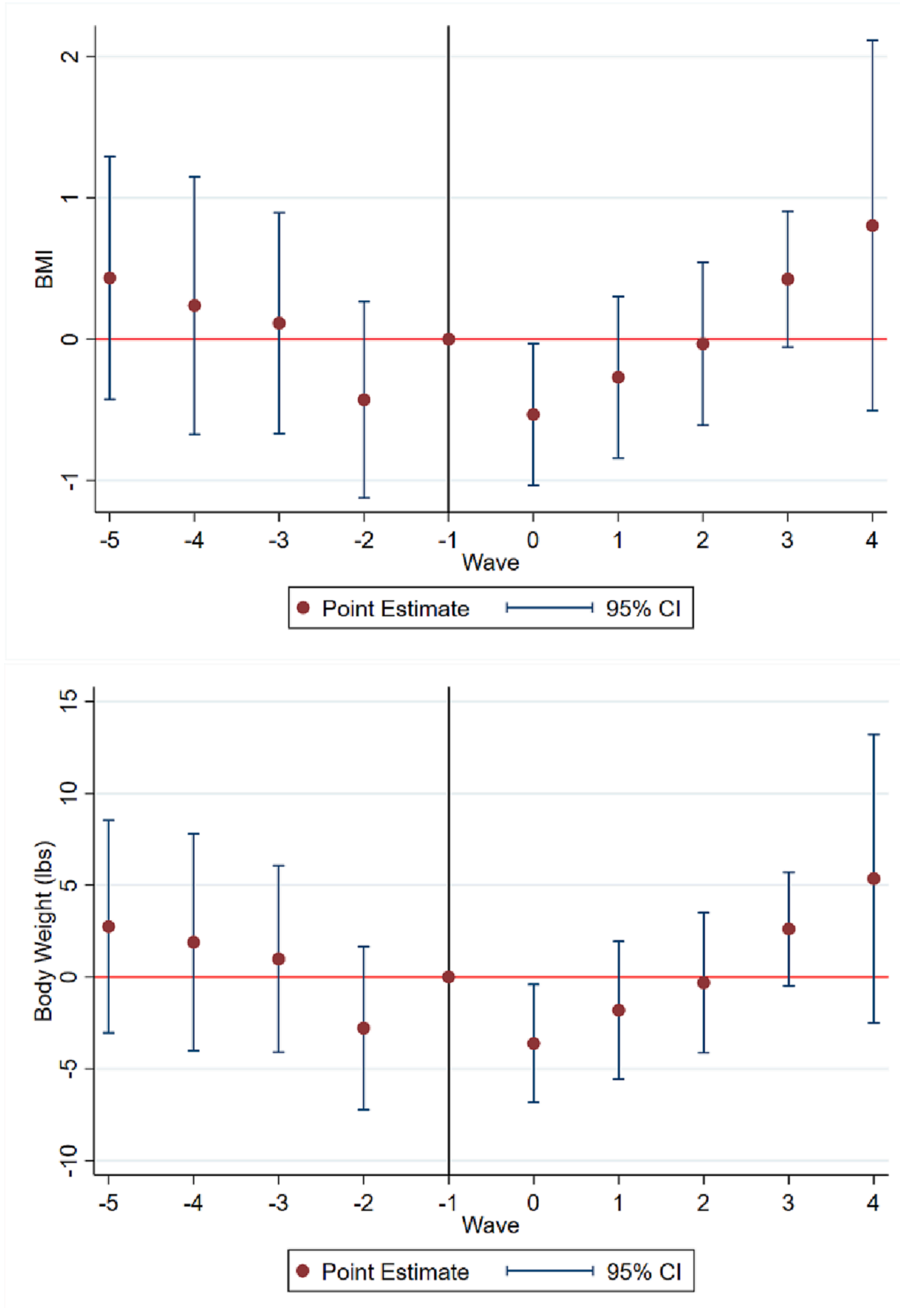

Fig. 2. An event study of tax reductions.

adults living in the bordering counties. The estimates are also significant at the 1% significance level.

7.2. An event study of tax reduction

We conduct an event study of tax reduction for two purposes. First, it mitigates the endogeneity concern by testing the parallel trend assumption. Second, it more clearly shows the impact of a single tax cut on body weight and provides a useful case study illustrating the consequence of grocery tax reduction/repeal. During our study window, many counties and states with grocery taxes changed their grocery tax rates multiple times. To simplify, we conduct the event study based on the counties that only experienced one decrease in the relative grocery tax rate. The control group contains individuals from counties without any tax changes. With a reduced sample size at 41,136, we estimate the following:

$$12)\ BMI_{ict} = \beta_0 + \sum_{j=-5}^{4}\beta_j D^j{}_{ct} + \boldsymbol{\theta Z}_{it} + \sigma_c + \psi_t + \lambda_c t + e_{ict},$$

where j is the wave running variable of the event, and $D^j{}_{ct}$ is a dummy variable measuring the event wave t relative to the real tax reduction wave t_c^*. If $t - t_c^* = j$ then $D^j{}_{ct} = 1$; otherwise, $D^j{}_{ct} = 0$. The tax reduction happens when $j = 0$, and the omitted wave is $j = -1$, the wave prior to the event. Therefore, $\beta_j{}'$ s for $j < -1$, corresponding to the four leads, indicate the anticipatory effects of tax reduction, and β_j's for $j \geq 0$, corresponding to the five lags, indicate the post treatment effects of tax reduction.

The event study plots of the anticipatory effects and post treatment effects are consistent with our main results (Fig. 2). The pre-trend is

Table 7
Alternative identifications for grocery sales tax rates.

Variables	(1) BMI	(2) Weight (pound)	(3) BMI	(4) Weight (pound)
Tax Ratio	0.426**	2.553**		
	(0.201)	(1.248)		
Grocery Food Tax			0.060**	0.357*
			(0.032)	(0.205)
Restaurant Food Tax			−0.070	−0.315
			(0.044)	(0.292)
Observations	75,598	75,598	77,769	77,769
R-squared	0.169	0.275	0.169	0.275
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
County Trend	Y	Y	Y	Y
Individual covariates	Y	Y	Y	Y

Note: Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance level, respectively.

parallel at 95% confidence interval (C.I.). We find that individual BMI decreases by 0.53 (95% C.I. is −1.033 to −0.032) due to one single tax reduction, translating to 3.62 lb (95% C.I. is −6.83 lb to −0.40 lb). The reduction in BMI fades away gradually overtime as time moves further away following the tax reduction. The magnitude of tax impact is larger than the main results for two possible reasons. The first is that the independent variable is a dummy variable, capturing tax rates decreases in the range from 0.1 to 6 percentage points with a mean of 1.36. The second possible reason is that the impact of tax reduction becomes weaker if it happens multiple times, while the event study here only looks at locations having one decrease in the tax. One potential reason for the fading tax impact beyond one year is the aforementioned tax salience. When a grocery tax is imposed or repealed, it attracts local media coverage. Later on, consumers may become less attentive to the tax because it is not reflected on the shelf price. Further, we estimated the average treatment effects of the tax reduction on BMI and bodyweight by applying generalized DID models and found the average treatment effects are negative and statistically significant. These results from the tax reduction example are consistent with our findings in the main BMI and weight results.

7.3. Alternative identifications for grocery sales tax rates

In addition to the relative grocery sales tax rate used in the main model, we estimate two alternative versions of the model for a robustness check: (1) the ratio between grocery and restaurant food sales tax rates is included as the main independent variable, and (2) the grocery and restaurant food sales tax rates are included as two separate independent variables. The results are shown in Table 7. The impacts of the grocery sales tax on BMI and body weight remain robust across different identifications. Both body weight and BMI increase significantly when either the tax ratio or the grocery sales tax rate increases.

8. Policy implications and conclusion

In this study, we examined the impacts of grocery taxes on BMI and body weight, as well as at-home and away-from home food expenditures, from both a theoretical and empirical perspective. We showed from a theoretical model that the grocery tax could affect body weight and food expenditures through changing the relative after-tax prices of grocery foods to restaurant foods. Using six waves of PSID panel data conducted from 2007 through 2017, we found support for the theoretical results empirically. There are three main policy implications of our findings.

First, we found that a one-percentage-point increase in grocery tax relative to restaurant tax led to a rise of BMI by 0.061, which translates to a body weight gain of about 0.361 lb. The results seem to be driven mainly by the overweight population, who are at the risk of becoming obese. This result is consistent with the finding of a recent study that a one percentage point increase in grocery taxes is associated with 0.588 percentage point increase in county-level obesity rates (Wang, et al., 2021). These findings highlight an important health policy consequence of increasing or decreasing grocery taxes (several states such as West Virginia are contemplating reinstating or increasing the grocery tax). If a local government decides to rely on grocery taxes as a source of revenue, the potential costs in terms of health outcome such as weight/BMI need to be taken into consideration as well in the benefit-cost analysis.

Second, we found that consumers substitute more restaurant foods for grocery foods when relative grocery taxes increase, corroborating earlier studies using cross-sectional survey [(Dong, et al., 2020, Zheng, et al., 2019)]. An important uniqueness of the current study is the examination of the heteronegeneous tax impacts by SNAP and income levels, allowing us to reveal the mechanism through which grocery taxes affect body weight. Our results show that grocery taxes mainly affect food expenditures for the low-income population. We also found that the tax does not affect the weight for SNAP households likely because SNAP benefits provide some shelter from the tax even though SNAP only covers less than 50% of the food-at-home expenditures (Tiehen et al., 2017). This suggests another health benefit of SNAP besides its widely-known function as the safety net to provide food assistance and protect child health (Bronchetti, et al., 2019). In 2021, 18% of eligible low-income households in the U.S. did not participate in SNAP (Cunningham, 2021). This cohort of the population constitutes one of the most vulnerable populations to the grocery taxes because they do not receive SNAP monetary benefits and therefore exemption from grocery taxes on those benefits, and could be the target population if a state decides to provide some tax relief such as in the form of a tax credit (e.g., Kansas provides a grocery tax credit through tax return). Also, from a public policy perspective, states with grocery taxes should consider additional outreach to encourage more SNAP eligible households to participate in SNAP.

Third, in terms of ways to combat obesity, it is useful to compare how grocery tax impacts compare with the findings of those of soda and junk food taxes, setting aside the fact that each tax serves a different purpose. According to the most optimistic estimation in literature, imposing a 20% soda tax reduces the body weight of an average individual by 1.54–2.65 lb every year (Dharmasena and Capps, 2012). Based on our findings, a similar range of body weight reduction could also be achieved by decreasing the grocery sales tax by 4.2–7.1 percentage points.

Several limitations of the study are worth noting. Since our dataset did not include food tax rates at municipal level (they exist in some cities, but historical data are difficult to obtain), ignoring grocery taxes at municipal level may cause our estimates to be biased due to the omitted variable bias. Additionally, our study did not consider tax rebates. There are three states that allow refunding grocery sales taxes to low-income, disabled, old and pregnant populations, but we were not able to identify who receive the tax rebates in our individual dataset. Third, we did not consider the potential impact of cross-border shopping behavior (the PSID does not report this) that results in tax avoidance (Beatty, et al., 2009, DeCicca, et al., 2013). Finally, the study estimates the effects of grocery and restaurant taxes on BMI and bodyweight with a focus on the substitution between grocery and restaurant foods. However, there are other ways individuals could react to the grocery tax including substituting less expensive grocery food for more expensive grocery food and/or more energy dense grocery food for less energy dense food in response to the tax, which could also help explain our empirical results. In the future, it would be useful to examine how grocery taxes affect the quality and quantity of grocery food purchases, including consumer choices between healthy and unhealthy foods within grocery foods, making use of more detailed data such as the scanner data. Our results should be interpreted with the above caveats in mind.

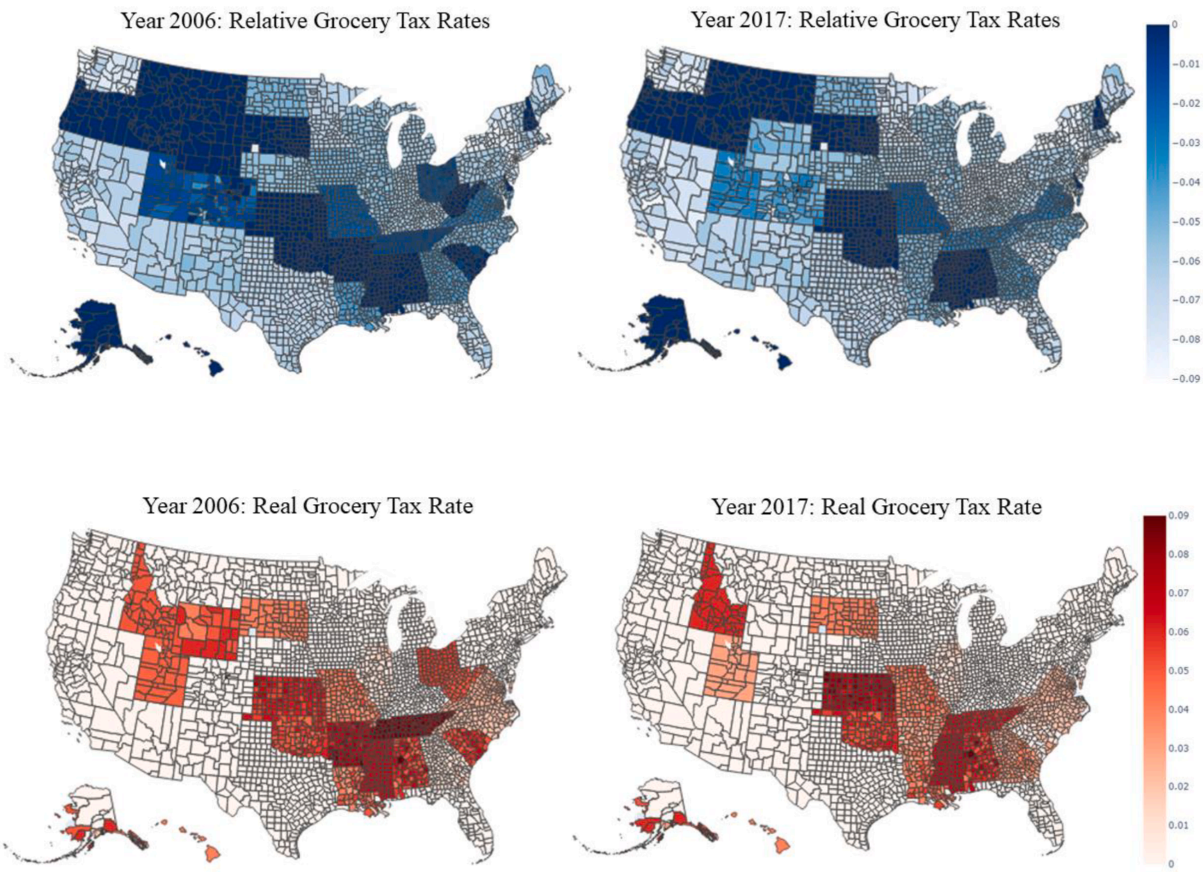

Fig. A1. Maps of the grocery sales tax changes at county level.

CRediT authorship contribution statement

Lingxiao Wang: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation. **Yuqing Zheng:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Harry M. Kaiser:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Proof of Food Consumption Proposition.

Suppose V_G and V_R are implicit utility functions of endogenous variables G, R, P_G, and P_R. Mathematically, we can write as $V_G(G^*, R^*, P_G, P_R) = 0$, and $V_R(G^*, R^*, P_G, P_R) = 0$ according to equation (6 and 7) (see Fig. A1).

In addition, G and R are functions of P_G and P_R, which can be expressed mathematically as $G(P_G, P_R)$ and $R(P_G, P_R)$. We follow the four steps below to derive $\frac{dG^*}{dP_G}$ and $\frac{dR^*}{dP_G}$, and then apply the Chain Rule to obtain $\frac{dG^*}{d\tau_G}$ and $\frac{dR^*}{d\tau_G}$.

Step 1: Calculate the total differentials of V_G, V_R, G and R.

$$dV_G = V_{GG}dG + V_{GR}dR + V_{GP_G}dP_G + V_{GP_R}dP_R = 0$$

$$dV_R = V_{RG}dG + V_{RR}dR + V_{RP_G}dP_G + V_{RP_R}dP_R = 0$$

$$dG = \frac{\partial G^*}{\partial P_G}dP_G + \frac{\partial G^*}{\partial P_R}dP_R$$

$$dR = \frac{\partial R^*}{\partial P_G}dP_G + \frac{\partial R^*}{\partial P_R}dP_R.$$

Step 2: Plugging dG and dR into dV_G and dV_R in Step 1, we can obtain:

$$dV_G = \left(V_{GG}\frac{\partial G^*}{\partial P_G} + V_{GR}\frac{\partial R^*}{\partial P_G} + V_{GP_G}\right)dP_G + \left(V_{GG}\frac{\partial G^*}{\partial P_R} + V_{GR}\frac{\partial R^*}{\partial P_R} + V_{GP_R}\right)dP_R = 0$$

$$dV_R = (V_{RG}\frac{\partial G^*}{\partial P_G} + V_{RR}\frac{\partial R^*}{\partial P_G} + V_{RP_G})dP_G + (V_{RG}\frac{\partial G^*}{\partial P_R} + V_{RR}\frac{\partial R^*}{\partial P_R} + V_{RP_R})dP_R = 0.$$

Since dP_G and dP_R are linearly independent, according to Step 2 we can obtain:

$$V_{GG}\frac{\partial G^*}{\partial P_G} + V_{GR}\frac{\partial R^*}{\partial P_G} + V_{GP_G} = 0\#(A1)$$

$$V_{GG}\frac{\partial G^*}{\partial P_R} + V_{GR}\frac{\partial R^*}{\partial P_R} + V_{GP_R} = 0\#(A2)$$

$$V_{RG}\frac{\partial G^*}{\partial P_G} + V_{RR}\frac{\partial R^*}{\partial P_G} + V_{RP_G} = 0\#(A3)$$

$$V_{RG}\frac{\partial G^*}{\partial P_R} + V_{RR}\frac{\partial R^*}{\partial P_R} + V_{RP_R} = 0\#(A4)$$

Step 3. To solve $\frac{\partial G^*}{\partial P_G}$ and $\frac{\partial R^*}{\partial P_R}$, we only need equations (A1) and (A3). The solution could be obtained using Cramer's Rule as

$$\frac{dG^*}{dP_G} = \frac{\partial G^*}{\partial P_G} = \frac{\begin{vmatrix} -V_{GP_G} & V_{GR} \\ -V_{GP_R} & V_{RR} \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}$$

$$\frac{dR^*}{dP_G} = \frac{\partial R^*}{\partial P_G} = \frac{\begin{vmatrix} V_{GG} & -V_{GP_G} \\ V_{RG} & -V_{GP_R} \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}.$$

Step 4. To finally calculate $\frac{dG^*}{dP_G}$ and $\frac{dR^*}{dP_R}$ in Step 3, we need to calculate $V_{GG}, V_{GR}, V_{RG}, V_{RR}, -V_{GP_G}$, and $-V_{GP_R}$. If we differentiate $V_G = U_C C_G - P_G U_z$ with G, we can obtain:

$$V_{GG} = U_{cc}{C_G}^2 + U_C C_{GG} - 2P_G U_{CZ} C_G + {P_G}^2 U_{ZZ} < 0.$$

Similarly, if we differentiate V_G with R, we can obtain:

$$V_{GR} = V_{RG} = U_{CC} C_G C_R - (P_R C_R + P_G C_G)U_{CZ} + U_C C_{RG} + P_R P_G U_{ZZ} < 0.$$

C_{RG} is the second-order cross partial derivative of food consumption, representing the change in the marginal consumption of restaurant food when grocery food increase marginally. Similar definition is applied for other second-order partial derivatives of food consumption such as C_{RR} and C_{GG}.

If we differentiate $V_R = U_C C_R - P_R U_z - b\delta$ with R, we can obtain:

$$V_{RR} = U_{cc}{C_R}^2 + U_C C_{RR} - 2P_R U_{CZ} C_R + {P_R}^2 U_{ZZ} < 0.$$

If we differentiate $V_G = U_C C_G - P_G U_z - b\epsilon$ with P_G and we can obtain:

$$V_{GP_G} = \frac{\partial V_G}{\partial P_G} = -U_Z.$$

If we differentiate $V_G = U_C C_G - P_G U_z - b\epsilon$ with P_R and we can obtain:

$$V_{GP_R} = \frac{\partial V_G}{\partial P_R} = 0.$$

On the other hand, since $\begin{pmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{pmatrix}$ is a Hessian Matrix, the second order condition implies $\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix} > 0$.

Therefore, we sign $\frac{dG^*}{dP_G}$ and $\frac{dR^*}{dP_G}$ as:

$$\frac{dG^*}{dP_G} = \frac{\partial G^*}{\partial P_G} = \frac{\begin{vmatrix} U_Z & V_{GR} \\ 0 & V_{RR} \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} = \frac{U_Z V_{RR}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} < 0$$

$$\frac{dR^*}{dP_G} = \frac{\partial R^*}{\partial P_G} = \frac{\begin{vmatrix} V_{GG} & U_Z \\ V_{RG} & 0 \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} = \frac{-U_Z V_{RG}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} > 0.$$

Applying the Chain Rule, we finally have:

$$\frac{dG^*}{d\tau_G} = \frac{dG^*}{dP_G} * p_G = \frac{\partial G^*}{\partial P_G} * p_G = \frac{\begin{vmatrix} U_Z & V_{GR} \\ 0 & V_{RR} \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} * p_G = \frac{p_G U_Z V_{RR}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} < 0$$

Table A1
An illustrative example of a 10% grocery tax (in $).

	No Grocery Tax		10% Grocery Tax		Change
	(1) Spending	(2) Purchasing Power	(3) Spending	(4) Purchasing Power	(4) – (2)
SNAP Households					
SNAP	40	40	40	40	0
Cash Grocery	60	60	53.66	48.78	−11.22
Restaurant	50	45.45	54.14	49.22	3.77
Total	150	**145.45**	147.80	**138.00**	−7.45
Non-SNAP Household					
SNAP	0	0	0	0	
Cash Grocery	100	100	95.01	86.37	−13.63
Restaurant	50	45.45	52.84	48.03	2.58
Total	150	**145.45**	147.85	**134.41**	−11.04

Note: a 10% restaurant tax is imposed in all cases.

Table A2
Generalized DID results for the tax reduction events.

Variables	(1) BMI	(2) Weight (pound)
Tax Reduction	−0.209**	−1.244**
	(0.099)	(0.614)
Observations	38,151	38,151
R-squared	0.879	0.921
Year FE	Y	Y
County FE	Y	Y
County Trend	Y	Y
Individual covariates	Y	Y

Note: Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

Table A3
Endogeneity tests for relative grocery sales tax rates.

Variables	(1) BMI	(2) Weight (pound)
TaxDif_{ct+1}	0.062	0.161
	(0.044)	(0.290)
Observations	65,503	65,503
R-squared	0.156	0.259
Year FE	Y	Y
County FE	Y	Y
County Trend	Y	Y
Individual covariates	Y	Y

Note: Standard errors are in parentheses and clustered at the county level; ***, **, and * denote 1%, 5%, and 10% significance levels respectively.

$$\frac{dR^*}{d\tau_G} = \frac{\partial R^*}{\partial P_G}{}^*p_G = \frac{\begin{vmatrix} V_{GG} & U_Z \\ V_{RG} & 0 \end{vmatrix}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}{}^*p_G = \frac{-p_G U_Z V_{RG}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}} > 0$$

Proof of Weight-Gain Proposition

$$\frac{dS^*}{dP_G} = \frac{\partial S}{\partial R}\frac{\partial R^*}{\partial P_G} = \delta\frac{-U_Z V_{RG}}{\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix}}$$

Since we know that $U_Z > 0$ and $\begin{vmatrix} V_{GG} & V_{GR} \\ V_{RG} & V_{RR} \end{vmatrix} > 0, < 0 V_{RG}$, then $\frac{dS^*}{dP_G} > 0$ is proved.

by applying the Chain Rule, we have that $\frac{dS^*}{d\tau_G} = \frac{dS^*}{dP_G}{}^*p_G > 0$. (see Tables A1-A3).

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