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

Kyle Rozema *Northwestern University*
Nicolas R. Ziebarth *Cornell University*

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 a novel household panel of monthly food stamp enrollment from the Current Population Survey, we enrich standard cigarette tax difference-in-differences models with an additional control group: nonsmoking households. Smoking households are treated with higher taxes, while nonsmoking 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 nonsmoking households in the same state.

1. Introduction

Over the past 2 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 policy makers: smokers respond strategically to increases in cigarette taxes by stockpiling (Chiou

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and Muehlegger 2014), switching to cigarettes with higher levels of tar and nicotine (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, Sen, and Stabile 2003; Lovenheim 2008; Goolsbee, Lovenheim, and Slemrod 2010; DeCicca, Kenkel, and Liu 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 their 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 percent 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 nontrivial. For example, initial applications for SNAP may take 5 hours to complete and usually require several trips to an administrative office (Ponza et al. 1999). The second type of cost is nonpecuniary in nature: stigma. Since Moffitt (1983), a 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 (for example, Hoynes and Schanzenbach 2009; Kleven and Kopczuk 2011; Hansen, Bourgois, and Drucker 2014). Official data show that, in 2015, the average monthly SNAP benefit was just $127 per person.[2] 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 cross-sectional nature of the data sets, we construct a novel CPS pseudopanel that follows households' food-stamp program enrollment throughout every month of a calendar year. This panel allows us to observe both smoking and nonsmoking households transitioning onto food stamps from one month to

[1] The Supplemental Nutrition Assistance Program (SNAP) was known as the Food Stamp Program until October 2008. Henceforth, we use "SNAP" and "food stamps" interchangeably.

[2] US Department of Agriculture, Persons, Households, Benefits, and Average Monthly Benefit per Person and Household: FY14 through FY17 National View Summary (https://www.fns.usda.gov/sites/default/files/pd/34SNAPmonthly.pdf).

another. Our identification strategy enriches difference-in-differences models by using nonsmoking households in a state as an additional control group. Smoking households in a state are treated with higher taxes, while nonsmoking households in the state are not.

To investigate the extent that cigarette tax increases translate into increases in cigarette expenditures, 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 program enrollment. For each $1 increase in cigarette taxes, cigarette prices as paid by consumers increase by $.80. 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 $18. However, 20 percent of all low-income smoking households consume at least 45 packs a month and thus would experience monthly income shocks of at least $36 for each $1 increase in cigarette taxes. Our 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 SNAP. A $1 increase in cigarette taxes increases the probability that eligible, but nonenrolled, smoking households take up food stamps by 3.2 percentage points from a baseline probability of about 25 percent. For the average $.56 state cigarette-tax increase in our sample period, the point estimate implies a 7 percent increase in the probability that eligible, but nonenrolled, smoking households take up food stamps. In contrast, nonsmoking households are not more likely to enroll in SNAP 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 (for example, Adda and Cornaglia 2006; DeCicca, Kenkel, and Liu 2013). Second, they contribute to the behavioral public finance literature in the sense that we study concepts of uncoordinated regulation (for example, Kenkel 1993; Mason and Swanson 2002). Whereas governments gain revenues from higher taxes, higher prices contribute to spending increases in public assistance programs. Finally, they contribute to the literature examining factors that affect the take-up of public assistance programs (for example, Ziliak, Gundersen, and Figlio 2003; Kabbani and Wilde 2003; Ribar, Edelhoch, and Liu 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 describes the data. Section 5 presents the results, and Section 6 concludes.

2. Background

Figure 1 shows that real cigarette prices increased by about 50 percent, from $4 to $6, between 2000 and 2011 (Orzechowski and Walker 2012). Real state cigarette tax revenues also increased by over 50 percent, from $10.6 billion in 2000

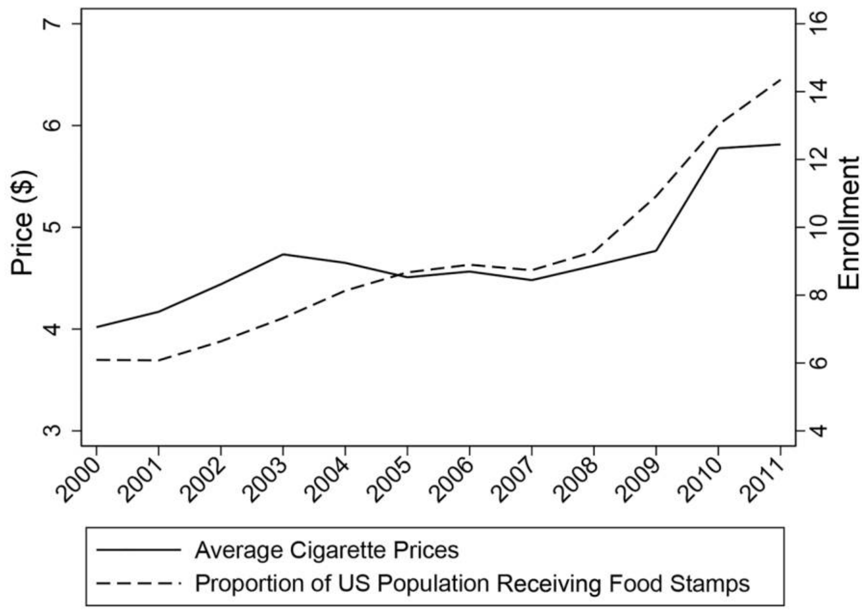

Figure 1. Cigarette prices and food-stamp enrollment

to $17.1 billion in 2011 (Orzechowski and Walker 2012). Figure 1 also shows that the share of the US population enrolled in SNAP more than doubled, from 6 percent to over 14 percent over the same time period.[3] Part of the large increase in SNAP enrollment has been attributed to both demand-side factors such as changes in the unemployment rate (Ziliak, Gundersen, and Figlio 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).

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.

2.1. Eligibility

There are two main eligibility requirements. First, households must meet income requirements, broken down into a gross and a net income test. The general threshold for the gross income test is 130 percent of the federal poverty line (FPL). In 2016, this amounted to $1,276 per month for a one-person household

[3] Data on SNAP enrollment are from US Department of Agriculture, Supplemental Nutrition Assistance Program (SNAP), Participation and Costs, 1969–2016 (http://www.fns.usda.gov/sites/default/files/pd/SNAPsummary.pdf) and population estimates are from US Census Bureau (2016b).

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: a standard deduction of between \$155 and \$168, 20 percent from earned income, dependent-care deductions or child-support payments, medical expenses for disabled or elderly persons, and other deductions. The resulting net income must not exceed 100 percent of the FPL.[4] In 2016, this amounted 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. 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.[5]

2.2. Benefits

The calculation of SNAP benefits is premised on the general expectation that households spend 30 percent of their income on food. The benefit level is therefore set such that 30 percent of the net income is subtracted from the maximum SNAP benefits, which depend on the household size.[6] In 2016, the maximum monthly benefit for a one-person household was \$194 and was \$649 for a four-person household. For example, if the monthly net income for a four-person household was \$1,500, then that household was expected to spend \$450 on food, and hence the available SNAP benefit was (\$649 − \$450 =) \$199 per month.

3. Empirical Approach and Identification

Equation (1) sets out our main econometric specification:

$$y_{it} = \alpha + \beta\tau_{st-1} \times h_{it} + \gamma\tau_{st-1} + \psi h_{it} + \theta \boldsymbol{X}_i + \xi u_{st} + \pi f_{ct} + \sigma_t + \rho_s + \varepsilon_{it}, \quad (1)$$

where y_{it} represents the dependent variable of interest for household i in state s in month-year t, τ_{st-1} is the state cigarette tax in state s lagged by 1 month, h_{it} is an indicator for smoking households, $\boldsymbol{X}_i$ is a vector of sociodemographic covariates, and u_{st} is the state unemployment rate. Food-price inflation f_{ct} is controlled for

[4] US Department of Agriculture, Supplemental Nutrition Assistance Program (SNAP), FY 2016 Income Eligibility Standards (https://www.fns.usda.gov/sites/default/files/snap/FY16-Income-Eligibility-Standards.pdf).

[5] US Department of Agriculture, Supplemental Nutrition Assistance Program (SNAP), Asset Limits, Supplemental Nutrition Assistance Program Participation, and Financial Stability (Summary) (https://www.fns.usda.gov/sites/default/files/ops/SNAPAssets-Summary.pdf).

[6] US Department of Agriculture, Supplemental Nutrition Assistance Program (SNAP), FY 2016 Allotments and Deduction Information (https://www.fns.usda.gov/sites/default/files/snap/FY16-Maximun-Allotments-Deductions.pdf).

at the census region c level, σ_t is the set of month-year fixed effects, and ρ_s is the set of state fixed effects. In our preferred specifications, we also include state time trends. For the panel data on household SNAP enrollment, we employ household fixed effects and 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.

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 τ_{st-1}, by contrast, yields the impact for nonsmoking households. Standard errors are routinely clustered on the state level (Bertrand, Duflo, and Mullainathan 2004).

We employ equation (1) using both cross-sectional and panel data on SNAP enrollment. Using the cross-sectional data, equation (1) links changes in cigarette taxes to smoking households' probability of enrolling in SNAP. Using the panel data with household fixed effects, equation (1) links changes in state cigarette taxes to smoking households' probability of transitioning onto SNAP. When using the monthly panel data on SNAP enrollment, we add a set of contemporaneous and lagged cigarette tax regressors, in both 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 state cigarette tax increases and an overproportional increase in SNAP enrollment for smoking households. Changes to SNAP at the federal level (see Section 2) are absorbed by the month-year fixed effects. State-level program changes are a threat to the identification strategy only if they are correlated with state cigarette-tax changes and would affect the take-up of low-income smoking households differently than the take-up of low-income nonsmoking 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, for example, through supply shocks or state taxes, then it would be difficult to disentangle the increase in SNAP enrollment due to higher food prices from that due to higher cigarette taxes. However, in that case, one would expect cigarette taxes to increase the likelihood that nonsmoking households would enroll in SNAP as well. As we 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. Figure A1 plots an index for normal food and cigarette prices for the four US regions over time using average cigarette prices from Orzechowski and Walker (2012) and average food prices from the US Bureau of Labor Statistics (BLS 2015a). In line with our prior beliefs, Figure A1 shows that the increase in nominal cigarette prices between 2000 and 2011 outpaced the increase in nominal food prices (for changes in real cigarette prices, see Figure 1). While nominal food prices increased by about 50 percent in all four regions (in the Northeast a bit more, in the West a bit less), nominal 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 a state of residence on the basis of preferences, among them cigarette taxes (Tiebout 1956; Zodrow and Mieszkowski 1986). Our approach, like the majority of similar approaches 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 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 changes in taxes biases our results. However, one would need to assume that moving out of state because of 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 of 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 data sets are CPS cross-sectional data, CPS pseudopanel data, and CEX cross-sectional data. The unit of observation is always the household because it is the relevant economic unit where decisions about enrolling in public assistance are made and where the means-testing requirements are applied. We merge in information about monthly state cigarette taxes (Orzechowski and Walker 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. Food Security Supplement and Tobacco Use Supplement

Two of the data sets that we employ are based on the CPS. The CPS is conducted by the US Census Bureau for the BLS. It is a monthly survey of approximately 60,000 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 4 consecutive months and then after 8 months are surveyed again for 4 months. A set of households in the main survey is also surveyed in the applicable supplemental survey of that month (US Census Bureau 2016a).

We combine the Tobacco Use Supplement (TUS) and the Food Security Supplement (FSS) of the CPS from 2001–11. As a general rule, each household is surveyed at most once in the TUS and FSS. We focus on CPS households that were included in both the TUS and the FSS. We use the TUS as the baseline survey and then merge it with the FSS SNAP enrollment information. Because the FSS is carried out in December of each year in our sample, we make use of the following TUS surveys: November 2001, February 2002, February 2003, November 2003, January 2007, and January 2011.

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

Food-Stamp Information. In each FSS, enrollment status in SNAP 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 elicits food-stamp-enrollment information only for households below 185 percent of the FLP. This is because only those households are, in principle, eligible for SNAP.[7] We therefore restrict the sample to households below 185 percent of the FPL.

4.1.1. Cross-Sectional Data

We first generate a cross-sectional data set that uses the TUS as the reference data set. This means that we make use of the sociodemographic information and cigarette-consumption data from the TUS and merge them with SNAP enrollment information of the same calendar month for households that completed the TUS in a month in which SNAP enrollment is observed in the FSS.[8] (The results are robust to using FSS demographics.) For the CPS cross-sectional data set, we define a smoking household as one that has at least one smoking member in the month that we observe information about both smoking status and SNAP enrollment. (We do not project the smoking or SNAP enrollment status forward or backward in time.)

Table 1 reports descriptive statistics. Of the food-stamp-eligible households in the sample, 10 percent are enrolled in SNAP, and almost a third have at least one member who currently smokes cigarettes. The mean smoking household consumes less than a pack per day, but there is significant heterogeneity in consumption, with a large share of households consuming at least two packs per day (12 percent) or three packs per day (3 percent). Multiplying the number of daily cigarettes consumed (in packs) by the cigarette prices and extrapolating to quarterly expenditures (to match the time frame of expenditures in the CEX), one observes that the average smoking household spends almost $400 on cigarettes per quarter. However, the expenditure distribution is skewed to the right, with a fifth of all households spending more than $500 per quarter on cigarettes.

[7] As explained in Section 2, the general gross-income test requires households to have income below 130 percent of the federal poverty line. However, because of the possibility of categorical eligibility that may make some households eligible, producers of the Current Population Survey (CPS) chose the 185 percent threshold for the filter question.

[8] The CPS is conducted by physical location. We follow the CPS instructions to limit households to the same individuals in the Tobacco Use Supplement and Food Security Supplement.

Table 1
Descriptive Statistics for the Current Population Survey

Variable	Mean	SD	Min	Max	*N*
Enrolled in SNAP	.10	.30	0	1	26,729
Smoking Household	.28	.45	0	1	26,729
Household Daily Cigarette Consumption	14.6	14.6	0	120	7,552
Cigarette Price ($)	4.41	1.10	0	20	7,552
Quarterly Cigarette Expenditure ($)	393	603	0	13,763	7,552
State Cigarette Tax ($)	.91	.69	.03	4.58	26,729
Change in State Cigarette Tax ($)	.56	.28	.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 degree	.28	.45	0	1	26,729
Household head employed	.44	.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	.34	1.04	0	12	26,729
Asian household members	.08	.57	0	16	26,729
Household head married	.39	.49	0	1	26,729
Age of household head	51.5	19.3	15	90	26,729

Source. Data are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey. State-month-level cigarette tax data are from Orzechowski and Walker (2012).
Note. Cigarette prices are top coded at $20. Cigarette price, consumption, and quarterly expenditures are for households that have at least one daily smoker. All monetary values are in 2016 dollars. Data for the change in state cigarette tax are conditional on there being a change.

State taxes vary between less than $.05 for Virginia from 2001 to 2004 and over $4 for New York after August 1, 2010. Figure A2 shows the rich state-time variation in the level of state cigarette taxes in the CPS data.[9] Conditional on an increase, the average tax increase was $.56. Most states increased cigarette taxes by relatively large amounts after longer periods without tax changes (see Figure A3, which uses CEX data).

The regression models adjust the sample by a standard set of socioeconomic characteristics, including household size, household income, race, and the education, age, and marital status of the head of the household. The average household has more than two members. Roughly half of all household members are male; the household head is on average over 50 years old, most likely white, and not married. Almost one-third have no high school degree.

4.1.2. Pseudopanel

We generated a CPS pseudopanel that again uses our selected TUS surveys as the reference data set. This means that we extract the time-invariant sociodemo-

[9] Figure A2 is a binned scatterplot of the proportion of smoking households enrolled in SNAP against state cigarette taxes at the state-month-year level using the panel of SNAP enrollment described below.

graphic information from the TUS. This is the reason why we call the data set a pseudopanel—because sociodemographic data are constant over time. What varies over time at the household level is SNAP 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 pseudopanel follows households for different lengths of time. First, for households sampled in a January TUS, we use 11 months of SNAP enrollment information from the previous year. This applies to the TUS of January 2007 and 2011, and we merge these data with the FSS of December 2006 and 2010.[10]

Second, we use the households in the November 2003 TUS and the December 2003 FSS to track household SNAP enrollment information for 10 months. Hence, as shown in Table A1, our pseudopanel includes observations from 2003, 2006, and 2010. Note that we deliberately restricted the pseudopanel to households with at least 10 months of SNAP enrollment information. One reason is that it allows us to carry out an event study with a relatively balanced set of observations. (The results are robust to using all households that were interviewed in the TUS and FSS between 2001 and 2011.)

4.2. Consumer Expenditure Survey

Since 1984, the CEX has been carried out by the BLS. The main unit of observation is the household, called the consumer unit (CU). The CEX is designed to be representative of the US noninstitutionalized civilian population. Each quarter about 7,000 interviews are conducted (BLS 2014).

The CEX consists of two main surveys: the Interview Survey (IS) and the Diary Survey. In the IS, CUs are interviewed every 3 months over the course of 15 months. Income and employment information is surveyed solely 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 SNAP information from 2001–12. Those files contain income, expenditure, and housing information at the CU level. Because we use 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.

We employ the CEX in addition to the CPS for three reasons: to check for the consistency with the CPS results, to exploit a sample that spans observations more evenly across calendar months and years (see Table A2), and to exploit the potentially more reliable expenditure information in the CEX. To make the findings comparable, we also condition the CEX on households at or below 185 percent of the FPL. In contrast to the CPS, the CEX does not have a filter question

[10] To be conservative, we omit the enrollment information from January 2006 and January 2010 because those surveyed at the end of the month might interpret the question about smoking status referring to "12 months ago" as meaning February 2003 and February 2010, respectively. The results are robust to the inclusion of SNAP enrollment data in January 2006 and January 2010.

Table 2
Descriptive Statistics for the Consumer Expenditure Survey

Variable	Mean	SD	Min	Max	*N*
Enrolled in SNAP	.12	.33	0	1	24,729
Smoking Household	.23	.42	0	1	24,729
Quarterly Cigarette Expenditure ($)	270	300	4	5,932	5,740
State Cigarette Tax ($)	1.01	.70	.03	4.49	24,729
Change in State Cigarette Tax ($)	.67	.41	.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 degree	.23	.42	0	1	24,729
Household head employed	.47	.50	0	1	24,729
Gross earned household income	12,891	16,401	0	125,570	24,729
Rural region	.0121	.1093	0	1	24,729
Household members	2.45	1.62	1	16	24,729
Male household head	.43	.49	0	1	24,729
White household head	.79	.41	0	1	24,729
Black household head	.15	.35	0	1	24,729
Household head married	.42	.49	0	1	24,729
Age of household head	54.0	20.1	16	87	24,729

Source. Data are from the Consumer Expenditure Survey merged with state-month-level cigarette tax data from Orzechowski and Walker (2012).
Note. Gross earned household income is bottom coded at $0. All monetary values are in 2016 dollars. Data for the change in state cigarette tax are conditional on there being a change.

for whether CUs are at or below 185 percent 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 185 percent of the FPL.

Table 2 provides descriptive statistics. Although cigarette expenditures are reported differently in the CEX than in the CPS—namely, total expenditures in the last quarter—the measures are remarkably consistent with those in the CPS.

We generate a set of sociodemographic factors that are comparable to those in the CPS. The CEX has sociodemographic characteristics similar to those in the CPS.

5. Empirical Results

We use cigarette tax increases as a case study for how taxes on inelastic consumption goods may induce eligible but nonenrolled 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 SNAP enrollment.

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 a

Table 3
State Cigarette Taxes, Cigarette Prices, and Expenditures

	Price of Last Pack		Quarterly Expenditures			
	(1)	(2)	(3)	(4)	(5)	(6)
State Cigarette Tax	.808**	.803**	21.6	30.4+	26.0*	24.3*
	(.097)	(.096)	(22.8)	(16.6)	(11.2)	(10.4)
Dependent variable mean	4.41	4.41	392	392	270	270
Sociodemographic controls	No	Yes	No	Yes	No	Yes
N	7,552	7,552	7,552	7,552	5,740	5,740

Source. Data for columns 1–4 are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey. Data for columns 5–6 are from the Consumer Expenditure Survey.
Note. Standard errors, in parentheses, are clustered at the state level. All samples condition on smoking households. All regressions include month fixed effects, year fixed effects, state fixed effects, regional food prices, and the state unemployment rate. Cigarette expenditures from the Consumer Expenditure Survey are from in the last quarter prior to the interview as reported by the household. State cigarette taxes are from the previous month.
+ $p < .1$.
* $p < .05$.
** $p < .01$.

specification similar to equation (1) but omit nonsmoking households. The dependent variable is the self-reported price of the last pack of cigarettes bought. Table 3 shows the results. In our preferred specification (column 2), we find that taxes are passed through to prices at a rate of .80. This pass-through rate is in line with the recent literature (Harding, Leibtag, and Lovenheim 2012; Lillard and Sfekas 2013).

Next we estimate the effect of higher cigarette taxes on cigarette expenditures, which are conveyed through the average pass-through rate of .80. We again employ a variant of equation (1) to estimate the effect of taxes on expenditures. When adjusting the CPS sample for sociodemographic factors, a $1 increase in cigarette taxes increases quarterly cigarette expenditures by $30. The estimates from the CEX yield very consistent and statistically significant increases in quarterly expenditures of roughly $24 for the average smoking household.

5.2. Cigarette Taxes and Food-Stamp Enrollment

5.2.1. Event Study

The panel nature of our CPS data set naturally gives rise to a visual assessment of food-stamp take-up 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. Only smoking households are treated by cigarette tax increases, and nonsmoking 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 is event time 0. We use a balanced panel of households that were present in the data for 4 months before and after a tax change (Simon 2016). We estimate equation (1) for whether a household transitions onto food stamps in a given month using household fixed effects but replace taxes with event-time indicator variables for each month around a state's cigarette tax increase. The approach assumes that taxes across states have the same effect on food-stamp take-up in the months around a tax change. Each event-time coefficient indicates the propensity of households to take up food stamps in a given month. We normalize the coefficients for smokers and nonsmokers in the first month of the event study ($t = -4$) to facilitate interpretation of the findings.

Figure 2 is an event-study graph in which we plot the estimated event-time coefficients (with 90 percent standard error bars). The propensity of smoking and nonsmoking households to take up food stamps in the 2–4 months before increases in taxes is very similar and stable, and the confidence intervals overlap. The propensity of nonsmoking households to take up food stamps does not increase over the period after the tax increase. However, the propensity of smoking households to take up food stamps begins to increase in the month before the tax increase and increases further in the month of the tax increase (becoming statistically different from nonsmoking households 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 take-up propensity for nonsmoking households.

One would expect the increase in enrollment to persist past the month of the tax change because many households that apply for food stamps in one month obtain benefits for the first time after the month in which they apply because of the timing of the application process. One would also expect the observed anticipatory effect because tax increases are usually enacted 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 typically occurs during the 8 weeks after taxes are enacted but before the higher taxes become effective. Given the timing of the food-stamp application process, stockpiling beginning 2 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 take up 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 a flat take-up propensity for nonsmoking households.

5.2.2. Regression Framework

Using the cross-sectional data, we now relate changes in state cigarette taxes to SNAP enrollment by estimating equation (1). The dependent variable is SNAP

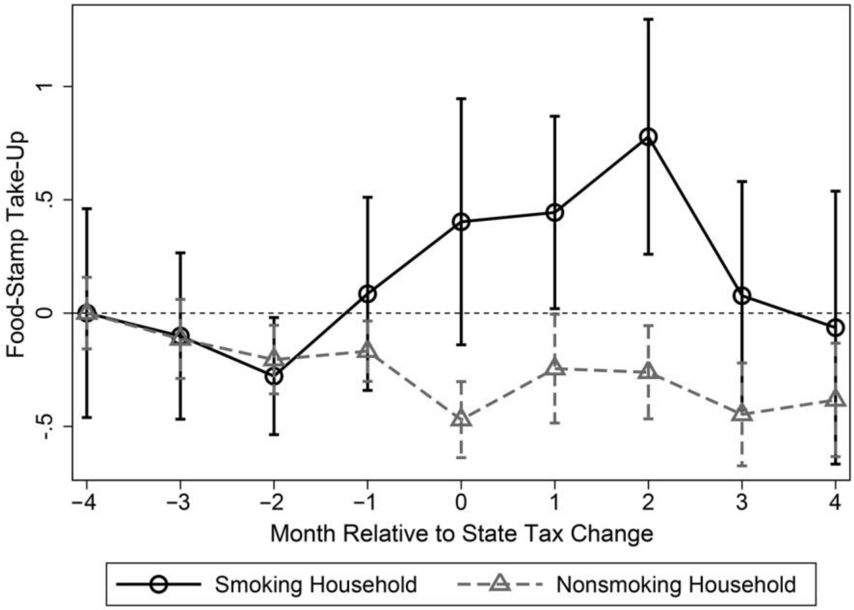

Figure 2. Event study: cigarette tax increases and food-stamp take-up

enrollment—a binary indicator of whether the household is currently enrolled in SNAP. The results are shown in Table 4.

The main effect of interest is the interaction between state cigarette taxes and smoking households, which indicates the statistical relationship between cigarette tax increases of $1 and the probability that low-income smoking households are enrolled in SNAP.[11] We find that each $1 increase in cigarette taxes increases the likelihood that low-income smoking households enroll in SNAP by between 3.1 and 3.3 percentage points. The results are consistent in the CEX, where we find that each $1 increase in taxes increases the likelihood of SNAP enrollment by between 2.5 and 3.4 percentage points. It is noteworthy that the coefficients of interest remain relatively 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 program enrollment is represented by the main effect on state cigarette taxes, which reflects the effect of tax increases on SNAP enrollment of nonsmoking households. Across all six specifications, the magnitude of the main effect is rather small, and its sign is ambiguous. The estimates show that

[11] We report results from a linear probability model because the interaction terms are readily interpretable (see Ai and Norton 2003; Karaca-Mandic, Norton, and Dowd 2012), but the results also hold for nonlinear estimation.

Table 4
State Cigarette Taxes and Food-Stamp Enrollment

	Current Population Survey ($N = 26{,}729$)			Consumer Expenditure Survey ($N = 24{,}729$)		
	(1)	(2)	(3)	(4)	(5)	(6)
State Cigarette Tax × Smoking Household	.032**	.033**	.031**	.033**	.034**	.025*
	(.008)	(.008)	(.007)	(.010)	(.011)	(.010)
State Cigarette Tax	.019+	−.012	−.011	.013+	.006	.006
	(.010)	(.011)	(.011)	(.008)	(.009)	(.008)
Smoking Household	.035**	.034**	.017*	.065**	.062**	.054**
	(.008)	(.008)	(.009)	(.015)	(.015)	(.013)
Mean Smoking Household	.145	.145	.145	.197	.197	.197
State time trend	No	Yes	Yes	No	Yes	Yes
Sociodemographic controls	No	No	Yes	No	No	Yes

Source. Current Population Survey data are from the Food Security Supplement and Tobacco Use Supplement.
Note. Standard errors, in parentheses, are clustered at the state level. All regressions include month-year fixed effects, interaction of month and year fixed effects, state fixed effects, regional food prices, and the state unemployment rate. State cigarette taxes are from the previous month.
+ $p < .1$.
* $p < .05$.
** $p < .01$.

the relationship between cigarette taxes and food-stamp program enrollment is driven by smoking households.

5.2.3. Monthly Transitions onto Food Stamps

Next we exploit within-household variation in SNAP enrollment from the CPS pseudopanel. Because we have already shown that the effect of cigarette taxes on SNAP enrollment emerges gradually during the posttax period (Figure 2), we estimate a distributed-lag model in which 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.[12] The sum of the coefficients provides the cumulative effect. We stop the series at three lags. (Very similar results are obtained with four and five lags.) The results are shown in Table 5.[13] We obtain consistent results with a first-difference specification (see Table A3), which provides evidence for the strict-exogeneity assumption (Grieser and Hadlock 2016).

[12] The distributed-lag model is a standard approach to estimating an effect that emerges gradually during the postreform period (see, for example, Deschênes and Moretti 2009; Paik, Black, and Hyman 2017).

[13] We obtain consistent results by estimating a fixed-effects model that includes only cigarette taxes in the previous month, that is, not a distributed-lag model. The point estimate using the preferred specification in column 3 of Table 5 on the interaction term is .027 (SE $= .008$; $p < .01$). The results are also robust, but smaller in size and only marginally significant, when we include full sets of state-month-year fixed effects and smoker-month-year fixed effects.

Table 5
Food-Stamp Enrollment: Monthly Pseudopanel

	(1)	(2)	(3)
State Cigarette Tax ($t = 0$) × Smoking Household	.021**	.022**	.021**
	(.007)	(.007)	(.007)
State Cigarette Tax ($t = -1$) × Smoking Household	.006	.006	.006
	(.004)	(.004)	(.004)
State Cigarette Tax ($t = -2$) × Smoking Household	.004	.004	.004
	(.007)	(.007)	(.007)
State Cigarette Tax ($t = -3$) × Smoking Household	−.001	.001	.000
	(.007)	(.007)	(.007)
Cumulative interaction effect	.030**	.033**	.032**
	(.008)	(.009)	(.009)
Cumulative main effect of State Cigarette Tax	−.007*	−.009**	−.008+
	(.003)	(.003)	(.004)
Covariates:			
State fixed effects	Yes	No	No
State time trend	Yes	No	Yes
Sociodemographic controls	Yes	No	No
Household fixed effects	No	Yes	Yes

Source. Data are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey.
Note. Standard errors, in parentheses, are clustered at the state level. All regressions include month-year fixed effects, interaction of month and year fixed effects, interaction of state fixed effects and Smoking Household, unemployment rate, and regional food prices. The four main tax effects in levels are included but not displayed because of space constraints. For all regressions, mean of Smoking Household = .247; N = 26,989 households and 285,685 household-months.
+ $p < .1$.
* $p < .05$.
** $p < .01$.

Column 1 includes household covariates and state time trends. 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 SNAP enrollment for nonsmoking households. In contrast, the interaction terms yield the relationship between tax increases and SNAP enrollment for smoking households. As can be seen, the contemporaneous coefficients are statistically significant and of economically relevant size.[14] The cumulated effect of a tax increase on SNAP enrollment in column 3 implies that a cigarette tax increase of $1 increases food-stamp program enrollment of eligible low-income smoking households by 3.2 percentage points from a baseline of 25 percent, that is, by 13 percent.

5.2.4. Duration Analysis

We take another look at the empirical question by conducting a duration analysis. Duration analyses are commonly used in labor economics to study the im-

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

Table 6

Duration Analysis of State Cigarette Taxes and Food-Stamp Take-Up

	Nonsmoking Households	Smoking Households
State Cigarette Tax	.157	.383**
	(.186)	(.136)
Household-months	156,266	55,550
Households	16,625	6,072

Source. Data are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey.

Note. Standard errors, in parentheses, are clustered at the state level. The sample is limited to households not participating in food stamps in the first month observed and includes households until the month they take up food stamps or fall out of the sample (censored). All regressions include month-year fixed effects, year fixed effects, interaction of month and year fixed effects, state unemployment rate, regional food prices, state time trends, and socioeconomic controls.

** $p < .01$.

pact of a variable on the length of unemployment spells (Van Den Berg 2001). They have also been used in health economics to study the onset of smoking (for example, DeCicca, Kenkel, and Mathios 2002). We employ a duration analysis for two main reasons: to perform a robustness check and to be able to interpret our empirical findings in a different manner and obtain an answer to the question of whether higher cigarette taxes decrease the time span until nonenrolled but eligible households take up food stamps. Whereas it may be unrealistic to assume that eligible but nonenrolled households would have never enrolled in SNAP in the absence of a tax increase, it is plausible that the tax increase shortens the time to take-up.

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

Table 6 reports the coefficients from estimating a Cox proportional hazard model. We split the sample and estimate the models separately for nonsmoking

Table 7
State Cigarette Taxes and Other Outcome Margins

	Quit Smoking (1)	Cigarettes per Day (2)	No Money for Food (3)
State Cigarette Tax × Smoking Household	.005*	−2.24**	.005
	(.002)	(.405)	(.009)
State Cigarette Tax	.004	.40**	.014
	(.003)	(.138)	(.011)
Smoking Household	−.021**	16.41**	.122**
	(.003)	(.551)	(.012)
Mean Smoking Household	.368	14.57	.500

Source. Data are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey.
Note. Standard errors, in parentheses, are clustered at the state level. State cigarette taxes are from the previous month. All regressions include month-year fixed effects, state fixed effects, interaction of state fixed effects and Smoking Household, regional food prices, and state time trends. $N = 26{,}792$.
* $p < .05$.
** $p < .01$.

and smoking households because of the readily interpretable coefficients. The specifications therefore avoid issues surrounding the calculation of marginal effects of interaction terms in nonlinear models.

The point estimate on cigarette taxes for nonsmoking households is insignificant and a little over one-third of that for smoking households. The interpretation of the statistically significant coefficient for smoking households is as follows: a $1 increase in cigarette taxes increases the hazard of eligible but nonenrolled households of taking up SNAP by 47 percent ($\exp(.383) = 1.47$). Overall, the duration analysis provides evidence that is consistent with the results from the linear probability models and allows for a complementary interpretation of the observed empirical pattern.

5.3. *Other Outcome Margins*

Table 7 tests for compensatory behavior outside of, and in addition to, SNAP enrollment by studying other outcome margins using the CPS cross section. We estimate the specification in equation (1) with different outcome variables. 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 is whether at least one household member quit smoking. A household is defined to be a quitting household if at least one member smoked cigarettes 1 year previously but does not smoke cigarettes at the time of the interview. Note that households with and without current smokers can have members who quit smoking within the past year. The results suggest that a $1 increase in cigarette taxes is associated with a .5-percentage-point (1.4 percent relative to the baseline of .368) increase in the probability that at least one household member quit smoking in the past year. Note, however, that this estimate captures only temporary quitting behavior; relapse may occur.

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 2.2 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 12-percentage-point higher risk of reporting that they ran out of money for food than nonsmoking households but find no evidence of a strong relationship with cigarette taxes.

Finally, we assess how food-related expenditures change for smoking and nonsmoking households after cigarette tax increases. For that purpose, we estimated equation (1) using the CEX data 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 provide only 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 8 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 $.80. Next, and consistent with the literature that shows a relatively inelastic demand for cigarettes (for example, Hansen, Sabia, and Rees 2017), columns 3–6 of Table 3 show that household cigarette expenditures increase significantly when taxes increase. Using the CPS, we obtain highly significant point estimates suggesting that quarterly cigarette expenditures increase by $30 for each $1 increase in state cigarette taxes. However, it is well documented that self-reported consumption and expenditure measures are underreported and contain measurement error (see, for example, Bee, Meyer, and Sullivan 2015), which may attenuate our expenditure estimates. A static calculation that considers the estimated demand response of 2.2 fewer daily cigarettes consumed per household (Table 7, column 2) would yield mean quarterly expenditure increases of $45 for each $1 increase in cigarette taxes ((22 packs per month on average − 2.2 cigarettes per day × 30 days in month/20 cigarettes per pack) × .80 × 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 SNAP enrollment by 3.2 percentage points among nonenrolled eligible smoking households (13.1 percent from a baseline of .247). The duration analysis presented in Table 6 offers an alternative and consistent interpretation of the empirical pattern. Independent of the model employed, nonsmoking households do not respond to cigarette tax increases by enrolling in food stamps.

Table 8
Summary of Findings

	Value
Change in equilibrium retail prices (mean $4.41) ($)	.80**
Change in quarterly cigarette expenditures (mean $392) ($)	30.4+
Change in SNAP enrollment:	
Nonsmoking households (baseline .141)	−.008+
Smoking households (baseline .247)	.032**
Change in the hazard of taking up SNAP (coefficient):	
Nonsmoking households	.157
Smoking households	.383**

Note. SNAP = Supplemental Nutrition Assistance Program.
+ $p < .1$.
** $p < .01$.

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 offset by increases in spending on food stamps:

$$\text{Offset} = \frac{N_S \times E_S \times \Delta_e \times \bar{B}}{N_S \times \Delta_\tau \times \bar{C}} = \frac{\Delta_e \times E_S \times \bar{B}}{\bar{C}},$$

where N_S is the number of smoking households, which cancels out of the expression; E_S is the proportion of smoking households eligible for food stamps (34 percent, our 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 (3.2 percentage points, column 3 of Table 5); $\bar{B}$ is the average smoking household's monthly food-stamp benefit ($156, our calculation from the CEX); and $\bar{C}$ is the average monthly cigarette consumption of smoking households (22 packs per smoking household per month, our 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 SNAP absent the tax increase. Our calculation suggests that roughly 8 percent 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 investigates whether tax increases on goods with price-inelastic demand induce eligible low-income households to enroll in public assistance programs. Using the CPS and the CES, we exploited temporal-spatial variation in cigarette taxes and food-stamp enrollment across US states from 2001 to 2012 to study this question empirically.

Exploiting a novel household panel of food-stamp enrollment, we enriched standard cigarette tax difference-in-differences models with an additional control group: nonsmoking households. Smoking households were treated with higher taxes, while nonsmoking households were not. We found that a $1 increase in cigarette taxes increased the probability that eligible, but nonenrolled, smoking households would take up food stamps by 3.2 percentage points from a baseline probability of about 25 percent. A duration analysis offered a complementary but consistent interpretation of the empirical pattern. Independent of the model employed, nonsmoking households do not respond to cigarette tax increases by taking up food stamps.

In addition to cigarette taxes, other consumption taxes such as sales taxes can have a meaningful effect on low-income households. This paper shows that eligible but nonenrolled 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 taxes and enrollment in public assistance programs.

Appendix

Additional Figure and Tables

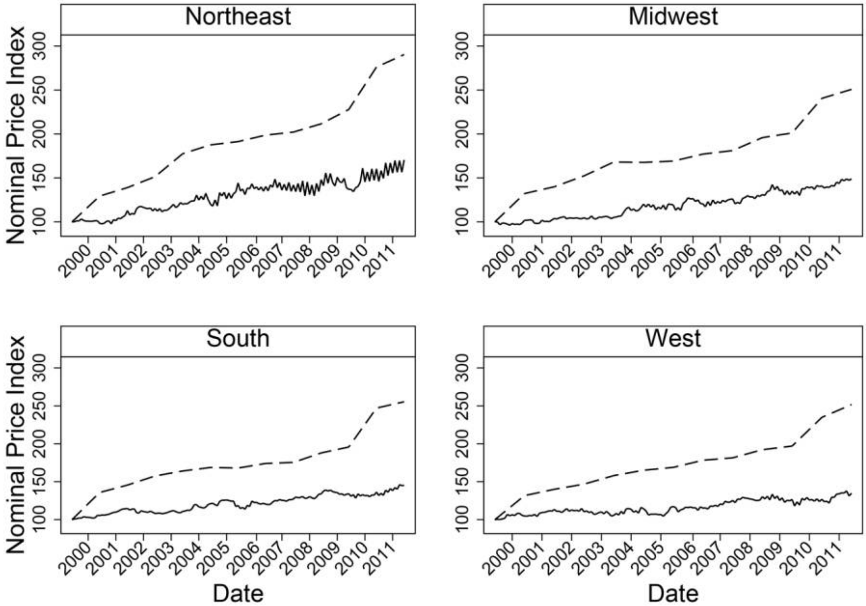

Figure A1. Food- (*solid line*) and cigarette-price (*dashed line*) inflation

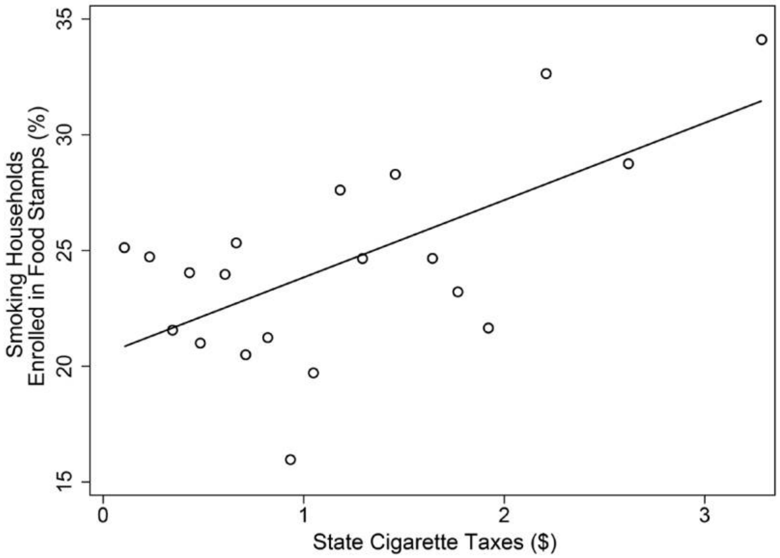

Figure A2. State cigarette taxes versus smokers enrolled in food stamps

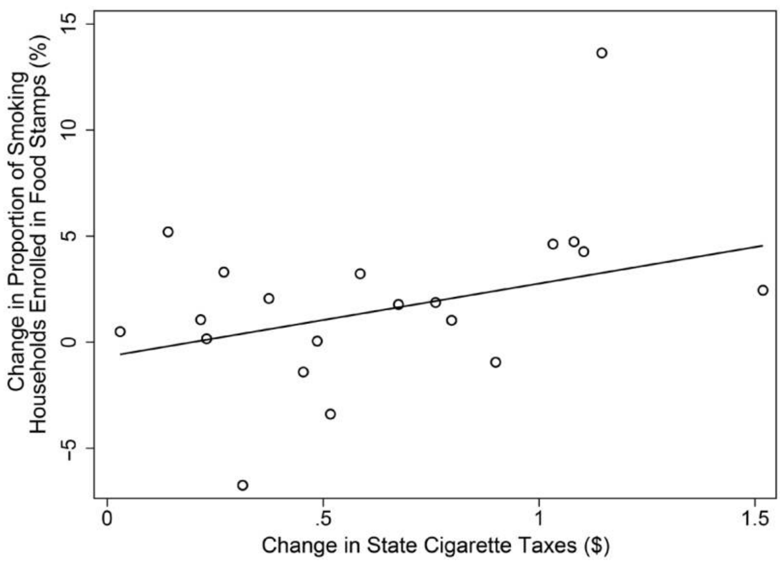

Figure A3. Change in state cigarette taxes versus smokers enrolled in food stamps

Table A1

Current Population Survey Pseudopanel Observations

	Frequency	%	Cumulative %
February 2003	7,578	2.7	2.7
March 2003	8,252	2.9	5.6
April 2003	8,252	2.9	8.4
May 2003	8,252	2.9	11.3
June 2003	8,252	2.9	14.2
July 2003	8,252	2.9	17.1
August 2003	8,252	2.9	20.0
September 2003	8,252	2.9	22.9
October 2003	8,252	2.9	25.8
November 2003	8,252	2.9	28.7
February 2006	7,817	2.7	31.4
March 2006	8,887	3.1	34.5
April 2006	8,887	3.1	37.6
May 2006	8,887	3.1	40.7
June 2006	8,887	3.1	43.8
July 2006	8,887	3.1	47.0
August 2006	8,887	3.1	50.1
September 2006	8,887	3.1	53.2
October 2006	8,887	3.1	56.3
November 2006	8,887	3.1	59.4
December 2006	8,887	3.1	62.5
February 2010	8,652	3.0	65.5
March 2010	9,850	3.5	69.0
April 2010	9,850	3.5	72.4
May 2010	9,850	3.5	75.9
June 2010	9,850	3.5	79.3
July 2010	9,850	3.5	82.8
August 2010	9,850	3.5	86.2
September 2010	9,850	3.5	89.7
October 2010	9,850	3.5	93.1
November 2010	9,850	3.5	96.6
December 2010	9,850	3.5	100.0

Table A2

Consumer Expenditure Survey Cross-Sectional Observations

	Frequency	%		Frequency	%
2001	2,592	10.5	January	2,057	8.3
2002	2,829	11.4	February	2,082	8.4
2003	2,937	11.9	March	2,091	8.5
2006	2,527	10.2	April	2,011	8.1
2007	2,248	9.1	May	2,148	8.7
2008	2,248	9.1	June	1,999	8.1
2009	2,304	9.3	July	1,990	8.1
2010	2,401	9.7	August	2,003	8.1
2011	2,346	9.5	September	2,143	8.7
2012	2,297	9.3	October	2,132	8.6
			November	2,033	8.2
			December	2,040	8.3

Table A3

Change in Food-Stamp Enrollment by Change in State Cigarette Tax: First-Differences Specification

	(1)	(2)	(3)
Δ State Cigarette Tax ($t = 0, t = -1$) × Smoking Household	.009+	.010*	.010*
	(.005)	(.005)	(.005)
Δ State Cigarette Tax ($t = -1, t = -2$) × Smoking Household	.006*	.008*	.008*
	(.003)	(.004)	(.004)
Δ State Cigarette Tax ($t = -2, t = -3$) × Smoking Household	.004	.005	.005
	(.007)	(.008)	(.008)
Cumulative interaction effect	.019*	.024+	.024+
	(.009)	(.012)	(.012)
Cumulative main effect of change in State Cigarette Tax	−.004*	−.007**	−.007**
	(.002)	(.003)	(.003)
Covariates:			
State fixed effects	Yes	No	No
State time trend	Yes	No	Yes
Sociodemographic factors	Yes	No	No
Household fixed effects	No	Yes	Yes

Source. Data are from the Food Security Supplement and Tobacco Use Supplement of the Current Population Survey.

Note. Standard errors, in parentheses, are clustered at the state level. All regressions include month fixed effects, year fixed effects, interaction of month and year fixed effects, interaction of state fixed effects and Smoking Household, change in unemployment rate, and change in regional food prices. Each column represents one first-differenced variant of equation (1), where the binary dependent variable indicates whether the household transitioned onto food stamps between months $t = -1$ and $t = 0$. The three main effects on changes in taxes are included but not displayed because of space constraints. For all regressions, mean of Smoking Household = .247; N = 26,989 households and 258,696 household-months.

+ $p < .1$.
* $p < .05$.
** $p < .01$.

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