Taxing Consumption and the Take-Up of Public Assistance: The Case of Cigarette Taxes and Food Stamps

Kyle Rozema* Nicolas R. Ziebarth†

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Abstract

We exploit cigarette tax variation across US states from 2001 to 2012 to show how taxing inelastic consumption goods can induce low-income households to enroll in public assistance programs. Using the CEX and a novel CPS household panel of monthly food stamp enrollment, we enrich standard cigarette tax difference-in-differences models with an additional control group: non-smoking households. Smoking households are "treated" with higher taxes while non-smoking households are not. Marginal smoking households respond to increases in cigarette taxes by taking-up food stamps at rates higher than smoking households in other states and non-smoking households in the same state.

Keywords: consumption taxes, cigarette taxes, public assistance programs, food stamps, program participation

JEL codes: L66, H21, H23, H26, H71, I18

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*Northwestern University Pritzker School of Law, 375 East Chicago Avenue, Chicago, IL 60611, e-mail: kyle.rozema@law.northwestern.edu.

†Cornell University, Department of Policy Analysis and Management, 106 Martha Van Rensselaer Hall, Ithaca, NY 14850, e-mail: nrz2@cornell.edu.

1 Introduction

Over the past two decades, policy makers in the United States have substantially increased cigarette taxes. Cigarette taxes raise government revenue and reduce cigarette consumption, but also alter behavior in ways unintended by policymakers: smokers respond strategically to increases in cigarette taxes by stockpiling (Chiou and Muehlegger, 2014), switching to higher tar and nicotine cigarettes (Farrelly et al., 2004), becoming more efficient smokers by extracting more nicotine out of cigarettes (Adda and Cornaglia, 2006, 2013), and purchasing cigarettes in nearby lower tax jurisdictions (Gruber et al., 2003; Lovenheim, 2008; Goolsbee et al., 2010; DeCicca et al., 2013).

This article shows that taxation of demand-inelastic consumption can induce low-income households to take-up public assistance programs. To make this point, we use the example of cigarette taxes, low-income smoking households, and the Supplemental Nutrition Assistance Program (SNAP).[1] We use cigarette taxes as a case study because of its useful technical properties, including the rich variation across and within US states over time. However, we believe that any tax on basic consumption goods—such as sales taxes—could also trigger the behavioral response that we study.

Like many other public assistance programs, SNAP is means-tested and enrollment is not automatic. Because people have to be informed about the existence of the program and actively enroll, take-up is imperfect. In 2001, for instance, an estimated 48% of all eligible households participated in SNAP (Lerman and Wiseman, 2002). In addition to information frictions, two main barriers can prevent households from taking up public assistance programs: transaction costs and stigma. Transaction costs include the costs to enroll, such as the time spent on paperwork and travel costs (Currie, 2004). These costs might be non-trivial. Using SNAP as an example, initial applications may take five hours to complete and usually require several trips to an administration office (Ponza et al., 1999). The second type of costs are non-pecuniary in nature: stigma. Since Moffitt's (1983) seminal work on welfare stigma, most program participation models acknowledge that households incur disutility from the social stigma involved in program participation, and a rich literature has documented the existence of stigma and its role in take-up decisions (e.g.,

[1] SNAP was formerly known as the Food Stamp Program (until 10/2008). Henceforth, we use SNAP and 'food stamps' interchangeably.

Hoynes and Schanzenbach, 2009; Kleven and Kopczuk, 2011; Hansen et al., 2014). Official data show that, in 2015, the average monthly SNAP benefit was just $127 per person (USDA, 2015). This relatively small amount helps explain why transaction costs and stigma may prevent eligible households from enrolling.

Our empirical analysis uses data from the Current Population Survey (CPS) and the Consumer Expenditure Survey (CEX) from 2001 to 2012. In addition to making use of the the cross-sectional nature of both datasets, we construct a novel CPS pseudo-panel that follows households' food stamp enrollment throughout every month of a calendar year. This panel allows us to observe both smoking and non-smoking households transitioning onto food stamps from one month to another. Our identification strategy enriches difference-in-differences models by using non-smoking households within a state as an additional control group. Smoking households within a state are "treated" with higher taxes while non-smoking households within the state are not.

To investigate the extent that cigarette tax increases translate into cigarette expenditure increases, we first assess the degree to which taxes increase equilibrium prices. We then estimate the effect of cigarette taxes on cigarette expenditures and finally on food stamp enrollment. For each $1 increase in cigarette taxes, cigarette prices as paid by consumers increase by $0.73. For the mean smoking household consuming 22 packs per month, a $1 increase in taxes without reductions in consumption would therefore translate into monthly spending increases of about $16. However, 20% of all low-income smoking households consume at least 45 packs a month, and thus would experience monthly income shocks of at least $30 for each $1 increase in cigarette taxes. Results from the CPS and CEX confirm significant increases in cigarette expenditures following cigarette tax increases.

Our main findings show that cigarette tax increases can induce low-income smoking households to enroll in food stamps. A $1 increase in cigarette taxes increases the probability that eligible, but non-enrolled, smoking households take-up food stamps by 3.2ppt from a baseline probability of about 25%. For the average $0.56 state cigarette tax increase in our sample period, the point estimate implies a 7% increase in the probability that eligible, but non-enrolled, smoking households take-up food stamps. In contrast, non-smoking households are not more likely to enroll in food stamps after cigarette tax increases.

Our findings contribute to several strands of the economics and public policy literatures. First, they contribute to the literature examining behavioral responses to taxation and tax avoidance behavior. Second, they contribute to the behavioral public finance literature in the sense that we study concepts of uncoordinated regulation (e.g., Kenkel, 1993; Mason and Swanson, 2002). Whereas governments gain revenues from higher taxes, higher prices contribute to spending increases in public assistance programs. Lastly, they contribute to the literature examining factors that affect the take-up of public assistance programs (e.g., Ziliak et al., 2003; Kabbani and Wilde, 2003; Ribar et al., 2008; Bitler and Karoly, 2015; Pei, 2017).

The organization of this article is as follows. Section 2 provides a brief background of SNAP. Section 3 describes the identification strategy and Section 4 the data. Section 5 presents the results and the final section concludes.

2 Background

Figure 1 shows that *real* cigarette prices increased by about 50% from \$4 to \$6 between 2000 and 2011. Real state cigarette tax revenues also increased by over 50% from \$10.6 billion in 2000 to \$17.1 billion in 2011 (Tax Burden on Tobacco, 2012). Figure 1 also shows that the share of the US population enrolled in food stamps has more than doubled from 6% to over 14% over the same time period. Part of the large increase in food stamp enrollment has been attributable to both demand side factors such as changes in the unemployment rate (Ziliak et al., 2003; Hanson and Oliveira, 2012; Ziliak, 2015; Bitler and Hoynes, 2016) and supply side factors such as the eligibility rules concerning vehicle asset limits and reporting requirements (Klerman and Danielson, 2011).

[Insert Figure 1 about here]

This section provides a brief background of the general rules governing SNAP eligibility requirements and the calculation of benefit levels. See Klerman and Danielson (2011) for an overview of the changes to SNAP during the 1990s and 2000s.

Eligibility. There are two main eligibility requirements. First, households must meet income requirements, broken down into a gross and net income test. The general threshold for the gross income test is 130% of the Federal Poverty Line (FPL). In 2016, this amounts to $1,276 per month for a one-person household and $2,628 per month for a four-person household. The net income test takes the household's gross income and then applies the following deductions to calculate a household's 'net income' (USDA, 2016): *(i)* a standard deduction of between $155 and $168, *(ii)* 20% from earned income, *(iii)* dependent care deductions or child support payments, *(iv)* medical expenses for disabled or elderly, and *(v)* other. The resulting net income must not exceed 100% of the FPL. In 2016, this amounts to $981 per month for a one-person household and $2,021 per month for a four-person household.

The second main eligibility requirement is an asset test. As of 2016, the general rule is that households must have $2,250 or less in 'countable' resources (USDA, 2016). The types of assets that are counted in the asset test differ across states. For instance, the asset test in 48 states excludes the value of the household's primary vehicle, and the asset test in 33 of those states excludes the value of all vehicles. The asset test is also applied differentially by household attributes. For instance, households with a disabled person or a person above the age of 60 have an asset threshold of $3,250 (USDA, 2016).

Benefits. The calculation of SNAP benefits is premised on the general expectation that households spend 30% of their income on food. The benefit level is therefore set such that 30% of the net income is subtracted from the maximum SNAP benefits, which depend on the household size (USDA, 2016). In 2016, the maximum monthly benefit for a one-person household is $194 and $649 for a four-person household. For example, if the monthly net income for a four-person household is $1,500, then this household is expected to spend $450 on food, and hence the available SNAP benefit is ($649 - $450 =) $199 per month.

3 Empirical Approach and Identification

Equation (1) sets out our main econometric specification.

$$y_{it} = \alpha + \beta\tau_{st_{-1}} \times h_{it} + \gamma\tau_{st_{-1}} + \psi h_{it} + \theta X_i + \xi u_{st} + \pi f_{ct} + \sigma_t + \rho_s + \varepsilon_{it} \tag{1}$$

where y_{it} represents the dependent variable of interest for household i in state s in calendar month t. $\tau_{st_{-1}}$ is the state cigarette tax in state s lagged by one month. h_{it} is an indicator for smoking households. X_i is a vector of socio-demographic covariates, and u_{st} is the unemployment rate. Food price inflation, f_{ct}, is controlled for at the census region c level. σ_t are calendar month fixed effects and ρ_s are state fixed effects. In our preferred specifications, we additionally include state time trends η_{s_t}. For the panel of household food stamp enrollment, we enrich the model by employing interactions between state fixed effects and the smoking household indicator ($\rho_s \times h_{it}$) to net out state-specific behavior of smoking households, and employ household fixed effects v_i, which absorb the time-invariant X_i and ρ_s.[2]

The interaction term $\tau_{st_{-1}} \times h_{it}$ yields the main variable of interest. It relates changes in cigarette taxes to SNAP enrollment, but only for smoking households. The main effect of taxes $\tau_{st_{-1}}$, by contrast, yields the impact for non-smoking households. The impact for non-smoking households should be small and not significant, whereas the interaction term should carry a significant coefficient. Standard errors are routinely clustered on the state level (Bertrand et al., 2004).

We employ Equation (1) using both cross sectional and panel data on food stamp enrollment. Using the cross-sectional data, Equation (1) links changes in cigarette taxes to smoker households' probability of enrolling in food stamps. Using the panel data with household fixed effects, Equation (1) links changes in state cigarette taxes to smoker households' probability to transition onto food stamps. When using the monthly panel data on food stamp enrollment, we add a set of contemporaneous and lagged cigarette tax regressors, both in levels and interactions with the smoking household indicator, to capture the full cumulative effect of a tax increase on take-up over several months.

The main identification assumption is that there are no other unobserved factors that are correlated with both state cigarette tax increases and an over-proportional increase in food stamp enrollment for smoking households. Changes to the SNAP program at the federal level (cf. Section 2) are absorbed by the calendar month fixed effects. State level program changes are only a threat to the identification strategy if they *(i)* were correlated with cigarette tax changes, and *(ii)* would

[2] In the most saturated specifications, we also experiment with including smoker-year-month and state-year-month fixed effects. While our main panel results are robust to these additional sets of two-way interactions, the results of the CPS cross section are not. The reason is that the specification with all two-way interactions is very data demanding and the CPS cross section is only based on six different month-year cross sections (Section 4.1).

affect the take-up of low-income smoking households differently than the take-up of low-income non-smoking households, which is unlikely to be the case.

Another potential confounding factor is food price inflation. If, for whatever reason, food prices were to increase at the same pace as cigarette taxes, e.g., through supply shocks or state taxes, then it would be difficult to disentangle the increase in food stamp enrollment due to higher food prices from those of higher cigarette taxes. However, in that case, one would expect cigarette taxes to increase the likelihood that non-smoking households enroll in food stamps as well. As we will show below, this is not the case; the effects are solely driven by smoking households. In addition, we control for the monthly food prices at the level of the four US census regions (f_{ct}) in all our models. Figure A1 in the Appendix plots food and cigarette prices for the four US regions over time. In line with our priors, Figure A1 shows that the increase in cigarette prices between 2000 and 2011 outpaced food price inflation. While food prices increased by about 50% in all four US regions (in the Northeast a little bit more, in the West a little bit less), cigarette prices more than doubled in all regions and even tripled in the Northeast.

In principle, there is a consensus in the economics literature that changes in state-level taxes are exogenous to individuals. However, it may be that people move or choose their state of residence based on preferences, among them cigarette taxes (Tiebout, 1956; Zodrow and Mieszkowski, 1986). Our approach, like the majority of approaches similar to ours in the literature, conditions the findings on the behavior of people in specific high or low-tax states. It is not obvious that people in low-tax state A would react in the same manner in a high-tax state B to changes in taxes. In addition, but again like most studies in the literature, we cannot entirely preclude that migration based on tax changes biases our results. However, one would need to assume that moving out of state due to higher cigarette taxes induces lower costs than food stamp take-up, which is unlikely to be the case.

Consequently, all estimates ought to be interpreted as intent-to-treat (ITT) estimates. In our opinion, ITT estimates are the policy-relevant estimates and provide evidence on how people respond to incentives in real-world settings. This means that we deliberately allow for compensatory behavior of smokers as a reaction to higher taxes, such as reducing cigarette consumption, cross-border shopping, switching cigarette brands, or becoming a more efficient smoker.

4 Data and Descriptive Statistics

This paper makes use of several data sources. Our three main datasets are *(a)* CPS cross-sectional data, *(b)* CPS pseudo-panel data, and *(c)* CEX cross-sectional data. The unit of observation is always the household because this is the relevant economic unit where public assistance enrollment decisions are made and where the means-testing requirements are applied. Below we describe each of the three datasets. We merge in information on monthly state cigarette taxes (Tax Burden on Tobacco, 2012), monthly state unemployment rates (BLS, 2015b), and monthly food price inflation (BLS, 2015a). All monetary values are adjusted to 2016 dollars using the CPI.

4.1 CPS: Food Security Supplement (FSS) & Tobacco Use Supplement (TUS)

Two of the datasets that we employ are based on the CPS. The CPS is conducted by the US Census Bureau for the Bureau of Labor Statistics (BLS). It is a monthly survey of approximately 60K US households, and is mainly used for labor force statistics. However, data on special topics ranging from tobacco use to food security are gathered periodically in "supplemental" surveys. All households in the CPS are interviewed in each of four consecutive months, then after eight months, are surveyed again for four months. A share of households surveyed in the main survey is also surveyed in the applicable supplemental survey of that month (U.S. Census Bureau, 2016a).

We combine the Tobacco Use Supplements (TUS) and the Food Security Supplements (FSS) of the CPS from 2001 to 2011. As a general CPS rule, each household is surveyed a maximum of one time in both of the TUS and FSS. Because of the 4-8-4 month surveying rule, not all households answer both the TUS and the FSS. We focus on CPS households that answered both the TUS and FSS. We use the TUS as baseline survey, and then merge in the FSS food stamp information. Because the FSS is carried out in December of each year in our sample, we make use of the following TUS supplements: November 2001, February 2002, February 2003, November 2003, January 2007, January 2011.

Smoking Information. The TUS reports the smoking status of each household member at the time of the survey. Importantly, the TUS also elicits retrospective smoking information and reports the smoking status of each household member as of 12 months before the TUS interview.

SNAP Information. In each FSS, enrollment status in food stamps is elicited separately for *each month* of the past calendar year (January until December of the year of the FSS). It is important to note that the CPS only elicits food stamp enrollment information for households below 185% of the federal poverty line (FLP). This is because only those households are, in principle, eligible for SNAP.[3] We therefore restrict the sample to households below 185% of the FPL.

(a) CPS Cross-Sectional Data

We first generate a cross-sectional dataset which uses the TUS as the reference dataset. (The results are robust to using the FSS demographics). This means that we make use of the information on socio-demographics and cigarette consumption from the TUS, and merge in food stamp enrollment information of the same calendar month for households that completed the TUS in a month in which food stamp enrollment is observed from the FSS.[4] For the CPS cross-sectional dataset, we define a "smoking household" as one that has at least one smoking member in the month where we observe information on both smoking status and food stamp enrollment. (We do not project the smoking or food stamp enrollment status forward or backward in time.)

Table 1 reports descriptive statistics. Of the 26,729 food stamp eligible households in the sample, 10.1% are enrolled in food stamps and 28%have at least one member who currently smokes cigarettes. The mean smoking household consumes less than a pack per day (14.6 cigarettes), but there is significant heterogeneity in consumption with a large share of households consuming at least 2 packs per day (12%) and 3 packs per day (3%). With a mean state tax of $0.91, the mean price of a pack of cigarettes is $4.41. Multiplying the number of daily cigarettes consumed (in packs) by the cigarette prices paid by each smoker in the household and extrapolating to quarterly expenditures (to match the time frame of expenditures in the CEX), one observes that the average smoking household spends $393 on cigarettes each quarter. However, the expenditure distribution is skewed to the right, with 20% of households spending more than $500 per quarter on cigarettes—just about one week of the average monthly income of $1,930.

[3]As explained in Section 2, the general gross income test requires households to have income below 130% FPL. However, because of the 'Categorical Eligibility' possibility that may make some households eligible, the CPS producers chose the 185% threshold for the filter question.

[4]The CPS is conducted by physical location. We follow the CPS instructions to limit households to the same family in the TUS and FSS.

State taxes vary between \$0.03 for Virginia from 2001 to 2004 and \$4.58 for New York after August 1, 2010. Figure A2 in the Appendix illustrates the rich state-time variation in the level of state cigarette taxes. Conditional on an increase, the average tax increase was \$0.56. Most states increase cigarette taxes in relatively large amounts after longer periods without tax changes (see Figure A3 in the Appendix).

[Insert Table 1 about here]

The regression models adjust the already relatively homogeneous sample by a standard set of socio-economic characteristics, including household size, household income, race, and the education, age, and marital status of the head of the household. The average household has 2.5 members. Roughly half of all household members are male; the household head is on average 52 years old, most likely white and not married. Almost 30% have no high school degree.

(b) CPS Pseudo-Panel

We generate a CPS pseudo-panel which again uses the TUS as the reference dataset. This means that we extract the time-invariant information on socio-demographics from the TUS. This is the reason why we call the dataset a "pseudo-panel"—because socio-demographics are constant over time. What varies over time at the household level is food stamp enrollment, which is available for each month of the calendar year.

Because the TUS is carried out irregularly and the FSS is always carried out in December, the pseudo-panel follows households for different lengths of time. First, for households sampled in the TUS in January of year t, we use 11 months of food stamp enrollment information of year $t-1$. This applies to the TUS of January 2007 and 2011 which we merge with the FSS of December 2006 and 2010.[5]

Second, we use the households of the November 2003 TUS and the December 2003 FSS to track household food stamp enrollment information for 10 months. Hence, as shown in Table A1 of the Appendix, our pseudo-panel includes observations from 2003, 2006, and 2010. Note that

[5] To be conservative, we omit the January 2006 and 2010 enrollment information because those surveyed at the end of the month might interpret the smoking status question referring to '12 month ago' as referring to February of 2003 and 2010, respectively. The results are robust to the inclusion of food stamp enrollment data in January 2006 and 2010.

we deliberately decided to restrict the pseudo-panel to households with at least 10 months of food stamp enrollment information. One reason is that it allows us to carry out an event study with a relatively balanced set of observations. The results, however, are robust to using all households that were interviewed in the TUS and FSS between 2001 and 2011.

In the CPS pseudo-panel, 17% of households are enrolled in food stamps in any given month. The take-up rate in a given month is naturally much smaller, on average 0.6%, meaning that each month 0.6% of the households in our sample transition onto food stamps. Along with the variation in state cigarette taxes, these 1,685 households who transition onto food stamps provide the identifying variation for our empirical analysis when employing the pseudo-panel.

4.2 Consumer Expenditure Survey (CEX)

Since 1984, the Consumer Expenditure Survey (CEX) has been carried out by the BLS. The main unit of observation is the so-called Consumer Unit (CU). The CEX is designed to be representative of the US non-institutionalized civilian population. Each quarter about 7,000 interviews are conducted (BLS, 2014).

The CEX consists of two main surveys: *(i)* the Interview Survey (IS), and *(ii)* Diary Survey (DS). In the IS, CUs are interviewed every three months over the course of 15 months. Income and employment information are solely surveyed in the second and fifth interviews while expenditure information is surveyed from the second to the fifth interview.

We focus on BLS provided family files, containing food stamp information from 2001 to 2012. Those files contain income, expenditure, and housing information at the CU level. Because we are using the public version of the CEX, only a subset of observations are available with state identifiers (BLS, 2014). We restrict the sample to CUs with complete income information and the second interview. This implies that we rely on representative cross sections for the CEX.

We employ the CEX in addition to the CPS for three reasons: *(a)* to check for the consistency of the CPS results, *(b)* to exploit a sample that spans observations more evenly across calendar months and years (see Table A2 in the Appendix), and *(c)* to exploit the potentially more reliable expenditure information in the CEX. To make the findings comparable, we also condition the CEX on low-income households at or below the 185% FPL. In contrast to the CPS, the CEX does not have a filter question for whether CUs are at or below 185% of the FPL. We employ the 2015 Poverty Guidelines as well as the annual gross CU income—as calculated by the BLS and provided in the CEX—to identify and restrict to households at or below the 185% FPL. Our final sample contains information on 24,729 households.

Table 2 provides descriptive statistics. Roughly 12% of households were enrolled in food stamps between 2001 and 2012. Slightly more than 23% of all low-income CEX households are smoking households. The average smoking households spends $270 on cigarettes each quarter. Although cigarette expenditures are reported in a different fashion in the CEX as compared to the CPS—namely, total expenditures in the last quarter—the measures are remarkably consistent with the CPS.

[Insert Table 2 about here]

Socio-Demographic Controls. We generated a set of socio-demographics that compares to those in the CPS. The CEX has similar socio-demographic characteristics to that in the CPS. The CEX sample has an average of 2.5 members per household (CPS: 2.5) and the average age of the household head is 54 years (CPS: 52 years). Forty-seven percent of all household heads are employed (CPS: 44%) and 23% are high school dropouts (CPS: 23%). The reported household income after taxes includes a very comphrehensive set of monetary income flows and is higher in the CEX ($29.6K vs. $21.7K).[6] In contrast, the CEX contains a slightly lower proportion of smoking households (23% vs. 28%).

5 Empirical Results

We use cigarette tax increases as a case study for how taxes on inelastic consumption goods may induce eligible but non-enrolled households to enroll in public assistance programs. Section 5.1 investigates how taxes increase equilibrium cigarette prices and cigarette expenditures. Section 5.2 investigates the effect of cigarette taxes on food stamp enrollment.

[6] To avoid confusion we decided to bottom code the 236 households whose reported overall post-tax income is negative and set the minimum values to zero.

5.1 Cigarette Taxes, Prices, and Household Expenditures

Using the cross-sectional CPS data, we first estimate the extent to which cigarette taxes are passed through to cigarette prices. For this exercise, we employ the specification in Equation (1) but omit non-smoking households. The dependent variable is the self-reported price for the last pack of cigarettes bought. Columns (1) and (2) of Table 3 show the results. Each column represents one specification that differs only by the inclusion of set of covariates as indicated in the lower portion of the table. In our preferred specification (Column (2)), we find that taxes are passed through to prices at a rate of 0.73. This pass-through rate is right in line with the recent literature (e.g., Harding et al., 2012).

[Insert Table 3 about here]

Next, we estimate the effect of higher cigarette taxes on cigarette expenditures, which are conveyed through the average pass-through rate of 0.73. We again employ Equation (1) to estimate the tax effect on expenditures. Columns (3) and (4) of Table 3 show the results using the CPS cross-sectional dataset and Columns 5 and 6 show the results using the CEX dataset. When adjusting the CPS sample for socio-demographics, a \$1 increase in cigarette taxes increases quarterly cigarette expenditures by \$29 (Column (4)). The estimates from the CEX (Columns (5) and (6)) yield a very consistent and statistically significant increase in quarterly expenditures by \$24 for the average smoking household.

5.2 Cigarette Taxes and Food Stamp Enrollment

Event Study. The panel nature of our CPS dataset naturally gives rise to a non-parametric visual assessment of food stamp enrollment before and after cigarette tax increases through an event study. The "treatments" (cigarette tax increases) are staggered in time and across households in different states over time. Only smoking households are 'treated' by cigarette tax increases and non-smoking households serve as controls.

We define the event time as calendar month minus the month taxes were increased for each household such that the month of the increase in cigarette taxes becomes event time 0. Following the standard balanced-panel event study approach in the literature (e.g., Simon, 2016), we use a balanced panel of households who were present in the data for four months before and after a tax change. We estimate Equation (1) with household fixed effects but replace taxes with event time indicator variables for each month around a state cigarette tax increase. The approach assumes that taxes across states have the same effect on food stamp enrollment in the months around a tax change. Each event time coefficient for smoking households indicates the propensity of smoking households to take-up food stamps in a given month, relative to households in other states and non-smoking households within the same state.

Figure 2 shows the event study graph where we plot the estimated event time coefficients (95% confidence standard error bars are reported). Following Chetty et al. (2014), we normalize the coefficients for both smokers and nonsmokers in the first month of the event study to facilitate interpretation of the findings. The propensity of smoking and non-smoking households to enroll in food stamps in the two to four months before increases in taxes is very similar, stable, exhibits almost no trend, and the confidence intervals overlap. The propensity of non-smoking households does not change over the entire period after the tax-increase. However, the propensity of smoking households to enroll in food stamps begins to increase in the month before the tax increase, and further increases in the month of the tax increase (becoming statistically significant at event time 0). In the months following the tax increase, the event time estimates for smoking households remain highly elevated at a level that is statistically different from the flat propensity to enroll for non-smoking households.

[Insert Figure 2 about here]

One would expect the increase in enrollment to persist past month t_1 because many households who apply for food stamps in t_0 obtain benefits for the first time after t_1 due to the timing of the application process. One would also expect the observed anticipatory effect because tax increases are enacted usually a number of months before the higher taxes become effective (Gruber and Kőszegi, 2001), and stockpiling behavior of smokers before a tax increase is well documented (Chiou and Muehlegger, 2014). The timing of stockpiling is very consistent with the observed timing of the anticipatory effect. In particular, Chiou and Muehlegger (2014) find that stockpiling behavior occurs over the course of 8 weeks after taxes have typically been enacted but before the higher taxes become effective. Given the timing of the food stamp application process, stockpiling beginning two months before a cigarette tax increase is exactly the time period in which smoking households enroll in food stamps in Figure 2.

In summary, Figure 2 shows a clear increase in the propensity of low-income smoking households to enroll in food stamps in the month of a cigarette tax increase and the months following the increase. In contrast, over the tax increase cycle, Figure 2 shows flat enrollment propensity for non-smoking households.

Regression Framework. Using the cross-sectional data, we parametrically relate changes in state cigarette taxes to food stamp enrollment by estimating Equation (1). The dependent variable is food stamp enrollment—a binary indicator of whether the household is currently enrolled in food stamps. The results are shown in Table 4. The columns in Table 4 show specifications differing by the set of covariates included and dataset employed. Columns (1) through (3) use the CPS cross-sectional dataset, and Columns (4) through (6) use the CEX dataset.

[Insert Table 4 about here]

The main effect of interest is the interaction term between state cigarette taxes and smoking households. It indicates the statistical relationship between cigarette tax increases of $1 and the probability that low-income smoking households are enrolled in food stamps.[7] We find that each $1 increase in cigarette taxes increases in the likelihood that low-income smoking households enroll in food stamps by between 3.2 and 4.3 percentage points (Columns (1) to (3)). Relative to the mean, the results are consistent in the CEX where we find that each $1 increase in taxes increases the likelihood of food stamp enrollment by 5.8ppt in our preferred specification (Column (6)). It is noteworthy that the coefficients of interest remain stable when we add covariates stepwise to the models. This reinforces that the identifying variation is exogenous.

Additional evidence against the notion of spurious correlations between tax increases and food stamp enrollment is represented by the main effect on state cigarette taxes, which reflects the effect of tax increases on food stamp enrollment of non-smoking households. Across all six specifications, the magnitude of the main effect is rather small, its sign ambiguous, and it is in

[7] We report results from a linear probability model because the interaction terms are readily interpretable (see Ai and Norton, 2004; Karaca-Mandic et al., 2012), but the results carry over to non-linear estimation.

only one specification statistically significant. The estimates show that the relationship between cigarette taxes and food stamp enrollment is exclusively driven through smoking households.

Monthly Transitions Onto Food Stamps. Next, we exploit within-household variation in food stamp enrollment from the CPS pseudo-panel. Because we have already witnessed that the actual effect of cigarette taxes on food stamp enrollment emerges gradually during the post-tax period (Figure 2), we estimate a distributed lag model where we include a set of contemporaneous and lagged tax effects in levels and interactions. The distributed lag model estimates month-by-month incremental changes in enrollment relative to the average enrollment before the tax change.[8] The sum of the coefficients provides the cumulative effect. We stop the series at three lags. (Very similar results are obtained in robustness checks with four and five lags.) The results are shown in Columns (1) to (3) of Table 5.[9] We get very consistent results with a first difference specification (see Table A3 in the Appendix), which provides evidence for the strict exogeneity assumption (Grieser and Hadlock, 2016).

[Insert Table 5 about here]

Column (1) includes household covariates. Column (2) includes household fixed effects, and Column (3) includes household fixed effects and state time trends. The main effect on state cigarette taxes indicates that tax increases do not increase food stamp enrollment for non-smoking households. The point estimates represent precisely estimated zeros. In contrast, the interaction terms yield the relationship between tax increases and food stamp take-up for smoking households. As seen, the contemporaneous coefficients and those lagged by one month are statistically significant and of economically relevant size.[10] The row below the lagged interaction terms yields the calculated cumulated effect of a tax increase on food stamp enrollment. The cumulative effect in Column (3) implies that a cigarette tax increase by \$1 increases food stamp enrollment of eligible low-income smoking households by 3.2ppt from a baseline of 25%, i.e., by 13%.

[8] The distributed lag model is a standard approach in estimating an effect that emerges gradually during the post-reform period (e.g., Deschenes and Moretti, 2009; Paik et al., 2017).

[9] We obtain consistent results by estimating a fixed effects model that includes only cigarette taxes in the previous month, i.e., not a distributed lag model. The point estimate using the preferred specification in Column (3) of Table 5 on the interaction term is 0.027^{***} (standard error 0.008). The results are also robust, albeit smaller in size and only marginally significant, when we additionally include full sets of state-year-month fixed effects as well as smoker-year-month fixed effects (results available upon request).

[10] The estimates slightly increase, albeit not in a statistically significant sense, when households with members who quit smoking within the past year are excluded from the sample.

Duration Analysis. Next, we take another slice at the empirical question by turning to a duration analysis. Duration analyses are commonly used in labor economics to study the impact of X on the length of unemployment spells (Van Den Berg, 2001). They have also been used in health economics to study the onset of smoking (e.g., DeCicca et al., 2002). We employ the duration analysis for two main reasons: *(i)* as a robustness check, and *(ii)* to be able to interpret our empirical findings in a different manner and obtain an answer to the question: do higher cigarette taxes decrease the *time span until* non-enrolled but eligible households take-up food stamps? Whereas it may be unrealistic to assume that eligible but non-enrolled households would have never enrolled in food stamps in the absence of a tax increase, it is plausible that the tax increase shortens the time span to take-up.

The basic setup of the model is as follows. Define the hazard function $h_t = \alpha_t exp(\beta X)$ as the households that take-up food stamps in time t divided by the number of 'at risk' households (the total number of non-enrolled but eligible households at time t). α_t is the 'baseline hazard' of a non-enrolled household taking up food stamps at time t, and X is a set of covariates as before. Note that the at risk population is limited to the subset of households who are not enrolled in food stamps in the first month we observe them. The sample excludes households once they take-up, so the sample size of the duration analysis differs slightly from the other models. In other words, h_t is interpreted as the conditional probability of taking up food stamps at time t, conditional on not being enrolled in food stamps. See Van Den Berg (2001) for further details on the estimation strategy.

Columns (4) and (5) of Table 5 report the coefficients from estimating the standard Cox Proportional Hazard model for non-smoking households and smoking households. We split the sample and run the models separately for non-smoking and smoking households because of the readily interpretable coefficients. The specifications therefore avoid issues surrounding the calculation of marginal effects of interaction terms in non-linear models.

As seen, the point estimate on cigarette taxes for non-smoking households is insignificant and the size is a little over one third of that for smoking households. The interpretation of the statistically significant coefficient for smoking households in Column (5) is as follows: a $1 increase in cigarette taxes decreases the average time-to-take-up by about 10 days (0.338 months). Overall, the duration analysis provides evidence that is very consistent with the results from the linear probability models and allows for a complement interpretation of the observed empirical pattern.

5.3 Other Outcome Margins

Table 6 tests for compensatory behavior outside of, and in addition to, food stamp enrollment by studying other outcome margins using the CPS cross-section. We estimate the specification above, but employ the outcome variables as indicated in the column headers of Table 6. The main variable of interest is again the interaction between state cigarette taxes and an indicator for smoking households.

The binary dependent variable in Column (1) indicates whether at least one household member quit smoking. A household is defined to be a quitting household if at least one member smoked cigarettes one year ago but does not smoke cigarettes at the time of the interview. Note that households with and without current smokers can both have members who quit smoking within the past year. The results in Column (1) suggest that a $1 increase in cigarette taxes is associated with a 0.96ppt (2.6% relative to the baseline of 0.36) increase in the probability that at least one household member quit smoking in the past year. Note, however, this estimate only captures temporary quitting behavior; relapse may occur.

[Insert Table 6 about here]

Column (2) uses the self-reported amount of daily household cigarette consumption as the dependent variable. The point estimate implies that a $1 increase in cigarette taxes reduces the number of daily cigarettes consumed by 2.5 cigarettes at the household level.

Column (3) exploits a self-reported measure that indicates whether the household ran out of money for food within the last month. We find that smoking households are at a 3.5ppt (9.3%) higher risk of reporting that they ran out of money for food than non-smoking households. The interaction term yields a relatively large point estimate of 5% of the mean which is, however, imprecisely estimated.

Finally, we assess how food-related expenditures develop for smoking and non-smoking households after cigarette tax increases. For that purpose, we estimated Equation (1) using the

CEX and (self-reported) quarterly household expenditures on food at home, food expenditures away from home, alcohol expenditures, and total expenditures. The findings (not reported) are imprecisely estimated and only provide suggestive evidence that low-income smoking households spend less money for food away from home and substitute toward eating more at home when taxes increase.

5.4 Summary of Effects and Mechanisms

Table 7 summarizes the findings.

The starting point and trigger in the causal chain of events is an increase in state cigarette taxes. Column (2) of Table 3 shows that a \$1 tax increase raises equilibrium cigarette prices by \$0.73. Next, and consistent with the literature that shows a relatively inelastic demand for cigarettes (e.g. Hansen et al., 2017), Columns (3) to (6) of Table 3 show that household cigarette expenditures increase significantly when taxes increase. Using the CPS, we obtain highly significant point estimates that suggest that quarterly cigarette expenditures increase by \$28.7 for each \$1 increase in state cigarette taxes. However, it is well documented that self-reported consumption and expenditure measures are under reported and contain measurement error (e.g., Bee et al., 2015), which may attenuate our expenditure estimates. A static calculation that considers the estimated demand response of 2.5 fewer daily cigarettes consumed per household (Table 6, Column (2)) would yield mean quarterly expenditure increases of \$40 for each \$1 increase in cigarette taxes ([22 packs per month on average - 2.5 cigarettes per day $\times$ 30 days in month / 20 cigarettes per pack]$\times$0.73$\times$3 months per quarter).

Our main findings are shown in Column (3) of Table 5: the cumulative effect of a \$1 cigarette tax increase is to increase food stamp enrollment by 3.2ppt among non-enrolled eligible smoking households (13.1% from a baseline of 0.247). The duration analysis presented in Columns (4) and (5) of Table 5 offers an alternative and consistent interpretation of the empirical pattern: a \$1 increase in taxes significantly reduces the average time to take-up for low-income smoking households by 10 days (0.338 months). Independent of the model employed, food stamp enrollment for non-smoking households is unaffected by cigarette tax increases.

[Insert Table 7 about here]

Whereas governments gain revenues from higher cigarette taxes, higher taxes contribute to spending increases in food stamps. To assess the degree that the estimated increase in enrollment of smoking households influences governmental tax revenue, consider a back-of-the-envelope calculation for the proportion of cigarette tax revenues that are offset by increases in spending on food stamps.

$$\text{Offset} = \frac{\mathrm{N}_s \times \mathrm{E}_s \times \Delta_e \times \bar{B}}{\mathrm{N}_s \times \Delta_\tau \times \bar{C}} = \frac{\Delta_e \times \mathrm{E}_s \times \bar{B}}{\bar{C}}$$

where N_s is the number of smoking households that cancels out of the expression, E_s is the proportion of smoking households that are eligible for food stamps (34%, own calculation from the CEX), Δ_e is the percentage point increase in enrollment among food stamp eligible smoking households from a $\Delta_\tau = \$1$ increase in taxes (3.2ppt, Column (3) of Table 5), $\bar{B}$ is the average smoking household monthly food stamp benefit ($156, own calculation from the CEX), and $\bar{C}$ is the average monthly cigarette consumption of smoking households (22 packs per smoking household per month, own calculation from the CPS). The numerator is the increase in food stamp spending from a $1 tax increase and the denominator is the increase in tax revenue from the tax increase. We note that this back-of-the-envelope calculation relies on a number of strong assumptions, including the counterfactual that smoking households would never have enrolled in food stamps. The back-of-the-envelope calculation suggests that roughly 8% of the additional cigarette tax revenue collected from a tax increase is offset by the resulting increase in spending on food stamps.

6 Conclusion

This paper investigated whether tax increases on goods with price-inelastic demand induced eligible low-income households to enroll in public assistance programs. Using the Current Population Survey and the Consumer Expenditure Survey, we exploited tempo-spatial variation in cigarette taxes and food stamp enrollment across US states from 2001 to 2012 to study this question empirically.

We enriched standard cigarette tax difference-in-differences models with an additional control group: non-smoking households. Smoking households within a state are "treated" with higher taxes while non-smoking households within the state are not. Exploiting a novel household panel of food stamp enrollment, we found that the average \$0.56 cigarette tax increase in our sample increased tobacco expenditures by food stamp eligible households significantly, inducing 7% of the eligible but non-enrolled smoking households to take-up food stamps. Duration models offered a complementary interpretation of the empirical pattern: a \$1 increase in taxes significantly reduced the average time to take-up for low-income smoking households by 10 days. Independent of the model employed, we found that food stamp enrollment for non-smoking households is unaffected by cigarette tax increases.

In addition to cigarette taxes, other consumption taxes such as sales taxes can have a meaningful effect on low-income households. This paper showed that low-income households respond to consumption tax increases on price-inelastic goods by enrolling in public assistance programs. More research is needed to fully understand the mechanisms and implications of the relationship between consumption taxes and enrollment in public assistance programs.

References

Adda, J. and F. Cornaglia (2006). Taxes, Cigarette Consumption, and Smoking Intensity. *American Economic Review 96*(4), 1013–1028.

Adda, J. and F. Cornaglia (2013). Taxes, Cigarette Consumption, and Smoking Intensity: Reply. *American Economic Review 103*(7), 3102–3114.

Ai, C. and E. Norton (2004). Interaction Terms in Logit and Probit Models. *Economics Letters 80*, 123–129.

Bee, A., B. D. Meyer, and J. X. Sullivan (2015). The validity of consumption data: Are the consumer expenditure interview and diary surveys informative? In C. Carroll, T. Crossley, and J. Sabelhaus (Eds.), *Improving the Measurement of Consumer Expenditures*, pp. 204–240. University of Chicago Press.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How Much Should We Trust Differences-In-Differences Estimates? *Quarterly Journal of Economics 119*(1), 249–275.

Bitler, M. and H. Hoynes (2016). The More Things Change, the More They Stay the Same? The Safety Net and Poverty in the Great Recession. *Journal of Labor Economics 34*(S1), S403–S444.

Bitler, M. and L. Karoly (2015). Intended and Unintended Effects of the War on Poverty: What Research Tells Us and Implications for Policy. *Journal of Policy Analysis and Management 34*(3), 639–696.

BLS (2014). Consumer Expenditure Survey. http://www.bls.gov/cex/, last retrieved on May, 21, 2014.

BLS (2015a). Average Price Data. http://download.bls.gov/pub/time.series/ap/, last retrieved on September 1, 2015.

BLS (2015b). Monthly State and Metropolitan Unemployment Rates. http://download.bls.gov/pub/time.series/la/, last retrieved on September 1, 2015.

Chetty, R., J. N. Friedman, and J. E. Rockoff (2014). Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates. *American Economic Review 104*(9), 2593–2632.

Chiou, L. and E. Muehlegger (2014). Consumer Response to Cigarette Excise Tax Changes. *National Tax Journal 67*(3), 621–650.

Currie, J. (2004). The Take Up of Social Benefits. NBER Working Paper 10488.

DeCicca, P., D. Kenkel, and F. Liu (2013). Excise Tax Avoidance: The Case of State Cigarette Taxes. *Journal of Health Economics 32*(6), 1130–1141.

DeCicca, P., D. Kenkel, and A. Mathios (2002). Putting Out the Fires: Will Higher Taxes Reduce the Onset of Youth Smoking? *Journal of Political Economy 110*(1), 144–169.

Deschenes, O. and E. Moretti (2009). Extreme Weather Events, Mortality, and Migration. *Review of Economics and Statistics 91*(4), 659–681.

Farrelly, M., C. Nimsch, A. Hyland, and M. Cummings (2004). The Effects of Higher Cigarette Prices on Tar and Nicotine Consumption in a Cohort of Adult Smokers. *Health Economics 13*(1), 49–58.

Goolsbee, A., M. Lovenheim, and J. Slemrod (2010). Playing with Fire: Cigarettes, Taxes, and Competition from the Internet. *American Economic Journal: Economic Policy 2*(1), 131–154.

Grieser, W. D. and C. J. Hadlock (2016). Panel Data Estimation in Finance: Preliminary Assumptions and Parameter Consistency. *Working Paper*.

Gruber, J. and B. Kőszegi (2001). Is Addiction Rational? Theory and Evidence. *Quarterly Journal of Economics 116*(4), 1261–1303.

Gruber, J., A. Sen, and M. Stabile (2003). Estimating Price Elasticities when there is Smuggling: The Sensitivity of Smoking to Price in Canada. *Journal of Health Economics 22*(5), 821–842.

Hansen, B., J. Sabia, and D. Rees (2017). Have Cigarette Taxes Lost Their Bite: New estimates of the Relationship between Cigarette Taxes and Youth Smoking. *American Journal of Health Economics 3*(1), 6075.

Hansen, H., P. Bourgois, and E. Drucker (2014). Pathologizing Poverty: New Forms of Diagnosis, Disability, and Structural Stigma under Welfare Reform. *Social Science & Medicine 103*(1), 76–83.

Hanson, K. and V. Oliveira (2012). How Economic Conditions Affect Participation in USDA Nutrition Assistance Programs. report. U.S. Department of Agriculture, Economic Research Service,.

Harding, M., E. Leibtag, and M. Lovenheim (2012). The Heterogeneous Geographic and Socioeconomic Incidence of Cigarette Taxes: Evidence from Nielsen Homescan Data. *American Economic Journal: Economic Policy 4*(4), 169–198.

Hoynes, H. and D. Schanzenbach (2009). Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program. *American Economic Journal: Applied Economics 1*(4), 109–139.

Kabbani, N. and P. Wilde (2003). Short Recertification Periods in the U.S. Food Stamp Program. *Journal of Human Resources 38*, 1112–1138.

Karaca-Mandic, P., E. Norton, and B. Dowd (2012). Interaction Terms in Nonlinear Models. *Health Services Research 47*(1), 255–274.

Kenkel, D. (1993). Drinking, Driving, and Deterrence: The Effectiveness and Social Costs of Alternative Policies. *Journal of Law and Economics 36*(2), 877–913.

Klerman, J. and C. Danielson (2011). The Transformation of the Supplemental Nutrition Assistance Program. *Journal of Policy Analysis and Management 30*(4), 863–888.

Kleven, H. and W. Kopczuk (2011). Transfer Program Complexity and the Take-Up of Social Benefits. *American Economic Journal: Economic Policy 3*(1), 54–90.

Lerman, R. and M. Wiseman (2002). Restructuring Food Stamps for Working Families. Technical report. mimeo.

Lovenheim, M. (2008). How Far to the Border?: The Extent and Impact of Cross-Border Casual Cigarette Smuggling. *National Tax Journal 61*(1), 7–33.

Mason, R. and T. Swanson (2002). The Costs of Uncoordinated Regulation. *European Economic Review 46*(1), 143–167.

Moffitt, R. (1983). An Economic Model of Welfare Stigma. *American Economic Review 73*(5), 1023–1035.

Paik, M., B. Black, and D. A. Hyman (2017). Damage Caps and Defensive Medicine, Revisited. *Journal of Health Economics 51*, 84–97.

Pei, Z. (2017). Eligibility Recertification and Dynamic Opt-in Incentives in Income-tested Social Programs: Evidence from Medicaid/CHIP. *American Economic Journal: Economic Policy 9*(1), 241–276.

Ponza, M., J. Ohls, L. Moreno, A. Zambrowski, and R. Cohen (1999). *Customer Service in the Food Stamp Program*. http://www.fns.usda.gov/sites/default/files/fspcust.pdf., last retrieved on 9 January 2015.

Ribar, D., M. Edelhoch, and Q. Liu (2008). Watching the Clocks: The Role of Food Stamp Recertification and TANF Time Limits in Caseload Dynamics. *Journal of Human Resources 43*(1).

Simon, D. (2016). Does Early Life Exposure to Cigarette Smoke Permanently Harm Childhood Welfare? Evidence from Cigarette Tax Hikes. *American Economic Journal: Applied Economics 8*(4), 128–159.

Tax Burden on Tobacco (2012). Historical Compilation.

Tiebout, C. (1956). A Pure Theory of Local Expenditures. *Journal of Political Economy 64*(5), 416–424.

U.S. Census Bureau (2016a). Current Population Survey: Complete Technical Documentation. https://www.census.gov/programs-surveys/cps/technical-documentation/complete.2013.html, last retrieved on March 1, 2016.

U.S. Census Bureau (2016b). Population and Housing Unit Estimates. http://www.census.gov/popest/,lastretrievedonMarch1,2016.

USDA (2015). *Supplemental Nutrition Assistance Program (SNAP)*. http://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap, last retrieved on January 19, 2015.

USDA (2016). *Supplemental Nutrition Assistance Program (SNAP): Eligiblity*. http://www.fns.usda.gov/snap/eligibility, last retrieved on March 5, 2016.

Van Den Berg, G. (2001). Duration Models: Specification, Identification, and Multiple Durations. In J. Heckman and E. Leamer (Eds.), *Handbook of Econometrics*, Volume 5, Chapter 55, pp. 3381–3460. Elsevier.

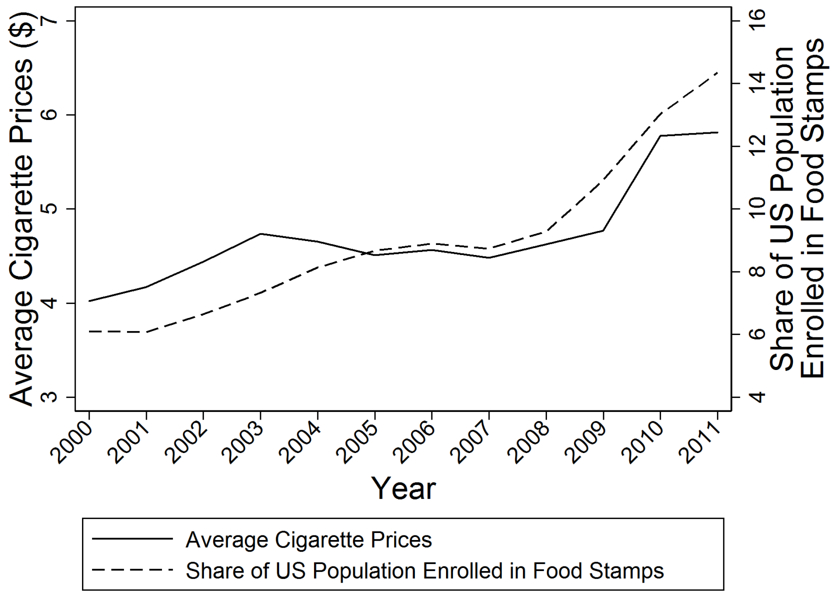
Ziliak, J. P. (2015). Temporary Assistance for Needy Families. NBER Working Paper Series 21038.

Ziliak, J. P., C. Gundersen, and D. N. Figlio (2003). Food Stamp Caseloads over the Business Cycle. *Southern Economic Journal 69*(4), 903–919.

Zodrow, G. and P. Mieszkowski (1986). Pigou, Tiebout, Property Taxation, and the Underprovision of Local Public Goods. *Journal of Urban Economics 19*(3), 356–370.

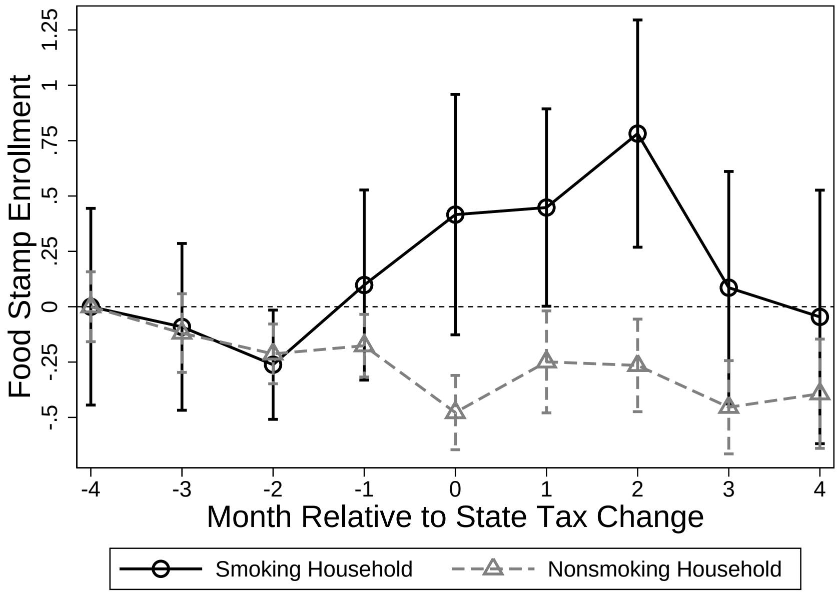
Figures and Tables

Figure 1: Cigarette Prices and Food Stamp Enrollment



Source: Tax Burden on Tobacco (for average cigarette prices), USDA (2015) (for food stamp enrollment), and U.S. Census Bureau (2016b) (for population).

Figure 2: Event Study—Cigarette Tax Increases and Food Stamp Enrollment



Source: CPS, FSS merged with TUS. Standard error bars report the 95% confidence interval for the estimated coefficient on the event time indicators.

Table 1: Descriptive Statistics for the Current Population Survey

Variable	Mean	Std. Dev.	Min.	Max.	N
Enrolled in Food Stamps	0.10	0.30	0	1	26,729
Smoking Household	0.28	0.45	0	1	26,729
Household Daily Cigarette Consumption	14.6	14.6	0	120	7,552
Cigarette Price ($)	4.41	1.10	0	20	7,552
Quarterly Cigarette Expenditures ($)	393	603	0	13,763	7,552
State Cigarette Tax ($)	0.91	0.69	0.03	4.58	26,729
Change in State Cigarette Tax ($) (conditional on change)	0.56	0.28	0.03	1.15	5,513
Covariates					
Monthly State Unemployment Rate	5.86	1.88	2.40	14.10	26,729
Household Head No High School	0.28	0.45	0	1	26,729
Household Head Employed	0.44	0.50	0	1	26,729
Gross Earned Household Income	23,154	14,937	2,633	115,231	26,729
# Household Members	2.53	1.62	1	16	26,729
# Male Household Members	1.17	1.07	0	9	26,729
# White Household Members	2.01	1.74	0	14	26,729
# Black Household Members	0.34	1.04	0	12	26,729
# Asian Household Members	0.08	0.57	0	16	26,729
Household Head Married	0.39	0.49	0	1	26,729
Age of Household Head	51.5	19.3	15	90	26,729

Source: CPS, FSS merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012). Cigarette prices are top coded at $20. Note that cigarette price, consumption, and quarterly expenditures are reported for households which have at least one daily smoker. All monetary values are in 2016 dollars.

Table 2: Descriptive Statistics for the Consumer Expenditure Survey

Variable	Mean	Std. Dev.	Min.	Max.	N
Enrolled in Food Stamps	0.12	0.33	0	1	24,729
Smoking Household	0.23	0.42	0	1	24,729
Quarterly Cigarette Expenditure ($)	270	300	4	5,932	5,740
State Cigarette Tax ($)	1.01	0.70	0.03	4.49	24,729
Change in State Cigarette Tax ($) (conditional on change)	0.67	0.41	0.01	1.69	3,493
Covariates					
Monthly State Unemployment Rate	6.75	2.35	1.80	14.80	24,729
Household Head No High School	0.23	0.42	0	1	24,729
Household Head Employed	0.47	0.50	0	1	24,729
Gross Earned Household Income	12,635	17,032	-114,782	125,570	24,729
Rural Region	0.0121	0.1093	0	1	24,729
# Household Members	2.45	1.62	1	16	24,729
Household Head Male	0.43	0.49	0	1	24,729
Household Head White	0.79	0.41	0	1	24,729
Household Head Black	0.15	0.35	0	1	24,729
Household Head Married	0.42	0.49	0	1	24,729
Age of Household Head	54.0	20.1	16	87	24,729

Source: CEX merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012). All monetary values are in 2016 dollars.

Table 3: State Cigarette Taxes, Cigarette Prices, and Cigarette Expenditures: CPS and CEX Cross Sections

	Price of Last Cigarette Pack Bought (CPS)		***Quarterly Cigarette Expenditures (CPS)***		***Quarterly Cigarette Expenditures (CEX)***	
	(1)	(2)	(3)	(4)	(5)	(6)
State Cigarette Tax	0.807***	0.728***	22.1	28.7*	26.0**	24.0**
	(0.098)	(0.109)	(23.1)	(16.8)	(11.2)	(10.5)
Dep. Var. Mean	4.41	4.41	392	392	270	270
Covariates						
Month FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Regional Food Prices	yes	yes	yes	yes	yes	yes
State Unempl. Rate	yes	yes	yes	yes	yes	yes
Socio-Demographics	no	yes	no	yes	no	yes
Observations	7,552	7,552	7,552	7,552	5,740	5,740
R^2	0.1880	0.2051	0.0178	0.3616	0.0182	0.0401

Source: Columns (1) to (4): CPS, FSS merged with TUS; Columns (5) to (6): CEX. * $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors are in parentheses and clustered at the state level. All samples condition on smoking households. Each column represents one regression as in Equation (1). The dependent variable in Columns (1) and (2) is the price of the last cigarette pack bought by the CPS smoking household. The dependent variable in Columns (3) and (4) measures calculated CPS annual household cigarette expenditures, based on the price and daily cigarette consumption information reported by the household. The dependent variable in Columns (5) and (6) measures CEX cigarette expenditures in the last quarter prior to the interview, as reported by the household. *State Cigarette Tax* indicates the state cigarette tax level in the previous month.

Table 4: State Cigarette Taxes and Food Stamp Enrollment: CPS and CEX Cross Sections

	CPS Cross Section			***CEX Cross Section***		
	(1)	(2)	(3)	(4)	(5)	(6)
State Cigarette Tax	0.032***	0.033***	0.043***	0.0335***	0.0342***	0.0249**
×Smoking Household	(0.008)	(0.008)	(0.012)	(0.0105)	(0.0107)	(0.0097)
State Cigarette Tax	0.019*	-0.010	-0.012	0.0124*	0.0061	0.0068
	(0.010)	(0.010)	(0.011)	(0.0072)	(0.0093)	(0.0078)
Smoking Household	0.035***	0.034***	0.054***	0.0643***	0.0623***	0.0535***
	(0.008)	(0.008)	(0.016)	((0.0146)	(0.0147)	(0.0128)
Mean Smoking Households	0.145	0.145	0.145	0.197	0.197	0.197
Covariates						
Month×Year FE	no	yes	yes	no	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Regional Food Prices	yes	yes	yes	yes	yes	yes
State Unemployment Rate	yes	yes	yes	yes	yes	yes
State Time Trend	no	yes	yes	no	yes	yes
Socio-Demographics	no	no	yes	no	no	yes
Observations	26,729	26,729	26,729	24,729	24,729	24,729
R^2	0.0651	0.0773	0.1888	0.0497	0.0577	0.1717

Source: Columns (1) to (3): CPS, FSS merged with TUS; Columns (4) to (6): CEX. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Each column represents one regression as in Equation (1). The binary dependent variable indicates whether the household is on food stamps in the current month. *State Cigarette Tax* indicates the state cigarette tax level in the previous month.

Table 5: State Cigarette Taxes and Food Stamp Take Up: CPS Monthly Pseudo Panel

	Linear Probability Model			*Duration Model*	
	Food Stamp Enrollment			*Nonsmoking Households*	*Smoking Households*
	(1)	(2)	(3)	(4)	(5)
State Cigarette Tax (t=-1)	-0.005	-0.001	-0.001	0.130	0.338*
	(0.003)	(0.002)	(0.002)	(0.162)	(0.200)
State Cigarette Tax (t=0)	0.003	0.022***	0.021***		
× Smoking Household	(0.021)	(0.007)	(0.007)		
State Cigarette Tax (t=-1)	0.012*	0.006	0.006		
× Smoking Household	(0.007)	(0.004)	(0.004)		
State Cigarette Tax (t=-2)	-0.000	0.004	0.004		
× Smoking Household	(0.007)	(0.007)	(0.007)		
State Cigarette Tax (t=-3)	-0.001	0.001	0.000		
× Smoking Household	(0.022)	(0.007)	(0.007)		
Cumulative Effect	0.033**	0.030***	0.032***		
	(0.009)	(0.009)	(0.009)		
Mean Smoking Households	0.247	0.247	0.247		
Covariates					
Month×Year FE	yes	yes	yes	yes	yes
State FE	yes	no	no	yes	yes
State FE× Smoking Household	yes	yes	yes		
Unemployment Rate	yes	yes	yes	yes	yes
Regional Food Prices	yes	yes	yes	yes	yes
State Time Trend	yes	no	yes	yes	yes
Socio-Demographics	yes	no	no	yes	yes
Household FE	no	yes	yes	no	no
Household-Month Observations	285,685	285,685	285,685	169,474	60,889
Unique Households	26,989	26,989	26,989	16,625	6,072
R^2	0.179	0.910	0.910		

Source: CPS, FSS merged with TUS. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses are clustered at the state level. Regressions are based on a monthly panel of household food stamp enrollment from the FSS. Each column in Columns (1) to (3) represents one regression as in Equation (1), where the binary dependent variable indicates food enrollment in calendar month t=0. The models in the first three columns also include a full set of contemporaneous and lagged monthly tax effects, in levels and interactions with household smoking status. The four interaction terms and the main effect on taxes are displayed. The other three main tax effects in levels are also included but not displayed due to space constraints. Columns (4) and (5) represent a duration analysis estimated by a Cox Proportional Hazard Model conducted separately for nonsmoking and smoking households. The duration analysis sample differs from the other samples in that *(i)* it is limited to households who are initially not participating in food stamps in the first month in which we observe them, and *(ii)* it only includes households until the month they take-up food stamps or fall out of the sample (censored).

Table 6: State Cigarette Taxes and Other Outcome Margins: CPS Cross Section

	HH Member Quit Smoking (1)	*Cigarettes Per Day* (2)	*Ran Out of Money for Food* (3)
State Cigarette Tax ×Smoking Household	0.010***	-2.52***	0.015
	(0.003)	(0.33)	(0.019)
State Cigarette Tax	0.004	0.62***	0.009
	(0.004)	(0.17)	(0.014)
Smoking Household	-0.009***	18.38***	0.035***
	(0.001)	(0.09)	(0.006)
Dep. Var. Mean	0.368	14.57	0.502
Covariates			
Month×Year FE	yes	yes	yes
State FE	yes	yes	yes
State FE× Smoking Household	yes	yes	yes
Unemployment Rate	yes	yes	yes
Regional Food Prices	yes	yes	yes
State Time Trend	yes	yes	yes
Observations	26,729	26,729	26,729
R^2	0.9366	0.4448	0.0822

Source: CPS, FSS merged with TUS. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Each column represents one regression as in Equation (1). *State Cigarette Tax* indicates the state cigarette tax level in the previous month.

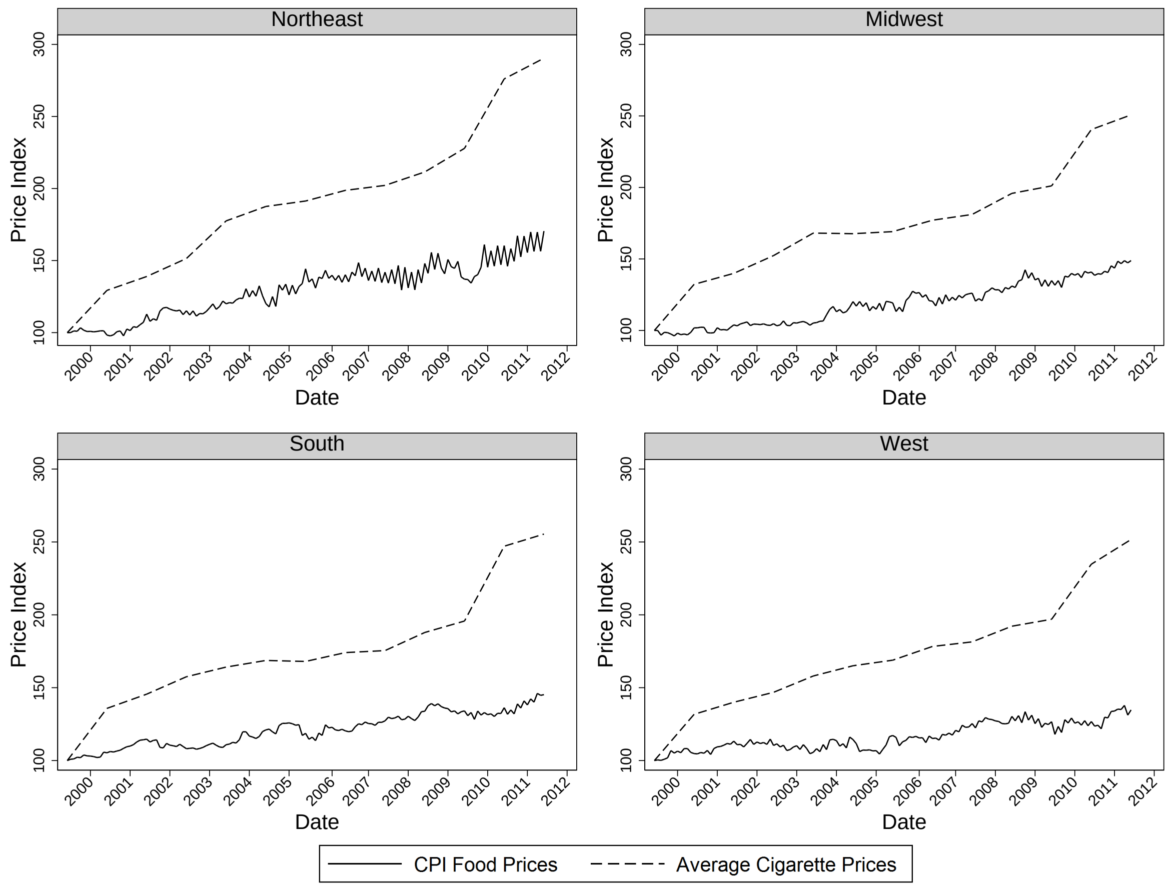
Table 7: Summary of Findings

Effect of $1 Increase in State Cigarette Taxes		
Δ Equilibrium retail prices (mean $4.41)	$0.73***	(Table 3, Column 2)
Δ Quarterly Cigarette Expenditures (mean $392)	$28.7*	(Table 3, Column 4)
Δ Food Stamp Enrollment		
- Smoking households (baseline 0.247)	0.032***	(Table 5, Column 3)
- Non-smoking households (baseline 0.141)	-0.001	(Table 5, Column 3)
Δ Months until Food Stamp Take-up		
- Non-smoking households	0.130	(Table 5, Column 4)
- Smoking households	0.338*	(Table 5, Column 5)

Notes: * p<0.1, ** p<0.05, *** p<0.01.

Appendix

Figure A1: Food Price and Cigarette Price Inflation



Source: Tax Burden on Tobacco (average cigarette prices) and BLS (for the average food prices).

Figure A2: State Cigarette Taxes and Share of Smokers on Food Stamps (CPS)

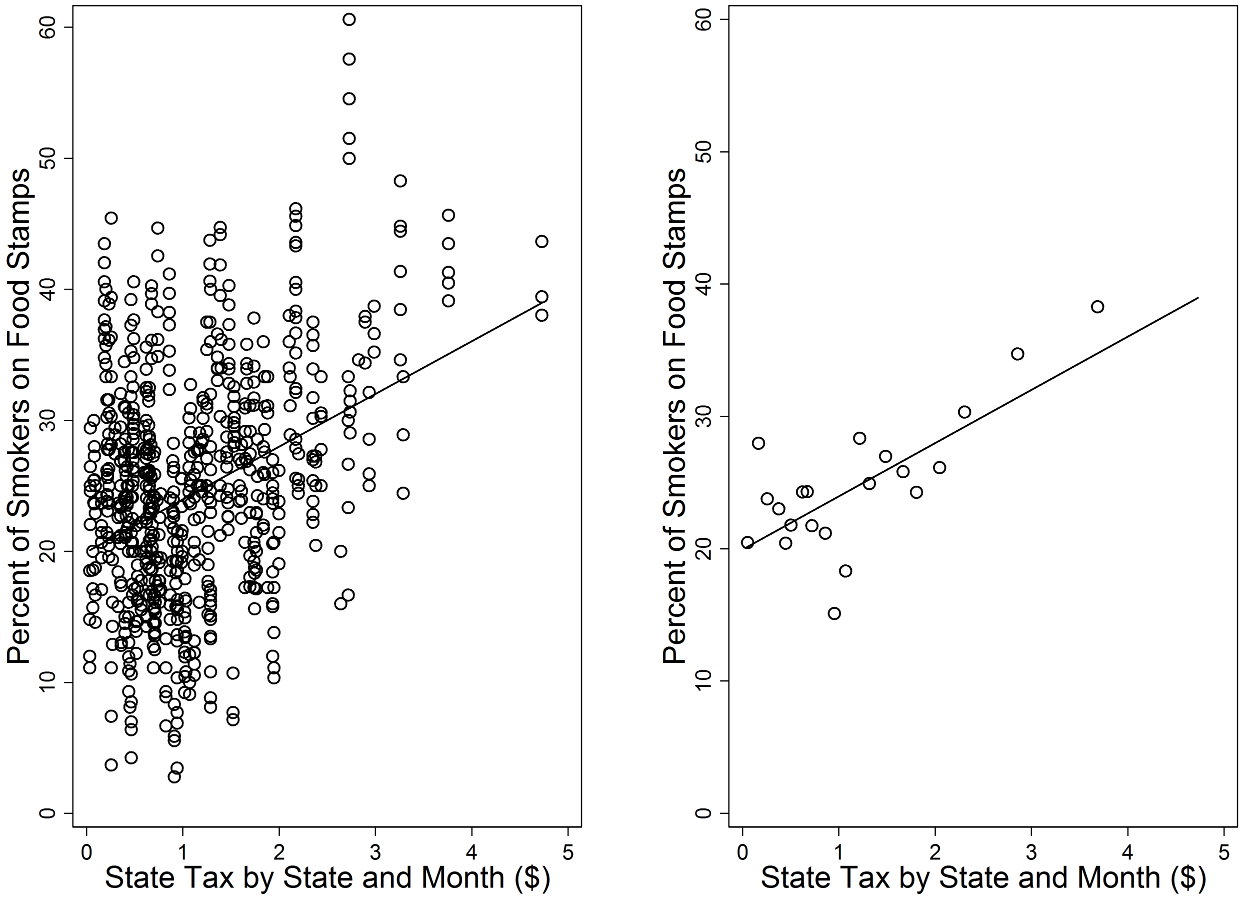


Figure A3: Yearly Change in State Cigarette Taxes and Share of Smokers on Food Stamps (CEX)

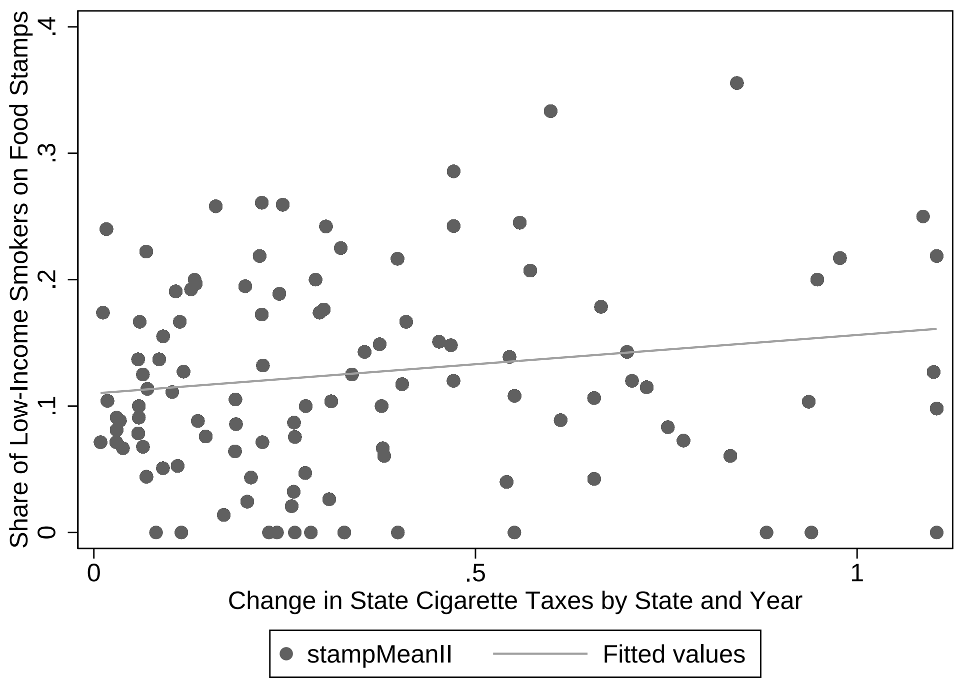


Table A1: CPS FSS-TUS Pseudo-Panel Observations Over Years and Months

Variable	Frequency	Percent	Cum.
Feb 2003	7,578	2.65	2.65
Mar 2003	8,252	2.89	5.54
April 2003	8,252	2.89	8.43
May 2003	8,252	2.89	11.32
June 2003	8,252	2.89	14.21
July 2003	8,252	2.89	17.10
Aug 2003	8,252	2.89	19.98
Sept 2003	8,252	2.89	22.87
Oct 2003	8,252	2.89	25.76
Nov 2003	8,252	2.89	28.65
Feb 2006	7,817	2.74	31.39
March 2006	8,887	3.11	34.50
April 2006	8,887	3.11	37.61
May 2006	8,887	3.11	40.72
June 2006	8,887	3.11	43.83
July 2006	8,887	3.11	46.94
Aug 2006	8,887	3.11	50.05
Sep 2006	8,887	3.11	53.16
Oct 2006	8,887	3.11	56.27
Nov 2006	8,887	3.11	59.38
Dec 2006	8,887	3.11	62.49
Feb 2010	8,652	3.03	65.52
March 2010	9,850	3.45	68.97
April 2010	9,850	3.45	72.42
May 2010	9,850	3.45	75.87
June 2010	9,850	3.45	79.31
July 2010	9,850	3.45	82.76
Aug 2010	9,850	3.45	86.21
Sep 2010	9,850	3.45	89.66
Oct 2010	9,850	3.45	93.10
Nov 2010	9,850	3.45	96.55
Dec 2010	9,850	3.45	100.00
Total	285,685	100.00	

Table A2: CEX Cross-Sectional Observations Over Years and Months

Variable	Frequency	Percent		Frequency	Percent
2001	2,592	10.48	Jan	2,057	8.32
2002	2,829	11.44	Feb	2,082	8.42
2003	2,937	11.88	Mar	2,091	8.46
2006	2,527	10.22	Apr	2,011	8.13
2007	2,248	9.09	May	2,148	8.69
2008	2,248	9.09	June	1,999	8.08
2009	2,304	9.32	July	1,990	8.05
2010	2,401	9.71	Aug	2,003	8.10
2011	2,346	9.49	Sept	2,143	8.67
2012	2,297	9.29	Oct	2,132	8.62
			Nov	2,033	8.22
			Dec	2,040	8.25
Total	24,729	100.00		24,729	100.00

Table A3: First Differences—Change in State Cigarette Taxes and Change in Food Stamp Enrollment

	Δ ***Food Stamp Enrollment***		
	(1)	(2)	(3)
Δ State Cigarette Tax (t=-1,t=-2)	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Δ State Cigarette Tax (t=0,t=-1)	0.014***	0.013***	0.013***
× Smoking Household	(0.004)	(0.005)	(0.005)
Δ State Cigarette Tax (t=-1,t=-2)	0.005	0.004	0.005
× Smoking Household	(0.004)	(0.004)	(0.004)
Δ State Cigarette Tax (t=-2,t=-3)	0.002	0.002	0.002
× Smoking Household	(0.006)	(0.008)	(0.008)
Cumulative Interaction Effect	0.020***	0.020*	0.020*
	(0.007)	(0.011)	(0.011)
Mean Smoking Households	0.247	0.247	0.247
Covariates			
Month×Year FE	yes	yes	yes
State FE	yes	no	no
State FE× Smoking Household	yes	yes	yes
Change in Unemployment Rate	yes	yes	yes
Change in Regional Food Prices	yes	yes	yes
State Time Trend	yes	no	yes
Socio-Demographics	yes	no	no
Household FE	no	yes	yes
Household-Month Observations	258,696	258,696	258,696
Unique Households	26,989	26,989	26,989
R^2	0.001	0.059	0.060

Source: CPS, FSS merged with TUS. * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses are clustered at the state level. Regressions are based on a monthly panel of household food stamp enrollment from the FSS. Each column in Columns (1) to (3) represents one regression as in Equation (1), where the binary dependent variable indicates change in food enrollment between calendar months t=0 and t=-1. The models in the first three columns also include a full set of contemporaneous and lagged changes in monthly taxes, in levels and interactions with household smoking status. The three interaction terms and the main effect on taxes are displayed. The other two changes in taxes are also included but not displayed due to space constraints.