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ABSTRACT

Behavioral Responses to Taxation: Cigarette Taxes and Food Stamp Take-Up*

This paper investigates a previously unexplored behavioral response to taxation: whether smokers compensate for higher cigarette taxes by enrolling in food stamps. First, we show theoretically that increases in cigarette taxes can induce food stamp take-up of non-enrolled, eligible smoking households. Then, we study the theoretical predictions empirically by exploiting between and within-household variation in food stamp enrollment from the Current Population Survey as well as data from the Consumer Expenditure Survey. The empirical evidence strongly supports the model predictions. Higher cigarette taxes increase the probability that low-income smoking households take-up food stamps.

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

Keywords: cigarette taxes, food stamp take-up, tax pass-through rate, unintended consequences

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1 Introduction

Cigarette taxes can nudge smokers to reduce cigarette consumption. But cigarette taxes also alter smokers' behaviors in unintended ways. For instance, they respond strategically to increases in cigarette tax increases 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 (Lovenheim, 2008; Goolsbee et al., 2010; DeCicca et al., 2013a). These responses undermine the behavioral rationale behind cigarette taxes.

This article provides evidence for another, previously unexplored, strategic response: that low-income smoking households respond to higher cigarette taxes by taking up food stamps. As Figure 1 shows, over the first decade of the 21st century, average cigarette prices doubled from \$3 to \$6 for a pack of cigarettes. The income share that a minimum wage earning smoker needs to support his smoking habit has more than doubled from less than 4% to over 10% (Figure 1). Over the same decade, absolute food stamp enrollment numbers have almost tripled, with the share of the population receiving food stamps more than doubling from 6% to 15% (Figure 2). This paper seeks to answer the question whether both developments are causally related in some way.

[Insert Figures 1 and 2 about here]

The first part of the paper studies a model of cigarette taxes and take-up of public assistance programs. Under standard assumptions informed by behavioral economics, we derive theoretical support for the main hypothesis: Increases in taxes on addictive goods can induce non-participating but eligible households to take up public assistance programs. The model shows that smoking households become more willing to pay the economic and stigma costs of participating in government transfer programs when cigarette taxes increase (Moffitt, 1983).

The model suggests that access to public assistance programs can partly neutralize the "nudge" of cigarette taxes. To shed some initial light on how this notion might influence aggregate cigarette consumption and food stamp enrollment, we present simulations in a stylized framework. The simulations (*i*) solidify the prediction from the marginal arguments that cigarette taxes can induce food stamp take-up, and (*ii*) reveal that prospect of enrolling in public assistance programs can preclude cigarette taxes from correcting behavioral distortions caused by self-control problems. Regardless of whether consumers value cigarette taxes as a commitment device (Gruber and Kőszegi, 2004; Kőszegi, 2005), the ability of cigarette taxes to actually serve that function for low-income smokers is challenged by the simulations.

The second part of this paper empirically tests the model predictions using data from the Current Population Survey (CPS) and the Consumer Expenditure Survey (CEX). We link these datasets to monthly cigarette tax data on the state level over one decade. In addition, we exploit the pseudo-panel structure of the CPS on food stamp enrollment. The main empirical analysis uses this within-household variation in food stamp enrollment (month-to-month) from the CPS. The panel structure allow us to study the take-up of food stamps in a dynamic setting, i.e., whether households transition onto food stamps from one month to another, exploiting exogenous simultaneous monthly state-tax variation. Using this novel dataset, we find strong evidence in favor of our hypothesis. A $1 increase in cigarette taxes increases the monthly probability that eligible, but non-enrolled, smoking households take-up food stamps by between 2 to 3ppt from a baseline probability of about 25%.

To investigate the mechanisms driving this behavior, we also study the impact of cigarette taxes on cigarette expenditures using cross sectional data from the CPS and the CEX. First, we show that cigarette prices as actually paid by consumers increase by $0.75 for every $1 increase in tax, i.e., we find a pass through rate of 0.75. Second, for the mean smoking household consuming 25 packs per month—or 300 packs per year—this implies that a $1 increase in cigarette taxes would translate into annual spending increases of $225. However, 20% of all low-income smoking households consume at least 45 packs a month, and thus experience annual income shocks of at least $400 for each $1 increase in cigarette taxes. Note that half of all enrolled households receive less than $100 in food stamp benefits per month. This relatively small amount helps explain why transaction costs may prevent eligible households from enrolling—at least until high cigarette taxes induce marginal smoking households to enroll. In fact, in 2001, only about fifty percent of all eligible households were enrolled in the food stamp program (Lerman and Wiseman, 2002; Ganong and Liebman, 2013). CPS between-household variation show that low-income smoking households are 50% more likely to be on food stamps as compared to low-income non-smoking households. Moreover, for every additional carton of cigarettes consumed, a smoking household's probability of being enrolled in food stamps increases by 0.8ppt for every dollar of cigarette taxes.

Our findings contribute to several strands of the economics literature. Most directly, our findings contribute to both the literature on tax avoidance behavior (Adda and Cornaglia, 2006; Lovenheim, 2008; Goolsbee et al., 2010; Harding et al., 2012; Adda and Cornaglia, 2013; DeCicca et al., 2013a; Chiou and Muehlegger, 2014) and the literature examining the factors that influence take-up of public assistance programs (Duclos, 1995; Kayser and Frick, 2000; Lerman and Wiseman, 2002; Currie, 2004; Heckman and Smith, 2004; Aizer, 2007; Hoynes and Schanzenbach, 2009; Kleven and Kopczuk, 2011; Hoynes and Schanzenbach, 2012; Ganong and Liebman, 2013).

We also contribute to the behavioral public finance literature in the sense that we incorporate in it concepts of uncoordinated regulation (Mason and Swanson, 2002). Because one policy can blunt the incentives imposed by another policy, we show that uncoordinated policy making can create inefficiencies, giving rise to the need for more sophisticated optimal taxation models. Along these lines, some research has examined interactions of alternative policies in the context of sin taxes. For instance, Don Kenkel (1993) showed that optimal taxes on alcohol are likely lower in places with tough drunk driving laws. In a similar light, our findings demonstrate that state tax policies may have important spillover effects to federal programs. Even though we do not employ an optimal taxation model, our findings nonetheless set forth the economic intuition that optimal sin taxes likely strike a balance between reducing substance use on the one hand and maintaining efficiency on the other, which may both depend on the structuring of other public policies. Our findings suggest a lower optimal sin tax than the one proposed by recent behavioral-informed optimal sin tax analyses (O'Donoghue and Rabin, 2003, 2006; Haavio and Kotakorpi, 2011).

The organization of this article is as follows. Section 2 develops a model of food stamp take-up to motivate and complement empirical analysis. It also develops the first framework attempting to analyze the inefficiencies created by uncoordinated tax policy and public assistance programs. Section 3 describes the data and Section 4 the empirical approach. Section 5 presents the results and the final section concludes.

2 Theoretical Framework

In this section, we develop a simple model of the relationship between taxes on addictive goods and voluntary government transfer programs. For concreteness, we use as our running example cigarettes and food stamps.[1] After deriving population predictions on how cigarette taxes impact food stamp participation in both a neoclassical and behavioral setting, we present simple simulations in a stylized behavioral application. The simulations reveal how uncoordinated food stamp and cigarette tax policies can impact cigarette consumption and the take-up of food stamps.

2.1 Consumer Problem

Suppose that the utility of a household depends on cigarettes c, a composite food good x, and food stamp enrollment costs S. Though we lump all possible enrollment costs into one mechanism, we expect two main costs to be at work. The first are pecuniary costs of taking up food stamps, such as the time spent on paperwork and travel costs. These costs might be non-trivial—with initial applications taking nearly five hours to complete, at least two trips to a food stamp office, and at least \$10 out-of pocket application costs (Ponza et al., 1999). The second type of costs are non-pecuniary in nature. Since Moffitt's (1983) seminal work on welfare stigma, most program participation models acknowledge that individuals have a distaste arising from enrollment in the program *per se*. Put simply, households receive disutility from the social stigma involved in program participation. A great deal of analytical and empirical work has documented the existence of stigma and its role in take-up decisions (Kleven and Kopczuk, 2011; Hoynes and Schanzenbach, 2009; Kim, 2003; Bishop and Kang, 1991; Hansen et al., 2014; Stuber and Kronebusch, 2004; Pudney et al., 2007; Currie, 2004; Daponte et al., 1999). In this paper, we do not empirically test for the existence of stigma, attempt to estimate the effect size of stigma on food stamp take-up, or empirically distinguish stigma from other pecuniary or non-pecuniary enrollment costs. Rather, conditional on stigma and all other enrollment costs playing some role in enrollment decisions, we simply study the impact of cigarette taxes on food stamp take-up.

We assume the households' utility function is separable in consumption (c and x) and enrollment costs (S). The household exogenously receives an income W that is low enough such that the household is eligible for food stamps. The household faces a standard budget constraint and chooses consumption levels of cigarettes c and food x. The household also chooses whether to participate in food stamps. Let $e = 1$ if the household chooses to enroll in food

[1] In the US, food stamp benefits were formerly provided through the Food Stamp Program. The program providing these benefits is currently named the Supplemental Nutrition Assistance Program (SNAP).

stamps and $e = 0$ if not. If the household chooses to enroll in food stamps ($e = 1$), they receive a monetary benefit FS, but also incur a disutility of $\phi(S)$. If the household does not enroll in food stamps ($e = 0$), the household's problem reduces to a standard two good utility maximization problem.

We assume that cigarette tax increases are passed 1:1 onto cigarette prices and do not affect prices of other goods. This assumption allows to abstract away from the issue of tax pass through and tax incidence (DeCicca et al., 2013b), and treats a change in excise taxes as a change in prices. Although we show that, in general, these assumptions hold up empirically, they do not materially change any of the model predictions. The household's problem is:

$$\max_{c,x,e} u(c,x) - \phi(S)e$$

$$\text{s.t.} \quad W + eFS \geq pc + x$$

$$c, x \geq 0,\ e \in \{0,1\},\ x \geq eFS$$

where p is the tax-inclusive price of cigarettes and the price of the composite food good has been normalized to one. Assume that $x > FS$ if $e = 1$ so that the household cannot spend the food stamp benefit on cigarettes. Following the tradition dating back to Ranney and Kushman (1987), let $\phi(S) = S$ so that the household does not realize marginal enrollment costs that vary with the size of the food stamp benefit, i.e., enrollment costs scale down the total utility from consumption.

Consider separately the household's maximization problem of choosing x and c when $e = 0$ and when $e = 1$. Let $v(p, W)$ and $v(p, W + FS)$ denote the household's indirect utility if $e = 0$ and $e = 1$, respectively. Then it is optimal to choose $e = 1$ if and only if:

$$v(p, W + FS) - v(p, W) \geq S$$

2.2 Population Predictions

Let S_i be the enrollment cost for household i. To derive population predictions, we must make assumptions about societal preferences and the distribution of S_i. Suppose the relevant population can be represented as having uniform preferences and earn the same income W. Households are similar in all ways but S.

To determine if increases in cigarette taxes induce households to take-up food stamps, one can easily show it is sufficient to analyze the impact of a tax increase on the household of marginal enrollment cost (the household who is indifferent between enrolling and not enrolling). To see why, let the household with marginal enrollment cost be $\bar{S} = v^*(p, W + FS) - v^*(p, W)$. Then, it must be that all households with $S_i < \bar{S}$ enroll in food stamps because their (utility) cost of enrolling is lower than the increase in utility resulting from the (monetary) benefits of enrolling. Any increase in $\bar{S}$ implies that more households enroll in food stamps because all households are identical other than in S_i. In mathematical terms, if $\bar{S} < \bar{S}'$ we have:

$$\frac{\partial \bar{S}}{\partial p} > 0 \iff \exists i \;\; s.t. \;\; \bar{S} < S_i < \bar{S}' \tag{1}$$

In words, Equation (1) says that if the enrollment costs of the marginal household is increasing in taxes, a tax increase will result in more households taking up food stamps.

2.2.1 Predictions in a Neoclassical Framework

Without loss of generality, suppose the food stamp benefit FS is infinitesimal, which allows us to write $v^*(p, W + FS) - v^*(p, W) = \frac{\partial v^*(p,W)}{\partial W}$ because FS is merely a change in wealth. To determine how $\bar{S}$ varies with p, we take a total derivative of $\bar{S}$ with respect to p:

$$\frac{d\bar{S}}{dp} = \frac{\partial \frac{\partial v^*(p,W)}{\partial w}}{\partial p} = \frac{\partial \lambda}{\partial p} \tag{2}$$

where λ is the Lagrange multiplier on the household's budget constraint (i.e., the shadow value), and the final expression follows directly from the envelope condition.

In optimization theory, note that λ is actually a choice variable; it is an element of "argmax" just like the bundles x and c. Therefore, we can apply comparative statics techniques to analyze how λ varies with p.[2] As it turns out, in the neoclassical framework with minimal functional form assumptions these comparative static techniques do not provide definite predictions on the sign of $\frac{\partial \lambda}{\partial p}$. Moreover, take-up and cigarette taxes are even unrelated under

[2]For instance, we could try to find supermodularity between λ, x, and p and apply Topkis Theorem (Topkis, 1998).

some typical functional form assumptions. For instance, under quasi-linear preferences $\Big($e.g., $u(c,x) = ln(c) + x\Big)$, one observes that $\lambda = 1 \ \ \forall p$, implying that cigarette prices (taxes) would have no effect on take-up. To summarize, smokers who behave as neoclassical consumers might compensate for higher cigarette taxes by smoking less, meaning cigarette tax increases might not induce smokers to take-up governmental assistance programs.

2.2.2 Predictions in a Behavioral Framework with Addition

We now use a stylized behavioral economics framework to derive predictions on the relationship between cigarette taxes and food stamp take-up. It is perhaps worth emphasizing that one can show $\frac{dS}{dp} > 0$ in a neoclassical framework under particular function form assumptions, such as with nonhomothethic preferences.[3] We focus on an addiction based behavioral framework because of our particular interest in whether access to food stamps can partly neutralize the effect of cigarette taxes on discouraging smoking. Our stylized example uses a "cue-triggered" type of addiction as in Bernheim and Rangel (2004). However, the same predictions flow from a handful of other behavioral departures to the rational framework, including Becker and Murphy's (1988) seminal *Theory of Rational Addiction* model, Gruber and Kőszegi's (2001) addiction model, and, more recently, Dragone's (2009) model that says any *change* in consumption from period to period comes at a utility cost. Any stylized model we could have presented would take an agnostic stance as to why cigarette demand is inelastic. We follow Bernheim and Rangel (2004) because of it's general acceptance and for the practical reason that it is more tractable than the other more complex, and usually dynamic, models.

Using a behavioral model prevents the analysis of indirect utility as in Section 2.2.1 precisely because addiction prevents optimization, viz., $v(p,W)$ is the optimized indirect utility function and the household is no longer optimizing. As such, we analyze $\frac{d\bar{S}}{dp}$ from Equation (1) by reverting back to the original utility function $u(c,x)$. We denote household *choices* (not optimizing behavior) as $\hat{x}(p,W), \hat{c}(p,W)$ and resulting utility from those choices as $\hat{u}(p,W)$.

Bernheim and Rangel (2004) define a consumer who has two selves: (*i*) a cognitive self that has rational preferences when in the "cold" state, and (*ii*) an addicted self that consumes the addictive good at any cost when in the "hot" state. Suppose that W and p are such that a tax increase triggers a change from the cold to the hot state for the household with $\bar{S}$. As

[3]The proof is available upon request.

before, we characterize $\frac{d\bar{S}}{dp}$ by totally differentiating $\bar{S}$ with respect to p, but this time where $\bar{S} = \hat{u}(p, W + FS) - \hat{u}(p, W)$:

$$\frac{d\bar{S}}{dp} = \left(\frac{\partial \hat{u}}{\partial \hat{x}}\frac{\partial x}{\partial p} + \frac{\partial \hat{u}}{\partial \hat{c}}\frac{\partial \hat{c}}{\partial p}\right)\Big|_{FS>0} - \left(\frac{\partial \hat{u}}{\partial \hat{x}}\frac{\partial x}{\partial p} + \frac{\partial \hat{u}}{\partial \hat{c}}\frac{\partial \hat{c}}{\partial p}\right)\Big|_{FS=0}$$

In the hot state, irrespective of underlying preferences and the price of cigarettes p, the addicted household consumes at least some amount of the addiction good $\hat{c} \geq a$. This can be thought of as an addiction constraint. For the household whose addition constraint is binding, we have: $\frac{\partial \hat{c}}{\partial p} = 0 \;\; \forall p$. Under the standard assumption that households must satisfy their true budget constraint, inelastic consumption of cigarettes implies that consumption of x will directly depend on the amount of cigarettes demanded $\hat{c}$: $\frac{\partial \hat{x}}{\partial p}\big|_{FS>0} = \frac{\partial \hat{x}}{\partial p}\big|_{FS=0} = -\hat{c}$. In words, every extra dollar the demand inelastic household spends consuming cigarettes from an increase in cigarette prices directly decreases the consumption of x. Again supposing that the food stamp benefit FS is infinitesimal, we have:

$$\frac{dS}{dp} = -\hat{c}\left(\frac{\partial \hat{u}}{\partial \hat{x}}\Big|_{FS>0} - \frac{\partial \hat{u}}{\partial \hat{x}}\Big|_{FS=0}\right) = -\hat{c}\frac{\partial \frac{\partial \hat{u}}{\partial \hat{x}}}{\partial W} = -\hat{c}\frac{\partial^2 \hat{u}}{\partial^2 \hat{x}} > 0 \tag{3}$$

where $\frac{\partial \hat{u}}{\partial \hat{x}}$ is the marginal utility of consumption. The inequality follows because of decreasing marginal utility $\frac{\partial^2 \hat{u}}{\partial^2 x} < 0$. The final expression follows directly from the fact that, by construction, any increase in wealth is used for consumption of x. Equation (3) differs from Equation (2) in that no functional form assumptions are required for (3) to hold. Addiction that leads to inelastic demand implies that a cigarette tax increase can induce the marginal household to take-up food stamps.

To summarize this finding in plain words: at time t_0, a smoking household does not enroll in food stamps. At t_1, cigarette taxes increase, but the smoking household nevertheless continues to smoke the same amount due to addiction (in a "hot state"). At t_2, the household falls back into a cold, rational state and—having spent too much on cigarettes due to self control problems—rationally enrolls in food stamps.

2.3 Simulation

In Section 2.2.2, our predictions were based on marginal arguments and focused on particular homogeneous households who varied only in S_i. In this section, we calibrate the importance of these results numerically by using simulations in a specific example that relies on both addiction and self control problems. These simulations are also used to help give us a sense of how uncoordinated food stamp and cigarette tax policies impact cigarette consumption and take-up due to optimization failures.

We randomly generate 50,000 households that vary in S_i, a_i, and W_i according to normal distributions. We then define a food stamp benefit level that decreases in wealth: $FS = fs + \frac{b}{W}$, where fs is the baseline benefit that every household is eligible for and b is the variable benefit level that we loop over in our simulation. Informed by the approach in O'Donoghue and Rabin (2003, 2006), we define a Cobb-Douglas-like instantaneous utility in time t as: $u_t = c_t^{\alpha} x_t^{\sigma} c_{t+1}^{-\gamma}$, where $\alpha, \sigma, \gamma > 0$ are exogenous parameters and the enrollment cost S acts to scale down total utility if the household enrolls in food stamps. The term c_{t+1} is the future negative health consequences of current period smoking. $\gamma < 1$ is the self control parameter. Supposing that the household has a discount rate of $\delta < 1$, we can rewrite utility for household decision making without a time dimension: $u = c^{\alpha-\delta\gamma}x^{\sigma}$. Note that the welfare actually realized by the household is: $U = c^{\alpha-\delta}x^{\sigma}$. We assume that each household must also satisfy her budget constraint ($W_i + e_i FS_i \geq pc_i + x_i$), addiction constraint ($c_i > a_i$), and cannot use food stamps to purchase cigarettes ($x \geq eFS$).

Under the conditions we have just set forth, we simulate the household behavior varying both p and b. Under each combination of p and b, we calculate (a) aggregate cigarette consumption $\left(\sum_i c_i\right)$, (b) the percentage of households enrolled in food stamps $\left(\frac{\sum_i e_i}{50{,}000}\right)$, and ($c$) the percentage of households who enroll in food stamps only because of self control problems $\Bigg(\frac{\sum_j j}{50{,}000}$, where $j = 1$ for households who enroll in food stamps $\left(u_i(p, W + FS) - S_i > u_i(p, W)\right)$ but who would not have enrolled without suffering from self control problems $\big(U_i(p, W + FS) - S_i \leq U_i(p, W)\big)$ and is otherwise 0 $\Bigg)$. Figures 3 to 5 plot the simulation results for outcomes (a) to (c), respectively.

[Insert Figures 3 to 5 about here]

Figure 3 shows that aggregate cigarette consumption typically decreases in cigarette taxes. However, for at least some combinations of food stamp benefits and cigarette taxes, an increase in cigarette taxes leads to an increase in cigarette consumption (anytime when moving to the right in Figure 3b results in a darker color gray). Figure 4 supports the prediction from the marginal argument in Equation (3). However, at high relative taxes and low relative food stamp benefits, one observes that increasing taxes can actually lead to lower enrollment rates. This occurs when households' addiction constraint begins to bind, implying that self control issues no longer drive take-up. Finally, one observes from Figure 5 that higher taxes are typically correlated with higher food enrollment attributable to optimization failures. We think of this outcome measure as one of "policy coordination efficiency."

Before we turn to our empirical analysis, we would like to emphasize that these simulations should not be interpreted as a general theoretical finding. Our goal here was not to prove that all low-income smoking households would take-up food stamps following a cigarette tax increase; rather, we simply demonstrate that such behavior can be explained within the context of behavioral frameworks that are commonly used in the literature.

3 Datasets

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

The CPS is conducted by the US Census Bureau for the Bureau of Labor Statistics. It is a monthly survey of approximately 60,000 households, mainly used for labor force statistics. However, data on special topics ranging from tobacco use to food security are gathered periodically in so-called supplemental surveys. The CPS surveys households for four months, then does not survey for eight months, and then surveys the same households again for four months. A share of households surveyed in the main survey is also surveyed in the applicable supplemental survey of that month.

Our main dataset combines the Tobacco Use Supplements (TUS) and the Food Security Supplements (FSS) of the CPS from 2001 to 2011. Each household is surveyed a maximum of one time in the TUS and FSS and, for the years we use, the FSS is carried out each year in December and the TUS is carried out in periodic "waves" with three surveys per wave.[4]

[4] The waves we use are: (1) June 2001, November 2001, and February 2002; (2) February 2003, June 2003, and November 2003; (3) May 2006, August 2006, and January 2007; and (4) May 2010, August 2010, and January 2011.

We match households who appear in both the FSS and the TUS. For example, we matched households in the January 2007 TUS with the same households in the December 2006 FSS.[5]

In matching households who participate in both the TUS and FSS, we construct two datasets: *(i)* a cross sectional dataset, and *(ii)* a pseudo-panel dataset. We refer to the panel as a pseudo-panel because we are unable to capture any time-variant socio-demographics such as income and household structure. However, we are able to construct a pseudo-panel that follows a household's enrollment in food stamps for each month of the year—the December FSS surveys monthly food stamp enrollment information separately for each month from January until December. By reshaping the data by household-month, we construct a pseudo-panel of monthly food stamp enrollment information. To reiterate, we use information in the TUS to distinguish between smoking and nonsmoking households and use the monthly food stamp enrollment information in the FSS to follow these smoking and nonsmoking households for up to 12 months.

In the interest of clarity, we define what we mean by two terms that we use henceforth. First, *food stamp enrollment* indicates whether a household received food stamp benefits in t_0. Second, *food stamp take-up* indicates whether a household transitioned onto food stamps between t_{-1} and t_0.

Sample Selection. Our target population is low-income households who are potentially eligible for food stamps. Hence we exploit the CPS filter question for food stamp information to restrict the sample to households below 185% of the Federal Poverty Line (FPL). We discard observations with missings on their observables.

Merging in State-Month Tax Data. The public version of CPS includes state identifiers and interview dates. Using this information, we merge in monthly data on state cigarette taxes from the Tax Burden on Tobacco (2012).

Cross-Sectional CPS Dataset. The cross-sectional dataset uses TUS information on household socio-demographics, current cigarette consumption, and prices paid for the last pack or carton of cigarettes purchased.[6] Then we merge the household's food stamp enrollment infor-

[5]Note that the CPS is conducted by physical location. For instance, if family X who was surveyed in December 2006 moved out of the physical addresses and family Y moved into that physical address in January 2007, the household identifiers in the CPS would be the same. We followed the CPS instructions to limit households to the same family in the TUS and FSS.

[6]Note that the 2001-2002 TUS did not ask respondents about the price of last cigarette purchased. For these years we impute missing self-reported cigarette prices with official state-year price information from the Tax Burden on Tobacco (2012). We apply the same imputation method for missings in the other years. Cigarette consumption information was only surveyed for households with at least one daily smoker. For the pseudo-panel, we also manually impute state-month tax information for the first months we observe a household to not loose these observations.

mation from the FSS that overlaps with the month the TUS was conducted. This leaves us with a cross-sectional sample of 26,729 household-year observations, where the reference month is the month of the TUS; we observe each household only once.[7] Table A1 in Appendix A shows the descriptive statistics and Table A2 shows the span of the observations across different year-months between 2001 and 2011.

Pseudo-Panel Dataset. The pseudo-panel links the month-by-month household food stamp enrollment information from the FSS with the smoking status of the households throughout the year from the TUS.[8] We then link the pseudo-panel with the monthly tax data and restrict the pseudo-panel to households with at least 6 months of food stamp enrollment information. [9] Table B1 in Appendix B shows the descriptive statistics for the CPS pseudo-panel, and Table B2 the distribution of the 285,685 monthly household observations over time. In addition to being able to study the monthly food stamp take-up using a panel, one main advantage of the pseudo-panel rests in the fact that between 7,500 and 10,000 observations are almost evenly distributed across all 12 calendar months over several years.

Dependent Variables

With regard to the the CPS cross-section in Table A1, the first dependent variable of interest is the price paid for the last pack of cigarettes.[10] This information is only available for the 4,008 low-income CPS households with at least one smoker. As seen, in the decade from 2001 to 2011, the mean nominal price was $3.50 with a standard deviation of $2.22. The second dependent variable in Table A1 is annual household cigarette expenditures.[11] The mean smoking house-

[7]Using the demographics from the FSS does not significantly change our results.

[8]The TUS surveys the smoking status of each household member at the time of the survey and one year before the survey. These two variables allow us to establish the smoking status of each household member in the time frame of the FSS for households who were surveyed in TUS months following FSS months.

[9]Due to the variation in monthly timing of the TUS—and because the FSS is always carried out in December—the pseudo-panel follows households for different lengths of time. For instance, the panel follows households for twelve months when the TUS was conducted in January, e.g., from January of the previous calendar year to December of the previous survey year.In 2007 and 2011, the TUS was conducted in December and in 2001 and 2003 in November.

[10]If the respondent reported purchasing a carton of cigarettes, the price was divided by 10. If the household has more than one smoker, we take the smoker-mean cigarette price, i.e., we do not weight by the number of cigarettes smoked per household member.

[11]Annual household cigarette expenditures are calculated by multiplying the number of daily cigarettes consumed by the price of the cigarette for each smoker member, normalizing that value to yearly expenditures, and summing these expenditures for all the household members. Note that this calculation uses the last pack's price paid and then extrapolates over the rest of the year. We thus underestimate expenditures in case of irregular cross-border shopping, i.e., if a household residing in New York purchased their last pack of cigarettes for $5 in New Jersey. We also underestimate expenditures in case of future price increases in the course of the year. In contrast, we overestimate expenditures if the price of the last pack was (unusually) high or if the smoker reduces consumption in the course of the year.

hold with 1.3 mean smokers consumes on average 25 packs of cigarettes per month and spends an annual amount of $1,030 on cigarettes, or $86 per month.

With regard to the pseudo-panel in Table B1, the two dependent variables of interest are the binary variables for food stamp enrollment and food stamp take-up. Among households in our sample, 17% are enrolled in food stamps in any given month.[12] 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 on food stamps. Along with the monthly state-level tax variation, these 1,685 households provide the identifying variation for our empirical analysis using the pseudo-panel.

Cigarette Taxes and Socio-Demographic Controls

Our main independent variable of interest is the state cigarette tax in a given month and state. The empirical models employ the state tax in the month prior to the interview because of the time lag between applying for food stamps and officially enrolling. Table A1 in the Appendix shows that the average state excise tax in our sample is $0.75, but varies between $0.025 for Virginia in 2001-2004 and $4.35 for New York after August 1, 2010, which yields nice identifying variation across and within states and over time. Note that we do not include city or county taxes such as in New York City and Cook County (Chicago). Because we use within state variation in taxes to identify the effect of taxes on food stamp enrollment and take-up, the state tax increases are of particular interest. Conditional on an increase in state taxes, the average tax increase is $0.56 in the cross sectional dataset and $0.60 in the pseudo-panel dataset.

The regression models adjust the already relatively homogeneous samples for the socio-economic characteristics shown in Panel B of Table A1. Referring to Panel B, the average household has 2.5 members and an annual earned income of $18,623. Almost 30% are smoking households. 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.

[12]Because we condition on households below 185% of the FPL, this is higher than the officially reported population share enrolled in food stamps. It has also been documented that the CPS under-reports food stamp participation (Meyer et al., 2009), which is probably why the mean among poor households is still relatively low. We re-ran the analysis using different definitions of eligibility and the results do not significantly change.

3.2 Consumer Expenditure Survey (CEX)

Since 1984, the Consumer Expenditure Survey (CEX) has been carried out by the US Census Bureau for the Bureau of Labor Statistics (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, every CU is interviewed five times every three months for a total 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 the BLS-provided family files with food stamp information from 2002 to 2012. Those files contain income, expenditure, and housing information at the CU level. The information mainly stems from the IS; however, detailed expenditure information from the DS are already merged into the family files by the BLS. Similarly, the family files contain aggregated information from the separate family member files.

As we use the public version of the CEX, only a subset of observations is available with clean unambiguous state identifiers (BLS, 2014). We use the state identifiers to merge in the state monthly tax information as provided by the Tax Burden on Tobacco (2012). We then restrict our sample to CUs with complete income information and the second interview.

We employ the CEX in addition to the CPS for three reasons: *(a)* to check for the consistency of our results, *(b)* to exploit a sample that spans observations more evenly across calendar months and years (as demonstrated in Table C2), and *(c)* to exploit the potentially more reliable collection of expenditure information in the CEX.

Dependent Variables

We make use of the CU expenditure information in the last quarter prior to the interview. As seen in Panel A of Table C1 in Appendix C, the retrospective CEX information yields quarterly tobacco expenditures of about $250, which are remarkably consistent with the calculated expenditures in the CPS. About 7% of all 36,893 observed households are on food stamps, which is consistent with the official data (see Figure 2).

Covariates

In contrast to our use of the CPS, we do not restrict the CEX to poor households. One reason we leave the sample unrestricted is the difficulty to replicate the exact CPS sample selection because the CEX does not provide any comparable filter question. While this approach may lead to different coefficient estimates, the general identification strategy remains valid as long as tax increases are orthogonal to households. On the plus side, we obtain estimates that are representative at the population level. Consequently, the sample characteristics as indicated by socio-economics differ slightly from those in the CPS. In the CEX, we have on average 2.8 members per household where less than half of them are male. The average income after taxes is $63K and almost all households live in urban regions. Half of all household heads are male and married; 84% of them are white (see Table C1 in Appendix C).

4 Empirical Approach and Identification

4.1 Empirical Approach

The econometric specification for the cross-sectional CPS and CEX datasets as well as for the CPS psuedo-panel dataset is as follows:

$$y_{ismt} = \alpha + \beta\tau_{smt_{-1}} + X_{it} + \phi_t + \gamma_m + \rho_s + \eta_{s_t} + \varepsilon_{it} \tag{4}$$

where y_{imt} represents various dependent variables for household i in state s in month m and year t, $\tau_{smt_{-1}}$ is the state cigarette tax in state s lagged by one month, and X_{it} is a vector of socio-demographic covariates. Depending on the specification, y_{imt} measures either *(i)* the price of the last cigarette pack bought, *(ii)* cigarette expenditures, or *(iii)* food stamp enrollment. The specification also includes month and year fixed effects (γ_m and ϕ_t), as well as state fixed effects (ρ_s). In some specifications, we additionally include state time trends η_{s_t}.[13] Standard errors are routinely clustered on the state level (Bertrand et al., 2004).[14]

The specification in Equation (4) applies to both the cross sections and the CPS pseudo-panel, where the only difference for the latter is that we observe households more than once.

[13]In additional robustness checks, we also included a lagged food stamp enrollment term $y_{ismt_{-1}}$. The robust results are available upon request.

[14]Clustering standard errors at the household level yields almost identical results.

Using the cross sectional data, Equation (4) links changes in state-month level cigarette taxes to the probability of participating in the food stamp program, in that particular state in that particular month. Using the pseudo-panel data, Equation (4) links changes in state-month level cigarette taxes to the probability that households *transition* onto food stamps.

In our most sophisticated and powerful specification with the pseudo-panel, in addition to the model above, we also employ a household fixed effects model. In these specifications, note that household fixed effects v_i replace X_{it} and ρ_s. All the time-invariant demographics in the pseudo-panel would drop out of the estimation because these are perfectly collinear with the household fixed effects. Moreover, households fixed effects are also perfectly collinear with state fixed effects because CPS does not survey households as they move from state to state (CPS is conducted by physical residence).

4.2 Identification

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, condition 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 bias our results. However, given the story of this paper, 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. Empirically, residential sorting based on cigarette tax increases should be negligible.

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 cross-border shopping, tax evasion, switching to more expensive or higher nicotine content cigarettes, or becoming a more efficient smoker.

Our empirical approach follows the standard identification convention in the cigarette tax literature. It identifies the tax effects netting out differences in socio-demographics as well as year and month time shocks. In addition, we allow for state fixed effects as well as state time trends. This means that, in our most conservative specifications, we identify the tax effect using within state tax changes that deviate from the average state-specific cigarette tax (or the state tax trend) as well as the average tax level of all US states in that particular year and month.

Thus, the main identification assumption is that there are no other unobserved factors that are correlated with both cigarette tax increases and an above trend increase in food stamp enrollment at the state-year or even state-month level. It is hard to imagine a concrete factor that strongly correlates with both cigarette tax changes and food stamp enrollment. One potential candidate that one may think of is an economic downturn. However, a rich set of month-year fixed effects net out general economic shocks in our models. Moreover, state time trends capture additional state-specific developments that could confound our estimates.

A more serious potential confounding factors that our fixed effects models have not accounted for 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 prices. However, in that case, one would then expect that cigarette taxes 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, Figure D1 in Appendix D plots food prices and cigarette prices for the four US regions. In line with our priors, Figure D1 nicely illustrates that the staggering 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.

5 Empirical Results

Figures 1 and 2 show staggering increases in cigarette taxes and potential spending among smokers on the one hand and food stamp enrollment on the other. The question that this paper intends to shed light on is whether both developments are causally related in some way.

We begin this section by studying the mechanisms relating cigarette taxes and food stamp enrollment. In a very first step, we investigate the distribution of important outcome measures in a non-parametric visual manner. Next, we show how cigarette taxes effect cigarette prices and cigarette expenditures.

In our main analysis, we naturally proceed to estimate the effect of cigarette taxes on food stamp enrollment (using cross sectional data) and then on food stamp take-up (using the pseudo-panel). We also provide a non-parametric visual assessment of food stamp enrollment before and after cigarette tax increases through scatter plots and an event study.

5.1 The Impact of Cigarette Taxes on Prices, Consumption, and Expenditures

5.1.1 Investigating Prices, Consumption, and Expenditures Descriptively

Figure 6 shows important determinants of the underlying mechanisms linking cigarette taxes and food stamp take-up. First of all, despite the $3.50 mean cigarette price, Figure 6a illustrates the significant variation in cigarette prices as actually paid by consumers in the last decade.[15]

[Insert Figure 6 about here]

Next, Figure 6b shows self-reported household cigarette consumption. As seen, while the mean smoking household consumes 25 packs of cigarettes per month, there is significant heterogeneity in consumption with a large share of households consuming 15 (17%), 30 (32%), 45 (7%), 60 (7%), and even 75 as well as 90 (1% each) packs per month.[16] The mean self-reported yearly household cigarette expenditures from the CEX (cf. Table C1) is $1,000, but expenditures exhibit a right-skewed distribution ranging from $17 to $4,000.[17]

Finally, Figure 6c and 6d plot the share of earned household income devoted to cigarette consumption for smoking households. Figure 6c shows the distribution for households not enrolled in food stamps and Figure 6d the distribution for households enrolled in food stamps.

[15]Note that we decided against top-coding the self-reported prices although the maximum value of $65 per pack likely represents measurement error. On the other hand, CNBC reports that Treasurer Silver Cigarettes may be as expensive as $39 per pack, and other luxury brands may be even more expensive (CNBC, 2015). Respondents may also have reported prices for a pack of cigars.

[16]The heaping in reported packs per months is a function of the heaping in reported cigarettes per day consumed by the households (Bar and Lillard, 2012).

[17]Multiplying the self-reported quarterly values in Table C1 by four and assuming a random and even distribution of interviews over all quarters. Note that multiplying the CPS consumption and price information in Figures 6a and 6b yields very similar results.

It is easy to see that households enrolled in food stamps spend a larger fraction of their income on cigarettes.

5.1.2 Regression Models Linking Taxes with Prices, Consumption, and Expenditures

Estimating the Tax Pass-Through Rate

We use a regression framework and the cross-sectional CPS dataset to estimate the extent to which cigarette taxes are passed through to cigarette prices. We employ Equation (4) for this exercise where the dependent variable is the self-reported price for the last pack of cigarettes bought. This is a standard tax pass-through regression (DeCicca et al., 2013b). Columns (1) and (2) of Table 1 show the results. Each column represents one regression model and the models only differ by the inclusion of sets of covariates as indicated in the lower portion of the table. Column (1) solely nets out month, year, and state fixed effects and finds that prices paid by consumers increase by $0.76 for every $1 increase in taxes. Column (2) includes socio-demographics and state time trends and finds a very similar and robust pass-through of $0.74 per $1 tax increase. These pass-through rates are absolutely in line with the recent literature (Harding et al., 2012).

[Insert Table 1 about here]

The Effect of Higher Cigarette Taxes on Cigarette Expenditures

Next, we estimate the effect of higher cigarette taxes on cigarette expenditures, which are conveyed through the average pass-through rate of 75%. Appendix A1 shows that—across the entire time period from 2001 to 2011—the 4,008 smoking households in the CPS paid on average $3.50 for a pack of cigarettes, consumed 25 packs per month, and had annual expenditures of $1,031. However, Figure 6 also illustrates that the variation in all these key parameters is quite substantial.

We again employ Equation (4) for this exercise where the dependent variable is now household cigarette expenditures. Columns (3) and (4) of Table 1 show the results using the CPS cross-sectional dataset and Columns (5) and (6) show the results using the CEX dataset. When adjusting the sample for socio-demographics, the average effect of a $1 cigarette tax increase on annual cigarette expenditures is $115 (Column (4)). However, the standard error is large

($69), which means that we cannot exclude expenditure increases of up to $250 (the 95% bound of the confidence interval). Note that a simple static calculation would yield monthly expenditure increases of $18.75 (25 packs consumed times $0.75). However, for smoker households with 2 packs a day (cf. Figure 3b), the increase would already be $30 per month, or $360 per year. The considerable variation shown in Figure 6 also explains the large standard errors in Columns (3) and (4) (Table 1).

The expenditure estimates from the CEX (Columns (5) and (6)) provide more precision and robust increases in quarterly tobacco expenditures of $25 for the average smoking household.[18] Note that the CEX estimates are based on retrospective expenditure self-reports concerning the last quarter prior to the interview. Thus the $100 expenditure increase per year can be seen as a lower bound estimate because future price increases are not yet fully internalized in these self-reports. This is reinforced by the static expenditure increase calculation of $225 for the average low-income smoking household (25 packs times 12 months times $0.75) as well as the estimated upper bound of $250 in Column (4). Recall that 20% of all low income smoking households consume at least 45 packs a months. Applying our estimated pass-through rate, a 45 pack consumption would result in an increase in annual expenditures of $400 for each $1 tax increase. Also recall Figures 6c and 6d show large heterogeneity in the share of income spent on cigarettes, and Figure 1 showed that the share of income spent on cigarettes of a minimum wage earning, pack-a-day smoker would have more then doubled from less than 4% to about 10%.

Importantly, note that the estimates for the impact of taxes on cigarette expenditures represent spending increases in addition to all other compensating behaviors of smokers and all reductions in cigarette consumption that may result from increased taxes. That is, even after smoking households may have reduced consumption (DeCicca et al. 2008a, 2008b), switched to cigarettes that are higher in tar and nicotine (Evans and Farrelly, 1998; Farrelly et al., 2004, 2007), extracted more nicotine per cigarette (Adda and Cornaglia, 2006, 2013), or purchased cigarettes in a nearby lower tax jurisdiction (Lovenheim, 2008; Goolsbee et al., 2010; DeCicca et al., 2013a), smoking households are still on average spending between $100 and $250 more on cigarettes per year for each $1 increase in taxes. Furthermore, for households that took-up food stamps following a tax increase, these expenditure estimates incorporate pre-existing (costly) compensation strategies that households may no longer engage in. We might expect

[18]Recall that the CEX estimates are based on all households, not just low-income households.

a scaling down of these behaviors post–take-up because enrollment results in a discontinuous increase in real income.

5.2 Cigarette Taxes and Food Stamp Enrollment

After having studied the underlying mechanisms of the relationship between cigarette taxes and food stamp enrollment, this section explicitly links the two developments as shown in the Figures 1 and 2.

5.2.1 The Compensation for Higher Tobacco Expenditures: Food Stamp Benefits

Figure 7 shows the distributions of food stamp benefits received and illustrates several crucial points. First, Figure 7a shows that the mean annual food stamp value of $171 per month—or $2,000 per year (Table C1)—exhibits strong variation among receiving households, but has been remarkably stable over time. This makes it unlikely that increased food stamp benefit levels are the main driving force of the increase in enrollment seen in Figure 2. Second, Figure 7b shows the distribution of household food stamp benefit values separately for smoking and non-smoking households. One observes distributions skewed to the right. More than half of all receiving households, 62%, receive less than the mean of $2,000 per year. About 50% receive less than $1,200 in food stamp benefits per year. Note that $100 per month appears as a relatively small amount which may explain why many eligible households do not enroll, e.g., because stigma or application costs outweigh the monetary monthly gain.

[Insert Figure 7 about here]

The fact that food stamp benefits have not increased over time, but food stamp enrollment has, suggests that other factors have overcome the enrollment costs we describe in the model section (e.g., stigma). Our model suggests increases in cigarette taxes could be one of the triggers. As shown, without other compensating strategies, the 20% of low income smoking households consuming at least 1.5 packs per day experience a negative annual income shock of at least $400 when taxes increase by $1. For 33% of all food stamp enrolled households, the food stamp benefit value would just compensate for a $1 tax increase.

Figure 7b also shows nearly identical distributions of food stamp benefits for smoking and non-smoking households. This speaks against the notion that food stamp receiving smoking households differ from food stamp receiving non-smoking households with respect to benefit determinants. It also excludes the explanation that smoking households enroll in food stamps at much higher rates due to higher benefits received.

5.2.2 Linking Cigarette Taxes and SNAP Enrollment in Administrative Data

Next, using administrative food stamp enrollment data from the Department of Agriculture (DOA)—the government agency that runs SNAP—Figures 8 and 9 graphically link cigarette tax levels (Figure 8) and changes in these taxes (Figure 9) to food stamp enrollment on the state level. Finally, Figure 10 links changes in taxes to changes in food stamp enrollment.

Figure 8 plots yearly state cigarette taxes and the share of the population on food stamps at the state level. One observes a clear positive correlation, although the picture exhibits some noise around the plotted line in Figure 8a. Figure 8b shows the mean value for each bin on the x-axis, which illustrates a strong positive relationship on the state-year level. These plots demonstrate that more households are on food stamps in states with higher cigarette taxes.

Figure 9 plots *changes* in state cigarette taxes between year t_{-1} and t_0 against the share of the state population on food stamps by year. While Figure 8 provides a pure correlation, the refined plot in Figure 9 yields already more evidence for a causal association. Figure 9 can also be interpreted as the graphical equivalent to a state fixed effects regression model whose identification is based on yearly state tax changes. From Figure 9, we make some conclusions. First of all, not surprisingly, Figure 9 demonstrates that there is less variation in tax changes than in tax levels (as in Figure 8), which likely reduces the statistical power of our regression models. Yet, even with tax changes there still exists is a lot of variation in terms of magnitude: one observes many tax increases around and below $0.4, but also several of size $0.6, $0.8, or $1. Finally, one observes an unambiguously positive association between yearly changes in cigarette state-level taxes and the share of the population on food stamps.[19]

[Insert Figures 8 to 10 about here]

[19] Figures A1 and C1 in the Appendix show the equivalent scatter plots for the CPS and CEX cross-sectional datasets used in our regressions models below. One can easily see that the just described pattern hold with the CPS and CEX samples as well. However, because the number of respondents in some (smaller) states is fairly low in the CPS and CEX, we have to deal with noise and do not observe respondents on food stamps in all states. This observation is particularly prevalent in Figure C1 as the many zero values on the y-axis show.

Finally, Figure 10 links *changes* in annual state cigarette taxes to *changes* in food stamp enrollment. This illustration yields the strongest evidence for the notion that cigarette taxes may induce smoking households to enroll in food stamps. Note that the the raw plot in Figure 10a exhibits significant variation around the plotted line and the high variance due to outliers flattens the positive relationship between changes in taxes and enrollment substantially. However, according to the binned plot in Figure 10b, a state cigarette tax increase by $0.8 is still associated with a speeding up of the enrollment increase from 0.75 to 1%.

Figure B1 in Appendix B serves as a additional robustness check by showing that this relationship also holds when using the CPS pseudo-panel. Note that Figure B1 is aggregated on the month-state level, implying that *(a)* the graph artificially reduces the true variation exploited in the econometric models (because the estimates are not based on state-level aggregates but rather the 1,685 households transitioning onto food stamps), *(b)* noise increases further, and *(c)* we observe many state-month observations without any households transitioning onto food stamps.

5.2.3 State Cigarette Taxes and Food Stamp Take-Up in a Regression Framework

Next, we parametrically relate changes in state cigarette taxes to food stamp enrollment by estimating Equation (4) using the cross sectional CPS and CEX datasets, where the dependent variable is an indicator for whether the household is currently enrolled in food stamps. The results are shown in Table 2; they are the parametric analogs to Figures 9 and C1. Table 2 follows our convention from above, with each column showing estimates differing only by the set of covariates. All models routinely control for month, year, and state fixed effects. Columns (1) through (4) use the CPS cross-sectional dataset, and Columns (5) through (8) use the CEX dataset.

[Insert Table 2 about here]

Columns (1) and (2) control for smoking status but do not differentiate the effect of taxes on enrollment by smoking status. As seen, tax increases of $1 are significantly related to a 3.3ppt higher probability of food stamp enrollment (Column (2)). Moreover, Column (2) shows that smoking households are about 50% more likely to be enrolled in food stamps as compared to non-smoking households (calculated by dividing the coefficient from baseline). These results hold up when using the CEX as shown in Columns (5) and (6).

Next, we distinguish the effect of taxes on food stamp enrollment by smoking status. To accomplish this, Columns (3) and (7) add an interaction term between cigarette taxes and the smoking household indicator. As seen, the tax level coefficient shrinks in size and becomes insignificant, whereas the interaction term carries a positive and highly significant coefficient of 3.8ppt in Column (3) for the CPS and 2.6ppt in Column (7) for the CEX. In words, these estimates show that the relationship between higher taxes and food stamp enrollment is exclusively driven by smoking households, and provide strong evidence that we are not picking up food stamp enrollment trends more generally.

Finally, Columns (4) and (8) of Table 2 employ even more refined specifications. Specifically, they interact the tax variable with *(i)* the number of cigarette packs consumed per month (Column (4)), and *(ii)* quarterly tobacco expenditures (Column (8)). The idea behind these specifications is to capture the presumably large effect heterogeneity as suggested by Figure 6. Indeed, Column (4) shows that every additional 10 packs of cigarettes consumed per month increases the probability that a household enrolls in food stamps by 0.8ppt from a (smoking household's) baseline of 14.5%. This finding is confirmed by the model in Column (8) although the interaction term between taxes and expenditures is imprecisely estimated. However, in terms of size, the coefficient suggests that for every $1,000 in additional consumption per year, the probability that a household is enrolled in food stamps increases by 0.12ppt or 1%.[20]

5.2.4 Other Outcome Margins: Quitting, Reducing, and Suffering

Table 3 tests for compensatory behavior outside of and in addition to food stamp enrollment by studying other outcome margins. Technically we run the same regression models as above, but employ the outcome variables as indicated in the column headers of Table 3. The dependent variable in Column (1) is a binary variable for whether at least one household member quit smoking. Note that households with no current smokers and households with current smokers can both have a member to have quit in the past year. Column (1) provides some evidence that

[20]Note that we choose to present the OLS results using a linear probability model rather than a non-linear model (e.g., logit or probit) because the interaction term is readily interpretable (see, for instance, Ai and Norton (2004); Karaca-Mandic et al. (2012)), but the results carry over to non-linear estimation as well.

a $1 increase in cigarette taxes is associated with a 1.6% increase in the probability that at least one household member quit smoking in the past year.[21]

Column (2) uses the self-reported amount of daily household cigarette consumption as the dependent variable. The imprecise point estimates shows that a $1 increase in cigarette taxes is associated with 2.6% reduction in daily cigarette consumption.

[Insert Table 4 about here]

Finally, Column (3) exploits a self-reported measure that indicates whether the household ran out of money for food within the last month. This measure would yield convincing evidence for the link between higher cigarette taxes, prices, and expenditures on the one hand, and food stamp enrollment on the other hand. Indeed we find a relatively large point estimate of 5% of the mean, which is marginally significant at the 12% level (not shown). In other words: With a statistically certainty of 88%, a $1 increase in cigarette taxes increases the probability that poor households ran out of money for food by 2ppt, from 38% to 40%.

5.2.5 Evidence from Monthly Transitions Onto Food Stamps

Our last econometric model uses the CPS monthly pseudo-panel as described in Section 3.1. Here we exploit within-household variation in food stamp enrollment.[22] Note that the overall monthly transition rate is a mere 0.6% and that we employ the same rich fixed effects models specifications as above—including month, year, and state fixed effects as well as state time trends. Even though the statistical power here is reduced as compared to the models in Table 2, the estimates are still based on 1,685 transitioning households in the decade between 2002 and 2011. The results are shown in Table 4. These food stamp take-up estimates are parametric analogs to Figures 10 and B1.

Columns (1) to (4) again only differ by the inclusion of sets of covariates. Column (1) includes state, month, and year fixed effects along with covariates, whereas Column (2) adds state time trends. As in Table 2, we add an interaction term to differentiate the tax impact by smoking status. As illustrated by the plain *state tax* coefficients, tax increases do not have a statistically

[21] Note that this estimate only estimates temporary quitting behavior in that we cannot account for relapses that occur after the interview, so it remains unclear whether this small but precisely estimated reduction represents permanent quitting behavior.

[22] Among other advantages such as being able to include household fixed effects, the panel structure permit estimation of dynamic models with lagged food stamp enrollment to consider state dependence. The results in Table 2 are robust in a dynamic setting where we include lagged food stamp enrollment.

significant positive relationship with food stamp enrollment for non-smoking households. It is worth emphasizing that the point estimates for non-smoking households represent a precisely estimated zero and even carry negative signs. The interaction terms *state tax*×*smoking HH* yield the relationship between taxes and food stamp take-up for smoking households. As seen, the effects are significant at the 1% level and relatively large in size.[23]

Next, Columns (3) and (4) include household fixed effects, which net out the latent differences between households' propensity to be enrolled in food stamps that were lumped into other parameters in the first two columns. Columns (3) to (4) differ from Columns (1) and (2) only in terms of the household fixed effects that replace the time-invariant household-level covariates and state fixed effects. Again, we find very consistent, precisely estimated, and robust point estimates for the interaction terms, whereas the size of the plain *state tax* coefficients for non-smoking households is negative and below 0.001. The findings in the first four columns let us conclude that, for each $1 increase in state cigarette taxes, the probability that eligible non-enrolled smoking households take-up food stamps increases by between 2 and 3ppt from a baseline probability of about 25% (see also Figure 11 below).

In a final step, we take another slice at the empirical question by turning to a duration analysis, the results of which are shown in Columns (11) and (12) of Table 4. Duration analyses are commonly used in labor economics to study the impact of X on the length of unemployment spells as well as in other sciences to study the impact of, for instance, drugs on mortality (in medicine) (Van Den Berg, 2001). They have also been used in health economics to study the onset of smoking (cf. DeCicca et al. (2002)). We employ the duration analysis for two main reasons: *(i)* as another 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 significantly decrease the time span until non-enrolled eligible households take up food stamps?

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-participating but eligible households at time t). α_t is the "baseline hazard" of a non-participating household taking up food stamps at time t, and X is a set of

[23]The estimates slightly increase, albeit not in a statistically significant sense, when households that quit smoking are excluded from the sample. This yields evidence that other behavioral reactions to tax increases naturally weaken the strength of our estimated relationship between taxes and food stamp enrollment. As before, note that we choose to present the OLS results due to the readily interpretable interaction term, but again the results carry over to non-linear estimation as well, where the household fixed effects model is a conditional fixed-effects model.

covariates as before. Note that the at risk population is limited to the subset of households starting at that date, so our sample size with 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 already being enrolled in food stamps. For lack of space, we withhold further detail on the estimation strategy; see Van Den Berg (2001) for a comprehensive review. Other than estimating a non-linear model, the approach here mainly differs from the other models in that *(i)* it is limited to households who are not participating in food stamps in the first month we observe them, and *(ii)* observations are only included for these households until the point at which they take-up food stamps.

Columns (5) and (6) report the coefficients from estimating the standard Cox Proportional Hazard model (Van Den Berg, 2001) for non-smoking households and smoking households, respectively. We decided to split the sample and run the models separately for non-smoking and smoking households because the readily interpretable coefficients speak directly to the question of interest (do higher cigarette taxes significantly decrease the time span until non-enrolled eligible households take up food stamps?).

The point estimate on tax for non-smoking households is insignificant, and the size is a little over one third of that for smoking households. The literal interpretation of the statistically significant coefficient for the smoking population in Column (6) is as follows: a \$1 increase in cigarette taxes decreases the average time-to-take-up by about 10 days (0.3381 months) for low-income smoking households. While these estimates cannot be directly compared to the estimates of the other models, they are nonetheless consistent with the magnitudes of the interaction terms in the first four columns. Moreover, Column (5) shows a much lower and statistically insignificant relationship between cigarette taxes and months-to-take-up for non-smoking households, which is consistent with the plain state tax coefficients in Columns (1) to (4). All together, the duration analysis provides evidence that is very consistent with the results from linear probability models and allows for a complement interpretation of the observed empirical pattern.

5.2.6 Event Study

The panel nature of our data naturally gives rise to a non-parametric visual assessment of food stamp enrollment before and after cigarette tax increases through an event study. Note that the "treatments" (cigarette tax increases) are staggered in time and across households in different states over 32 different calendar months (Table B2). The fact that only smokers are "treated" by cigarette tax increases leads to non-smoking households serving as a useful counterfactual. We define the event time as calendar month minus the month cigarette taxes were increased for each household so that the year-month of the increase in cigarette taxes becomes event time 0. In other words, we stacked the household month-year data around cigarette tax changes. To eliminate compositional changes in the event study, we rely on a balanced panel of households who were present in the data for +/- four months of a tax change.[24] Figure 11 shows the event study graph for the balanced panel. The x-axis indicates up to four months prior and post the increases, and the y-axis plots the percent of eligible low income households on food stamps.

[Insert Figure 11 about here]

As seen in Figure 11, the share of non-smoking households enrolled in food stamps is remarkably stable over time, exhibits almost to trend, and lies significantly below the enrollment level for smoking households. In contrast, starting two months before the tax increase, one observes a strong increase in food stamp participation among smoking households. The fact that the enrollment probability increases slightly before the actual implementation of the tax increase makes sense, given the typical pre-announcement of such tax measures by state legislatures. We also expect the increase in enrollment to persist past t_1 for a number of reasons. The main reason is that we expect many households who apply for food stamps in t_{-1} to obtain benefits for the first time after t_1 due to delays in the application process. The typical short-term compensatory behavior of smokers to stockpile cigarettes before the tax increase could also explain why the increase in enrollment does not abruptly come to an end at t_1 (Chiou and Muehlegger, 2014). For low-income smoking households, Figure 11 shows a 3ppt increase in the probability of enrolling in food stamps following a tax increase from a baseline probability of 25%. In contrast, over the tax increase cycle, we observe flat enrollment likelihoods for non-smoking households with almost no trend.

Overall, the event study is perfectly in line with our rich fixed effects pseudo-panel take-up regressions in Table 4. In sum, in combination with the other graphs and regression estimates,

[24]We limit the event study to +/- four months and observations with no missing food stamp enrollment information in these months in order to minimize compositional changes in the data. In the pseudo-panel, we do not observe a complete year of food stamp enrollment information (see Section 3.1). As we move from months since cigarette taxes increased (t=0), households drop out of the sample.

Figure 11 yields additional, strong visual evidence for a causal link between cigarette tax increases and food stamp take-up.

6 Discussion and Conclusion

This paper investigates whether sin taxes on addictive goods can induce eligible low-income households to enroll in government transfer programs. First, we show theoretically that cigarette taxes can cause low-income smoking households to take-up food stamps. Second, we empirically examine the model predictions using the CPS and the CEX, matched with monthly cigarette tax data. We find that an average cigarette tax pass-through rate of 0.75 triggers an average increase in yearly household cigarette expenditures between $100 and $250. We also find that low-income smoking households are 50% more likely to enroll in food stamps relative to their non-smoking counterparts. Exploiting variation in state cigarette taxes across the US states over one decade, we then show that cigarette tax increases are significantly associated with higher food stamp enrollment. We find strong evidence that these effects are exclusively driven by smoking households: when taxes increase by $1, each additional carton of monthly cigarette consumption increases food stamp enrollment by 0.8ppt.

In our main empirical analysis, we study the take-up of food stamps, i.e., whether households transition onto food stamps from one month to another. Exploiting month-to-month within-household variation in food stamp enrollment from a pseudo-panel, we find that a $1 increase in cigarette taxes increases the monthly take-up probability for low-income smoking households by between 2 and 3ppt from a baseline probability of about 25%. Duration models show that a $1 increase in cigarette taxes reduces the average time to take-up by 10 days. Overall, the findings suggest that the recent expanded use of cigarette taxes to curb smoking has likely contributed to the recent increase in food stamp enrollment. Moreover, insomuch that the option to enroll in public assistance programs can decrease the effectiveness of cigarette taxes in nudging people to reduce smoking, our findings may also help explain the recent stagnation in cigarette consumption despite unprecedented rises in cigarette taxes.

Rather than viewing the welfare implications of cigarette tax increases in a vacuum, governments should consider the potential for policy spillover effects and coordinate policy making by taking into account the inefficiencies one policy can impose on another. For example, in 2013, President Obama proposed a 48% increase in the federal cigarette excise tax (from $1.01

to \$1.95) to fund an important early childhood education program. The Office of Management and Budget estimated that the tax hike would generate \$8 billion in yearly tax revenues, assuring full funding for the education program (Office of Management and Budget, 2014). To the extent that our results are generalizable, our estimates suggest that such a tax hike would increase food stamp enrollment by about 400,000 low-income smoking households, thereby offsetting \$500 million of the calculated annual increase in revenues.

According to our findings, there also exist important spillover effects from state to federal policies: when state policymakers decide to increase cigarette taxes and collect the tax revenue, the federal government partly compensates for this increased state tax revenue with higher expenditures for food stamps. The findings are thus relevant from a jurisdictional tax policy design perspective. They suggest that citizens in low tax states partially subsidize the food stamp enrollment in high tax states. One potential policy suggestion to avoid this outcome would be for the majority of cigarette taxes to be imposed at the federal level rather than the state level. Such a move would also alleviate concerns that differences in state taxes create inefficiencies due to cross border cigarette shopping (Lovenheim, 2008; Chiou and Muehlegger, 2008; Merriman, 2010). Potential avenues for future research would be to investigate the extent to which optimal sin taxes depend on the structuring of other public policies as well as the optimal revenue allocation between federal, state, and local governments.

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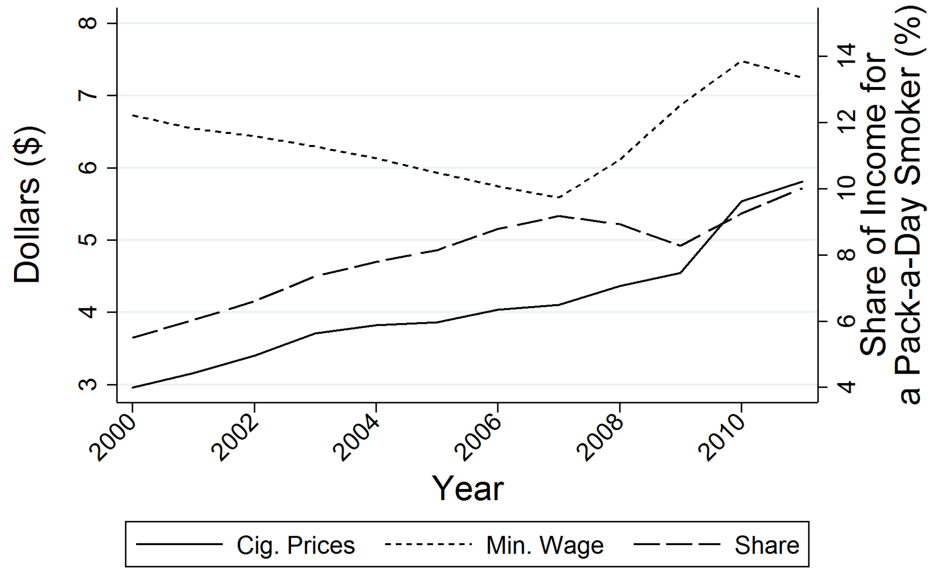
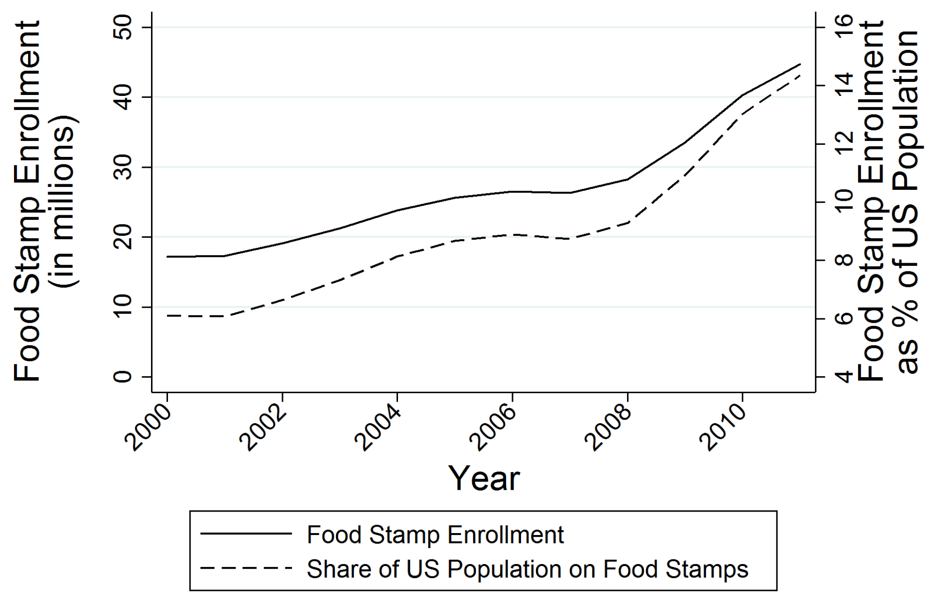
Figures and Tables

Figure 1: Cigarette Prices, Minimum Wages, and the Income Share a Pack-a-Day Minimum Wage Earning Smoker Has to Spend on Cigarettes



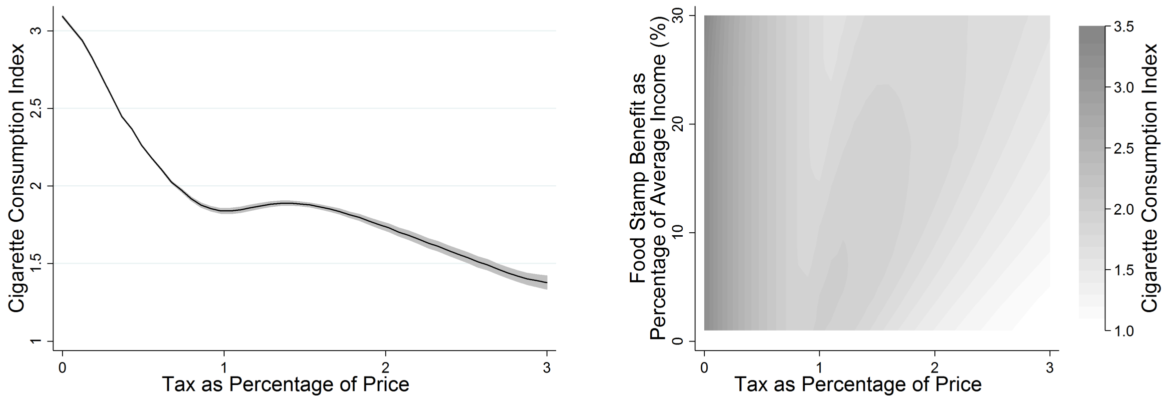
Source: Tax Burden on Tobacco (for average cigarette prices) and Bureau of Labor Statistics (for the average minimum wage), own illustration.

Figure 2: SNAP Enrollment in Absolute and Relative Terms



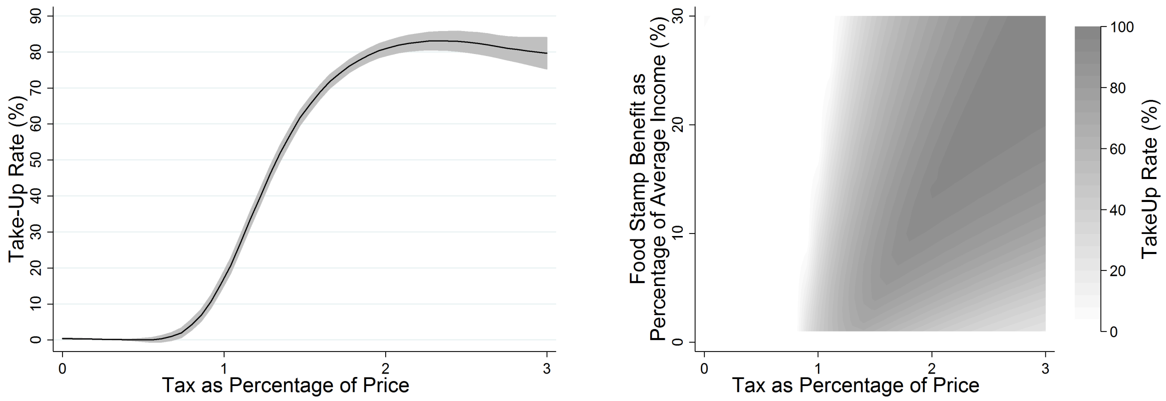
Source: Official yearly statistics from the Department of Agriculture (for food stamp enrollment) and Census Bureau (for population), own illustration.

Figure 3: Simulated Cigarette Consumption over (a) Cigarette Taxes, and (b) Cigarette Taxes and Food Stamp Benefit Level



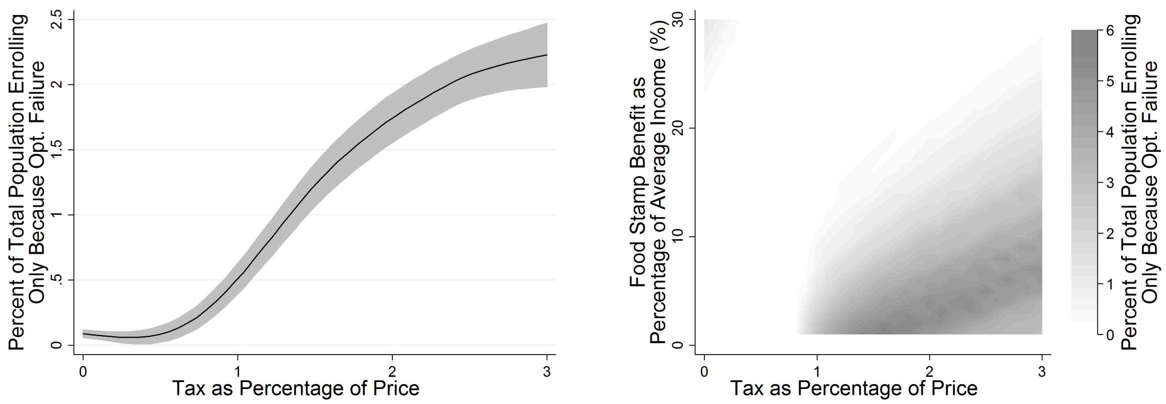
Source: Own simulation

Figure 4: Simulated Food Stamp Take-Up Rate over (a) Cigarette Taxes, and (b) Cigarette Taxes and Food Stamp Benefit Level



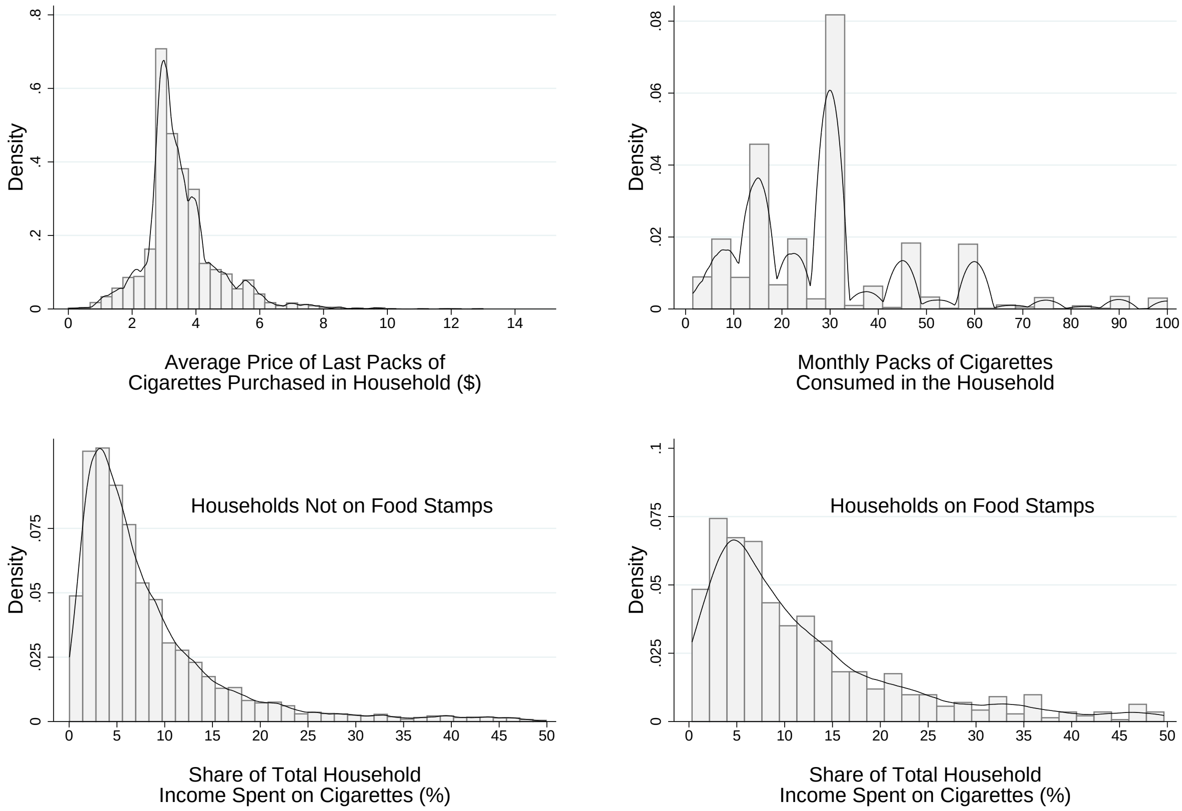
Source: Own simulation

Figure 5: Simulated Percent Enrolled in Food Stamps Only Because of Optimization Failure over (a) Cigarette Taxes, and (b) Cigarette taxes and Food Stamp Benefit Level



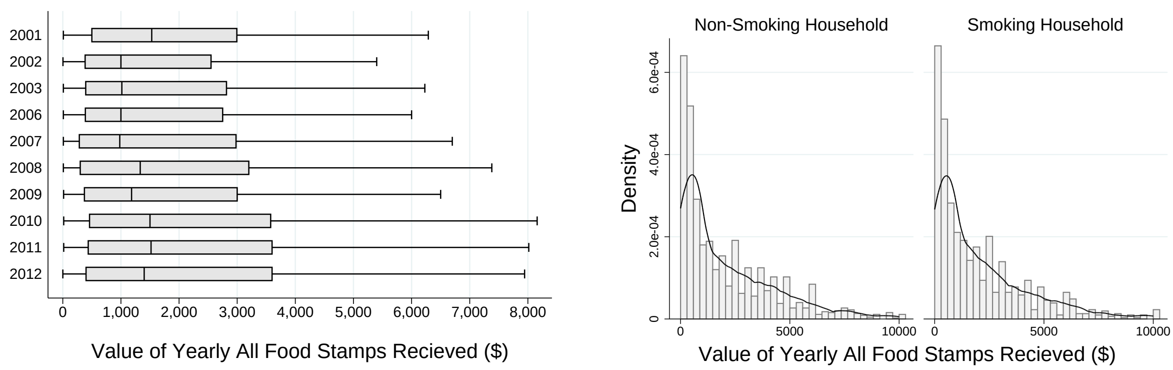
Source: Own simulation

Figure 6: (a) Cigarette Prices Paid, (b) Cigarette Consumption (Packs per Month), (c) Cigarette Expenditures as Share of Household Income for Households Not on Food Stamps, and (d) Cigarette Expenditures as Share of Household Income for Households on Food Stamps



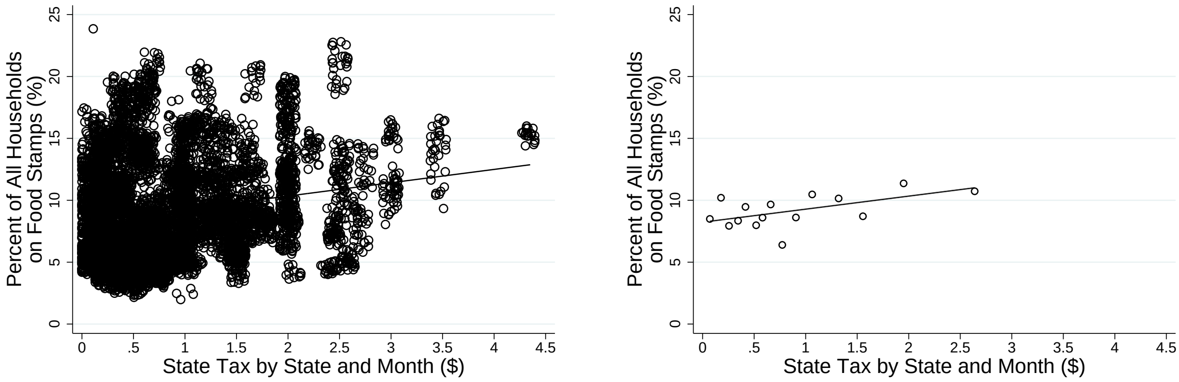
Source: CPS, FSS merged with TUS, own illustration.

Figure 7: Monetary Value of Food Stamps, by Year and Smoking Status



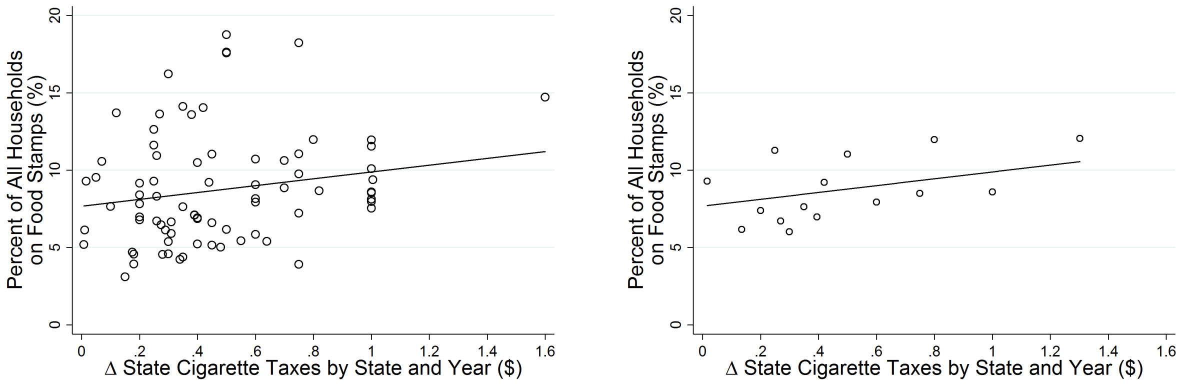
Source: CEX, own illustration.

Figure 8: State Cigarette Taxes and Share of Households on Food Stamps



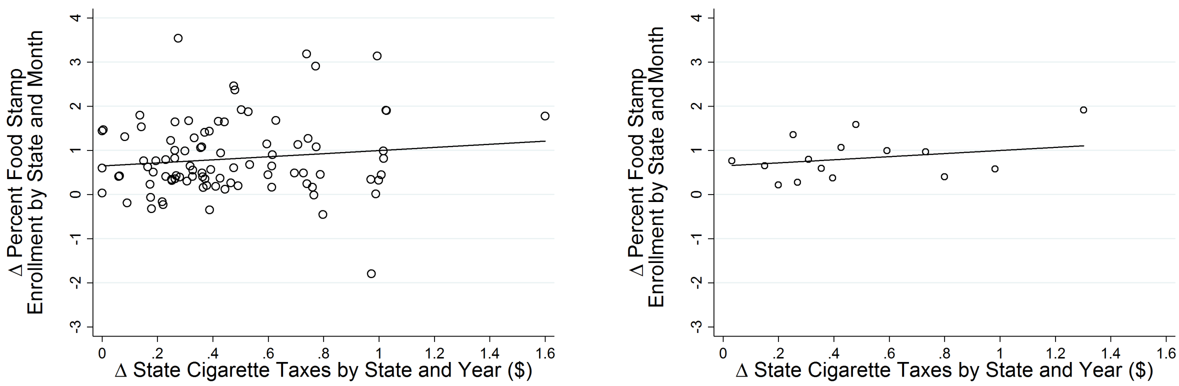
Source: Administrative data from Department of Agriculture, 2000 to 2012. The mean percent of population on food stamps for each bin is reported.

Figure 9: Change in State Cigarette Taxes and Share of Households on Food Stamps



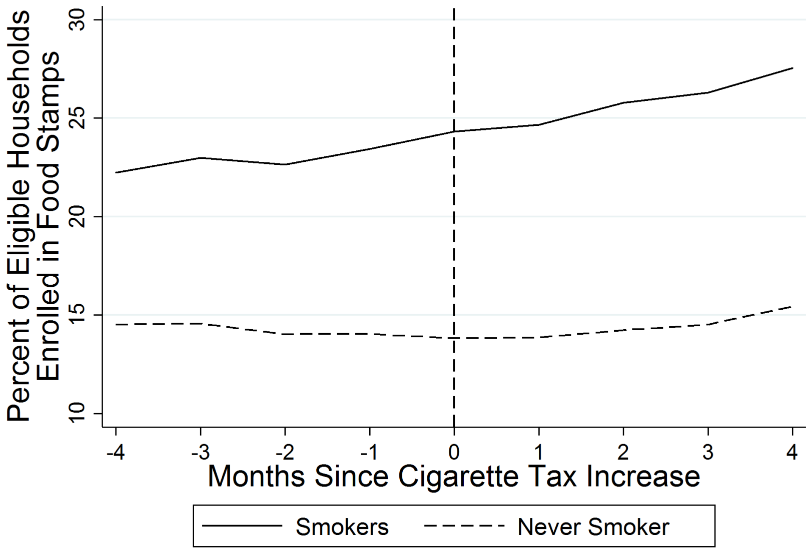
Source: Administrative data from Department of Agriculture, 2000 to 2012. The plots are conditional on positive changes in state cigarette tax rates between year t_{-1} and t_0. The mean percent of population on food stamps for each bin is reported.

Figure 10: Change in State Cigarette Taxes and Change in Share of Households on Food Stamps



Source: Administrative data from Department of Agriculture, 2000 to 2012. The plots are conditional on positive changes in state cigarette tax rates between year t_{-1} and t_0. The mean percent of population on food stamps for each bin is reported.

Figure 11: Event Study: Food Stamp Enrollment for Smokers and Non-Smokers Relative to Cigarette Tax Increases



Source: CPS, FSS merged with TUS, own illustration.

Table 1: State Cigarette Taxes, Cigarette Prices, and Cigarette Expenditures: CPS and CEX Cross Sections

	Price of Last Cigarette Pack Bought (CPS)		*Annual Cigarette Expenditures (CPS)*		*Quarterly Cigarette Expenditures (CEX)*	
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
State cigarette tax	0.7599***	0.7361***	63.12	114.74	25.89***	25.42***
	(0.1588)	(0.1786)	(56.01)	(68.57)	(8.34)	(8.61)
Mean	3.49	3.49	1,030	1,030	248	248
Covariates employed						
Month FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
Socio-Demographics	no	yes	no	yes	no	yes
State Time Trend	no	yes	no	yes	no	yes
Observations	4,008	4,008	4,008	4,008	9,456	9,456
R-squared	0.1834	0.2115	0.0568	0.0923	0.1369	0.1549

Source: Columns (1) to (4): CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration; Columns (5) to (6): CEX 2001-2012 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration. * $p<0.05$, ** $p<0.01$, *** $p<0.001$; standard errors are in parentheses and clustered at the state level. Regressions are based on CPS and CEX cross sections as in Appendix A2 and C1. Each column represents one regression as in Equation (4). 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 (non-daily smoking households not defined). The dependent variable in Columns (5) and (6) measures CEX tobacco expenditures in the last quarter prior to the interview, as reported by the household. The variable of interest indicates the state cigarette tax level in month t_{-1}.

Table 2: State Cigarette Taxes and Food Stamp Enrollment: CPS and CEX Cross Sections

	CPS Cross Sections				*CEX Cross Sections*			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
State Cigarette Tax	0.0354***	0.0327***	-0.0119	-0.0062	0.0074	0.0077	-0.0055	-0.0013
	(0.0097)	(0.0105)	(0.0127)	(0.0131)	(0.0049)	(0.0045)	(0.0089)	(0.0012)
Smoking Household		0.0579***	0.0283*			0.0493***	0.0261***	
		(0.0087)	(0.0115)			(0.0056)	(0.0089)	
×Tax			0.0379***				0.0259***	
			(0.0085)				(0.0076)	
Consumption/Expenditures				-0.0002				0.0028**
				(0.0002)				(0.0012)
×Tax				0.0008**				0.0012
				(0.0003)				(0.0012)
Mean	0.1008	0.1008	0.1008	0.1008	0.0699	0.0699	0.0699	0.0699
Covariates employed								
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
State FE	yes	yes	no	no	yes	yes	no	no
Socio-Demographics	no	yes	yes	yes	no	yes	yes	yes
State Time Trend	no	no	yes	yes	no	no	yes	yes
Observations	26,729	26,729	26,729	26,729	36,893	36,893	36,893	36,893
R-squared	0.0628	0.1791	0.1855	0.1836	0.0211	0.1544	0.1579	0.1529

Source: Columns (1) to (4): CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration. Columns (5) to (8): CEX 2001-2012 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration. * $p<0.05$, ** $p<0.01$, *** $p<0.001$; standard errors are in parentheses and clustered at the state level. Each column represents one regression as in Equation (4). The binary dependent variable indicates whether the household is on food stamps in the current month, t_0. The variable of interest indicates the state cigarette tax level in month t_{-1}.

Table 3: State Cigarette Taxes and Other Outcome Margins: CPS Cross Section

Variable	HH Member Quit (1)	HH Cig. Per Day (2)	HH Ran Out of Money for Food (3)
State Cigarette Tax	0.0059*	-0.1093	0.0191
	(0.0024)	(0.2042)	(0.0121)
Mean	0.3601	4.1173	0.3812
Covariates employed			
Month FE	yes	yes	yes
Year FE	yes	yes	yes
Socio-Demographics	yes	yes	yes
State Time Trend	yes	yes	yes
Month$\times$Year FE	yes	yes	yes
Observations	26,729	26,729	26,729
R-squared	0.9364	0.5134	0.0769

Source: CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration. * $p<0.05$, ** $p<0.01$, *** $p<0.001$; standard errors are in parentheses and clustered at the state level. Each column represents one regression as in Equation 4. The variable of interest indicates the state cigarette tax level in month t_{-1}.

Table 4: State Cigarette Taxes and Food Stamp Take Up: CPS Monthly Pseudo Panel

	Linear Probability Models				*Duration Models*	
					Smoke = 0	***Smoke =1***
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
State Tax	-0.0048	-0.0071*	-0.0085*	-0.0071	0.1304	0.3381*
	(0.0024)	(0.0023)	(0.0027)	(0.0034)	(0.1623)	(0.2003)
State Tax$\times$*Smoking HH*	0.0219**	0.0214**	0.0313**	0.0305**		
	(0.0061)	(0.0061)	(0.0090)	(0.0089)		
Mean	0.1716	0.1716	0.1716	0.1716		
Covariates employed						
Month FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month$\times$Year FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	no	no	yes	yes
State Time Trend	no	yes	no	yes	yes	yes
Socio-Demographics	no	yes	no	no	yes	yes
Household FE	no	no	yes	yes	no	no
Lagged Enrollment	no	no	no	no	no	no
Observations	285,685	285,685	285,685	285,685	169,474	60,889
R^2	0.0064	0.0070	0.0064	0.0074	n/a	n/a

Source: CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own calculation and illustration. * $p<0.05$, ** $p<0.01$, *** $p<0.001$; standard errors are in parentheses are clustered at the state level; within R-squared reported. Regressions are based on a pseudo-panel that makes use of the retrospective monthly information on household food stamp take-up in the FSS. Each column in Columns (1) to (4) represents one regression as in Equation (4), where the binary dependent variable indicates food enrollment in month t. The variable of interest indicates the state cigarette tax level in month t_{-1}. Columns (5) and (6) represent a duration analysis estimated by a Cox Proporational Hazard Model conducted separately for nonsmoking and smoking households, respectively. For consistency, the columns show the actual coefficients on state taxes. Within the separate analyses for nonsmoking and smoking households, the observations in duration analysis differ from the regression approach in that (*i*) they are limited to households who are not participating in food stamps in the first month we observe them, and (*ii*) observations are only included for these households until the point at which they take-up food stamps or fall out of the sample (censored).

Appendix A: Descriptive Statistics CPS Cross Section

Table A1: Descriptive Statistics CPS FSS-TUS Cross Sectional Data

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Cigarette Price ($)	3.4954	2.2214	0.08	65	4,008
Annual Tobacco Expenditures ($)	1030.49	867.41	13.14	23,725	4,008
Enrolled in Food Stamps in t_0	0.1009	0.3012	0	1	26,729
Households with at least One Quitting Member	0.3601	0.4800	0	1	26,729
Household Daily Cigarette Consumption (# cigarettes)	4.1173	10.1596	0	120	26,729
Ran Out of Money for Food this Month	0.3812	0.4865	0	1	26,729
B. Covariates					
State Cigarette Tax in t_{-1}	0.7468	0.6165	0.025	4.35	26,729
Change in State Cigarette Tax between t_{-1} and t_0 (conditional on change)	0.6001	0.4854	0.008	1	410
# Household Members	2.5297	1.6224	1	16	26,729
Smoking Household	0.2825	0.4502	0	1	26,729
# Quitting Household Members	0.8546	1.4901	0	15	26,729
# Smoking Household Members	0.3565	0.6311	0	6	26,729
Family Income $<$ 185% FPL	1	0	1	1	26,729
Earned Family Income	18,623	12,365	0	87,500	26,729
# Male Household Members	1.17	1.0739	0	9	26,729
# White Household Members	2.0133	1.7392	0	14	26,729
# Black Household Members	0.3405	1.0429	0	12	26,729
# Asian Household Members	0.0792	0.5693	0	16	26,729
Household Head Employed	0.4441	0.4969	0	1	26,729
Household Head No High School	0.2782	0.4481	0	1	26,729
Age of Household Head	51.50	19.33	15	90	26,729
Household Head Married	0.3920	0.4882	0	1	26,729

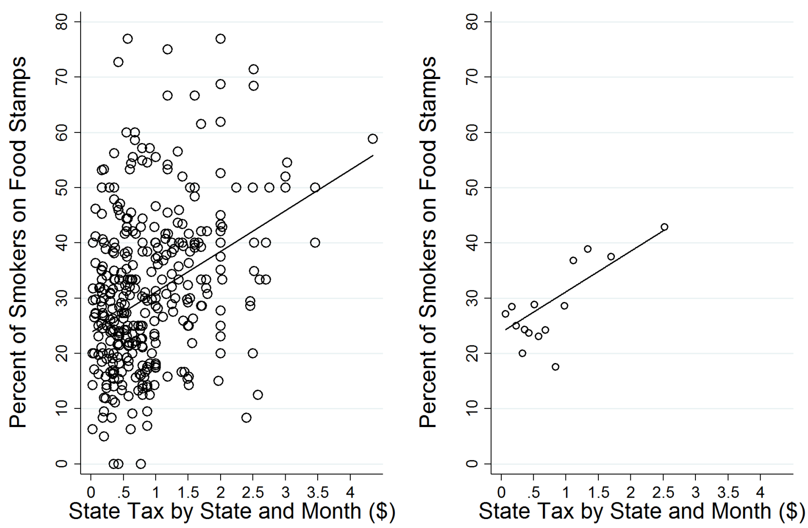
Source: CPS, FSS merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration. Note that cigarette price and annual expenditures are reported for households which have at least one daily smoker.

Table A2: CPS FSS-TUS Cross Sectional Observations by Year-Months

Variable	Frequency	Percent	Cumulative
Nov 2001	8,117	30.37	30.37
Feb 2002	1,241	4.64	35.01
Feb 2003	2,215	8.29	43.30
Nov 2003	8,252	30.87	74.17
Jan 2007	3,331	12.46	86.63
Jan 2011	3,573	13.37	100.00
Total	26,729	100.00	

Source: CPS, FSS merged with TUS, own illustration.

Figure A1: State Cigarette Taxes and Share of Smokers on Food Stamps (CPS)



Source: CPS, FSS on last 12 month information merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Appendix B: Descriptive Statistics CPS Pseudo-Panel

Table B1: Descriptive Statistics CPS FSS-TUS Pseudo-Panel Data

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
On Food Stamps in t_0	0.1716	0.3771	0	1	285,685
Food Stamp Take-Up btw. t_{-1} and t_0	0.0059	0.0765	0	1	285,685
B. Covariates					
State Cigarette Tax in t_{-1}(\$)	1.0176	0.7341	0.025	4.35	285,685
Change in State Cigarette Tax between t_{-1} and t_0(\$) (conditional on change)	0.5585	0.4312	0.05	1.60	3,656
# Household Members	2.5995	1.6523	1	16	285,685
Smoking Household	0.3677	0.6399	0	1	285,685
# Quitting Household Members	0.0208	0.1494	0	15	285,685
# Male Household Members	1.2042	1.0814	0	9	285,685
# White Household Members	2.0127	1.7834	0	14	285,685
# Black Household Members	0.3751	1.0937	0	12	285,685
# Asian Household Members	0.0829	0.5765	0	16	285,685
Earned Family Income	18,536	116,935	0	87,500	285,685
Family Income $<$ 185% FPL	1	0	1	1	285,685
Household Head Employed	0.4361	0.4959	0	1	285,685
Household Head No High School	0.2604	0.4388	0	1	285,685
Age of Household Head	49.96	19.03	15	90	285,685
Household Head Married	0.3777	0.4848	0	1	285,685

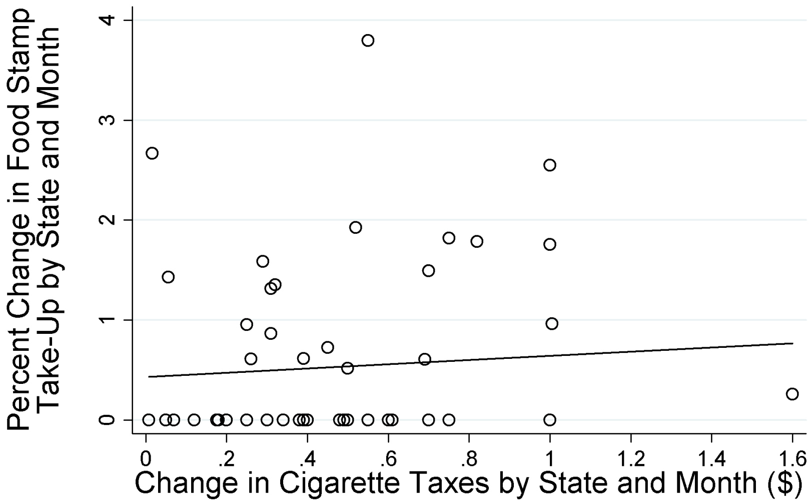
Source: CPS, FSS on last 12 month information merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Table B2: 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	

Source: CPS, FSS on last 12 month information merged with TUS, own illustration.

Figure B1: Monthly Change in State Cigarette Taxes and Change in Food Stamp Enrollment (CPS)



Source: CPS, FSS on last 12 month information merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Appendix C: Descriptive Statistics CEX Cross Section

Table C1: Descriptive Statistics CEX

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Quarterly Tobacco Expenditure ($)	248.42	296.26	4.33	8,450	9,456
(CEX Smoker Households Only)					
On Food Stamps in t_0	0.0699	0.2549	0	1	36,893
Value of Food Stamps ($)	2056	2155	1	14,000	2,578
(Food Stamp Households Only)					
B. Covariates					
State Cigarette Tax in t_{-1}	0.9015	0.6642	0.025	4.35	36,893
Change in State Cigarette Tax Between t_{-12} and t_0	0.0839	0.2544	0	1.6	36,893
Smoking Household	0.2563	0.4366	0	1	36,893
Age of Household Head	40.2738	10.7839	18	59	36,893
Rural Region	0.0078	0.0877	0	1	36,893
# Household Members	2.8241	1.5827	1	16	36,893
# Male Household Members Over 16	0.9854	0.6853	0	8	36,893
Household Head White	0.8046	0.3965	0	1	36,893
Household Head Black	0.1219	0.3272	0	1	36,893
Household Head Married	0.528	0.4992	0	1	36,893
Household Head Male	0.5000	0.5000	0	1	36,893
Number of Household Earners	1.5807	0.8372	0	8	36,893
Annual Income After Taxes	63,209	60,139	-149,661	1,110,485	36,893

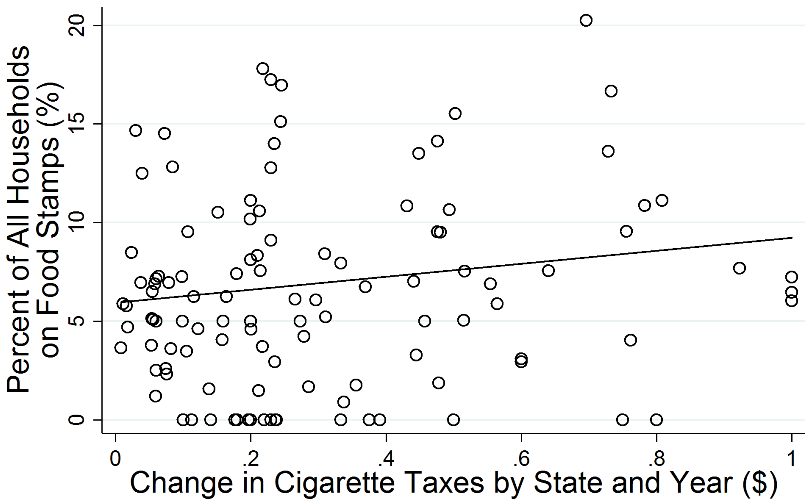
Source: CEX merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Table C2: CEX Cross-Sectional Observations Over Years and Months

Variable	Frequency	Percent		Frequency	Percent
2001	3,843	10.42	Jan	3,142	8.52
2002	4,109	11.14	Feb	3,142	8.52
2003	4,333	11.74	Mar	3,113	8.44
2006	3,933	10.66	Apr	3,141	8.51
2007	3,500	9.49	May	3,135	8.50
2008	3,422	9.28	June	3,077	8.34
2009	3,551	9.63	July	3,054	8.28
2010	3,522	9.55	Aug	3,014	8.17
2011	3,401	9.22	Sept	3,055	8.28
2012	3,279	8.89	Oct	3,108	8.42
			Nov	2,993	8.11
			Dec	2,919	7.91
Total	36,893	100.00		36,893	100.00

Source: CEX, own illustration.

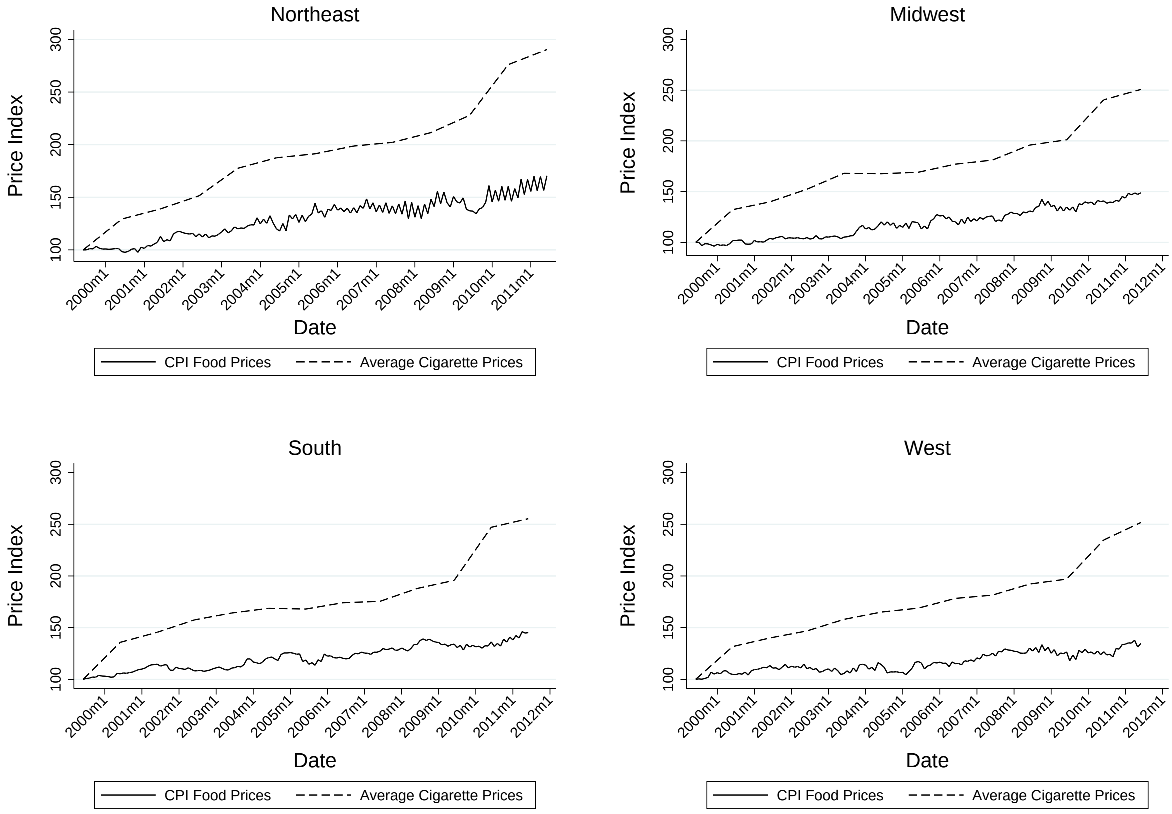
Figure C1: Yearly Change in State Cigarette Taxes and Share of Smokers on Food Stamps (CEX)



Source: CEX merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Appendix D: Cigarette Price and Food Price Inflation

Figure D1: Food Price and Cigarette Price Inflation



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