Canadian Centre for Health Economics
Centre canadien en économie de la santé

Working Paper Series
Document de travail de la série

BEHAVIORAL RESPONSES TO TAXATION: CIGARETTE TAXES AND FOOD STAMP TAKE-UP

Kyle Rozema, Nicolas R. Ziebarth

Working Paper No: 150015

www.canadiancentreforhealtheconomics.ca

October 20, 2015

Canadian Centre for Health Economics
Centre canadien en économie de la santé
155 College Street
Toronto, Ontario

CCHE/CCES Working Paper No. 150015
August 2015

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

Kyle Rozema[*,a], Nicolas R. Ziebarth[†,b]

[a] *Northwestern University School of Law*
[b] *Cornell University*

Abstract

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

[*]375 East Chicago Avenue, Chicago, IL 60611. Email: *kyle.rozema@law.northwestern.edu*
[†]Department of Policy Analysis and Management, 106 Martha Van Rensselaer Hall, Ithaca, NY 14850, e-mail: *nrz2@cornell.edu*

1 Introduction

Cigarette taxes can nudge smokers to reduce cigarette consumption (DeCicca et al., 2002, 2008, 2013a; Lillard et al., 2013; Hansen et al., 2015). But cigarette taxes also alter smokers' behaviors in unintended ways. For instance, they respond strategically to increases in cigarette taxes by stockpiling (Chiou and Muehlegger, 2014), switching to higher tar and nicotine cigarettes (Farrelly et al., 2004), becoming more efficient smokers by extracting more nicotine out of cigarettes (Adda and Cornaglia, 2006, 2013), and purchasing cigarettes in nearby lower tax jurisdictions (Gruber et al., 2003; Lovenheim, 2008; Goolsbee et al., 2010; DeCicca et al., 2013a). These responses undermine the rationale behind cigarette taxes.

This article provides evidence for another, previously unexplored, behavioral response: that low-income smoking households respond to higher cigarette taxes by taking up food stamps.[1] Figure 1 shows that the first decade of the twenty-first century witnessed a doubling of both average cigarette prices (from \$3 to \$6 for a pack of cigarettes) and the US population share receiving food stamps (from 6% to 15%). We investigate whether these developments could be causally related.

[Insert Figure 1 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 our hypothesis that 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; Currie, 2004).

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 high cigarette taxes do not necessarily decrease aggregate cigarette consumption in the presence of optimization

[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). Henceforth, we use "SNAP" and "food stamps" interchangeably.

failures. Regardless of whether consumers value cigarette taxes as a commitment device to reduce smoking (Gruber and Kőszegi, 2004; Kőszegi, 2005), the prospect of enrolling in public assistance programs can preclude cigarette taxes from serving that function.

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) from 2001 to 2012. In our preferred specification, we exploit the CPS questions on month-to-month food stamp enrollment to construct a pseudo-panel. This allows 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 simultaneous variation in monthly state cigarette taxes. Using this novel dataset and difference-in-difference (DD) models stratified by smoking status, we find strong evidence for 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%. Non-smoking households are not more likely to transition onto food stamps after cigarette tax increases.

To investigate the mechanisms driving this behavior, we estimate the effect of cigarette taxes on cigarette expenditures and compare it to the size of food stamp benefits received by households. We find that cigarette prices as actually paid by consumers increase by $0.77 for every $1 increase in tax, i.e., we find a pass through rate of 0.77. For the mean smoking household consuming 22 packs per month—or 264 packs per year—this implies that a $1 increase in cigarette taxes would translate into annual spending increases of $203. This is exactly what our CPS regression models confirm. 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.

In 2001, only about half of all eligible households were enrolled in food stamps, i.e., the take-up rate was only 50% (Lerman and Wiseman, 2002; Ganong and Liebman, 2013). Our data show that half of all enrolled smoking households receive less than $100 in food stamp benefits per month. This relatively small amount helps explain why transaction costs and stigma may prevent eligible households from enrolling—at least until high cigarette taxes induce marginal smoking households to enroll.

Our findings contribute to several strands of the economics literature. Most directly, our findings contribute to the literature on tax avoidance behavior (Dickert-Conlin and Chandra, 1999; Adda and Cornaglia, 2006; Lovenheim, 2008; Goolsbee et al., 2010; Harding et al., 2012;

Lillard et al., 2013; Adda and Cornaglia, 2013; DeCicca et al., 2013a; Chiou and Muehlegger, 2014) and consumer responses to taxation and income changes more generally (Shapiro and Slemrod, 2003; Sahm et al., 2012; Broda and Parker, 2014; Burns and Ziliak, 2015). In addition, we contribute to the literature examining the factors that influence take-up of food stamps (Moffitt, 1989; Fraker et al., 1995; Lerman and Wiseman, 2002; Ziliak et al., 2003; Blundell and Pistaferri, 2003; Hanratty, 2006; Gundersen and Kreider, 2008; Hoynes and Schanzenbach, 2009; Leete and Bania, 2010; Kaushal and Gao, 2011; Hoynes and Schanzenbach, 2012; Ganong and Liebman, 2013; Ziliak, 2015b) and public assistance programs in general (Duclos, 1995; Kayser and Frick, 2000; Currie, 2004; Heckman and Smith, 2004; Aizer, 2007; Fang and Silverman, 2009; Figlio et al., 2009; Kleven and Kopczuk, 2011; Ziliak, 2015a).

We also contribute to the behavioral public finance literature in the sense that we consider concepts of uncoordinated regulation (Kenkel, 1993; Mason and Swanson, 2002). We 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. Because one policy can blunt the incentives imposed by another policy, our findings suggest that optimal taxation models should account for the inefficiencies that arise from uncoordinated policies (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 the empirical analysis. 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 participation in voluntary government transfer programs. For concreteness, we use as our running example cigarettes and food stamps. 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 (Currie, 2004). 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, i.e., stimga costs.[2]

We assume the households' utility function to be 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 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.

The model assumes that cigarette tax increases are passed 1:1 onto cigarette prices and do not affect prices of other goods. This assumption allows us to abstract away from the issue of tax pass-through (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 thus:

[2]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.

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

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

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

where p is the tax-inclusive price of cigarettes. 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 incur marginal enrollment costs that vary with the size of the food stamp benefit, i.e., enrollment costs simply 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, but differ in S.

To determine if increases in cigarette taxes induce households to take-up food stamps, it is sufficient to analyze the impact of a tax increase on the marginal household's enrollment costs (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 holds that all households with $S_i < \bar{S}$ enroll in food stamps because their disutility of enrolling is lower than the increase in utility due to the 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 are increasing in taxes, then 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.[3] In the neoclassical framework with minimal functional form assumptions, however, 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 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.

2.2.2 Predictions in a Behavioral Framework with Addiction

We now employ an addiction based behavioral economics framework to derive predictions on the relationship between cigarette taxes and food stamp take-up. 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

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

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 would take an agnostic stance as to why cigarette demand is inelastic. We follow Bernheim and Rangel (2004) because of its 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; $v(p, W)$ 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. As 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 some amount of the addiction good $\hat{c} \geq a$. This can be thought of as an addiction constraint. For the household whose addiction 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 prices directly decreases the consumption of x. Again assuming that the food stamp benefit FS is infinitesimal, we have:

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

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: 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. Even though part of the rationale for increasing cigarette taxes is to correct for time inconsistency, the self control problem can manifest itself in behavior on other margins, such as taking up public assistance programs, and partially prevent the taxes from playing their intended role.

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 should not be interpreted as general theoretical findings. Our goal here is 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 using standard behavioral frameworks.

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 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: $U = c^{\alpha-\delta}x^{\sigma}$. For each tax level τ and benefit level b, we assume that each household must also satisfy her budget constraint ($W_i + e_i FS_i \geq (p+\tau)c_i + x_i$), addiction constraint ($c_i > a_i$), and cannot use food stamps to purchase cigarettes ($x \geq eFS$).

Under these conditions, we simulate the household behavior varying both τ and b. Under each combination of τ and b, we calculate *(i)* aggregate cigarette consumption $\left(\sum_i c_i\right)$, *(ii)* the share of households enrolled in food stamps $\left(\frac{\sum_i e_i}{50{,}000}\right)$ and calculate a cigarette consumption index by normalizing aggregate consumption under a policy regime of τ and b by dividing by aggregate consumption in the baseline case of $\tau = 0$ and $b = 0$. We also simulate *(iii)* the share of households who enroll in food stamps only because of self control problems.[4] Figures 2 to 4 plot the simulation results for outcomes *(i)* to *(iii)*.

[Insert Figures 2 to 4 about here]

Figure 2 shows that aggregate cigarette consumption typically decreases in cigarette taxes. However, for 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 results in a darker color gray in Figure 2b). Figure 3 supports the prediction from the marginal argument in Equation (3). In general, cigarette taxes induce addicted smoking households to take-up food stamps. 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, Figure 4 shows that higher taxes are typically associated with higher food enrollment attributable to optimization failures.

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 peri-

[4]This share is $\frac{\sum_j j}{50{,}000}$, 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 $\left(U_i(p, W+FS) - S_i \leq U_i(p, W)\right)$.

odically in "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. The FSS is always carried out in December. Notably, the FSS surveys food stamp enrollment information separately for each month of the calendar year from January until December. This allows us to establish a "food stamp enrollment panel" for each household.

The TUS surveys the smoking status of each household member at the time of the survey (scheduled in different calendar months of the year, depending on the year). Importantly, the smoking status of each household member is not only elicited for the actual date of the survey but also retrospectively, 12 months prior to the interview. This allows us to establish a "smoking status panel" for each household member.

The TUS and FSS are structured such that we can observe food stamp enrollment and smoking status for exactly the same calendar months. Appendix A describes in detail how we merged the TUS and the FSS to obtain: *(i)* a cross-sectional dataset, and *(ii)* a pseudo-panel dataset.

The cross-sectional dataset uses FSS information on food stamp enrollment and TUS information on household demographics, cigarette consumption, and prices paid for the last pack or carton of cigarettes purchased. This leaves us with a cross-sectional sample of 26,729 household-year observations. Table B1 in Appendix B shows the descriptive statistics and Table B2 shows the span of the observations across different year-months between 2001 and 2011.

The pseudo-panel merges the "smoking status panel" with the "food stamp enrollment panel". Appendix A provides more details on how this is exactly achieved. We call the constructed dataset a pseudo-panel because demographics such as income and the household structure are time-invariant.[5] Table C1 in Appendix C shows the descriptive statistics for the CPS pseudo-panel, and Table C2 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.

[5]We use demographics from the TUS because the cross-section reference month is that for the TUS, but the results do not change significantly if we use demographics from the FSS.

For each household observation in the two datasets (for which we observe food stamp enrollment) we merge in cigarette taxes from a dataset on monthly state cigarette taxes. This tax information comes from the Tax Burden on Tobacco (2012). We employ the state tax in the month prior to the interview because of the time lag between applying for food stamps and officially enrolling, which we further discuss in Section 5.2.6.

Sample Selection. Our target population is low-income households who are potentially eligible for food stamps. We rely on the CPS filter question for food stamp information to restrict the sample to households below 185% of the Federal Poverty Line (FPL). Note that the CPS provides an indicator variable for whether households fall below 185% of the FPL, so we simply restrict our sample based on this predetermined (to us) poverty status. We also discard observations with missings on their observables.

Dependent Variables

With regard to the the CPS cross-section in Table B1, the first dependent variable of interest is the price paid for the last pack of cigarettes.[6] This information is only available for the 7,552 low-income CPS households with at least one smoker. As seen, in the decade from 2001 to 2011, the mean nominal price was \$3.56 with a standard deviation of \$1.81.

The second dependent variable in Table B1 is annual household cigarette expenditures.[7] The mean smoking household with 1.3 mean smokers consumes on average 22 packs of cigarettes per month and spends an annual amount of \$1,254 on cigarettes, or about \$100 per month.

The main dependent variable of interest in both the cross section and pseudo-panel is the indicator for *food stamp enrollment*, which indicates whether a household received food stamp benefits. Table C1 also provides information on *food stamp take-up*, which indicates whether a household transitioned onto food stamps between two calendar months. In the pseudo-panel,

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

[7] Annual household cigarette expenditures are calculated by multiplying the number of daily cigarettes consumed by cigarette prices for each smoker, and by normalizing that value to yearly expenditures. Then expenditures are summed over 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 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 over the course of the year.

17% are enrolled in food stamps in any given month.[8] The take-up rate in a given month is naturally much smaller, on average 0.6%, meaning that each month 0.6% of the households in our sample transition onto food stamps. Along with the monthly state-level tax variation, these 1,685 households who transition onto food stamps during the sample period provide the identifying variation for our empirical analysis when employing the pseudo-panel.

Cigarette Taxes and Socio-Demographic Controls

Our main independent variable of interest is the state cigarette tax in the preceding month. Table B1 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. Conditional on an increase in state taxes, the average tax increase is $0.46 in the cross-sectional dataset and $0.56 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 B1 (and Table C1). 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.

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.

[8]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.

We focus on the BLS-provided family files with food stamp information from 2001 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 state identifiers (BLS, 2014). We use the state identifiers to merge in the monthly state cigarette tax information for the month prior to the interview from the Tax Burden on Tobacco (2012). We then restrict the sample to CUs with complete income information and the second interview. This implies that we rely on representative cross sections when exploiting the CEX.

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 D2), and *(c)* to exploit the potentially more reliable collection of expenditure information in the CEX. We also condition the CEX on low-income households below the 185% FPL.[9]

Dependent Variables

As seen in Panel A of Table D1 in Appendix D, the retrospective CEX question yields average quarterly tobacco expenditures of $232 per household, which is remarkably consistent with the calculated expenditures in the CPS. About 18% of all 24,729 observed low-income households are on food stamps.

Cigarette Taxes and Socio-Demographic Controls

Although the wording and the type of the questions asked differ between the CPS and the CEX, we tried to generate a comparable set of covariates. Comparing Table D2 and Table B1, both samples show very similar socio-demographic characteristics. In the CEX, we have on average 2.5 members per household (CPS: 2.5) and the average age of the reference respondent is 54 years (CPS: 52 years). Almost all CEX households live in urban regions. Forty-seven percent of

[9]In contrast to the CPS, the CEX does not have a filter question on whether CUs are below or above 185% of the FPL. We generate this variable ourselves by employing the 2015 Poverty Guidelines and the BLS calculated (based on self-reports) annual gross CU income. To not screen out too many SNAP eligible households as a result of income reporting errors, we apply the 2015 thresholds to all years and round up, i.e., use a threshold value of $22,000 for a one person household instead of $21,774.50.

all household heads are employed (CPS: 44%) and 23% are high school dropouts (CPS: 23%). However, the CEX reports lower annual pre-tax household earnings (\$10.7K vs. \$18.6K) and less smoking households (23% vs. 28%).

4 Empirical Approach and Identification

4.1 Empirical Approach

Equation 4 sets out our main econometric specification for the cross-sectional CPS and CEX datasets as well as for the CPS pseudo-panel dataset.

$$y_{ismt} = \alpha + \beta \tau_{sm_{-1}t} \times h_{it} + \gamma \tau_{sm_{-1}t} + \psi h_{it} + X_{it} + \phi_m + \sigma_t + \rho_s + \rho_s \times h_{it} + \varepsilon_{it} \tag{4}$$

where y_{imt} represents the dependent variable of interest for household i in state s in month m and year t. $\tau_{sm_{-1}t}$ is the state cigarette tax in state s lagged by one month. h_{it} is an indicator for smoking households. X_{it} is a vector of socio-demographic covariates, ϕ_m are month fixed effects, and σ_t year fixed effects. In augmented specifications we replace month and year fixed effects with month of year fixed effects. ρ_s is a vector of state fixed effects. We enrich the model by employing interactions between state fixed effects and the smoking household indicator ($\rho_s \times h_{it}$) to net out state-specific behavior of smoking households. Moreover, in some specifications, we additionally include state time trends η_{s_t}. In the models using the pseudo-panel data, we employ household fixed effects v_i, which absorb the time-invariant X_{it} and ρ_s. The interaction term $\tau_{sm_{-1}t} \times h_{it}$ yields the main variable of interest. It is used to estimate the impact of cigarette taxes for smoking households. Standard errors are routinely clustered on the state level (Bertrand et al., 2004).

Equation (4) applies to both the cross sections and the CPS pseudo-panel. Using the cross-sectional data and food stamp enrollment as the outcome, Equation (4) links changes in state-month level cigarette taxes to smoker households' probability of enrolling in food stamps. Using the pseudo-panel data with household fixed effects v_i and food stamp enrollment as the outcome, Equation (4) links changes in state cigarette taxes to smoker households' probability to transition onto food stamps.

4.2 Identification

Our empirical approach follows the standard identification convention in the cigarette tax literature. It represents a difference-in-differences (DD) model where cigarette tax variation across states and over time represents the main identifying variation. However, our approach additionally uses within state variation between smoking and non-smoking households, and uses the latter as an additional control group. In that respect, the model in Equation (4) is a Difference-in-Difference-in-Differences (DDD) model.

The model considers differences in socio-demographics as well as common calendar year and calendar month time shocks. Enhanced specifications include rich sets of month-year fixed effects to consider common monthly time shocks which may be correlated with both tax increases and food stamp enrollment, such as recessions (e.g. Ziliak et al. (2003)). We also allow for state fixed effects and state time trends. Thus, in our most conservative specifications, we identify the tax effect using within state tax changes that deviate from the average state-specific cigarette taxes over ten years (in addition to its linear trend) as well as the average tax level of all US states in that particular year and month.

The main identification assumption is that there are no other unobserved factors that are correlated with both cigarette tax increases and an overproportional increase in food stamp enrollment at the state-year or even state-month level. One potential candidate is an economic downturn. However, the set of month-year fixed effects nets out general economic shocks in our models. Moreover, state time trends capture additional state-specific developments.

A more serious potential confounding factor is food price inflation. If, for whatever reason, food prices were to increase at the same pace as cigarette taxes, e.g., through supply shocks or state taxes, then it would be difficult to disentangle the increase in food stamp enrollment due to higher food prices from those of higher cigarette prices. However, in that case, one would expect cigarette taxes to increase the likelihood that non-smoking households enroll in food stamps as well. As we will show below, this is not the case; the effects are solely driven by smoking households. In addition, Figure E1 in Appendix E plots food prices and cigarette prices for the four US regions. In line with our priors, Figure E1 illustrates that the increase in cigarette prices between 2000 and 2011 outpaced food price inflation. While food prices increased by about 50% in all four US regions (in the Northeast a little bit more, in the West a little bit less), cigarette prices more than doubled in all regions and even tripled in the Northeast.

In principle, there is a consensus in the economics literature that changes in state-level taxes are exogenous to individuals. However, it may be that people move or choose their state of residence based on preferences, among them cigarette taxes (Tiebout, 1956; Zodrow and Mieszkowski, 1986). Our approach, like the majority of approaches similar to ours in the literature, 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.

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.

5 Empirical Results

Figure 1 shows large increases in cigarette prices 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 underlying mechanisms relating cigarette taxes and food stamp enrollment. In a very first step, we present non-parametric graphic evidence on the distribution of important outcome measures. Next, we show how cigarette taxes affect cigarette prices as paid by consumers as well as cigarette expenditures.

In our main analysis, we 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). Finally, we provide a visual assessment of food stamp enrollment before and after cigarette tax increases through an event study.

5.1 The Impact of Cigarette Taxes on Prices and Expenditures

5.1.1 Investigating Prices, Consumption, and Expenditures Descriptively

Figures 5 and 6 show distributions of important underlying factors linking cigarette taxes and food stamp enrollment. First, despite the $3.56 mean cigarette price, Figure 5a illustrates the significant variation in cigarette prices as actually paid by consumers in the last decade.[10]

[Insert Figures 5 and 6 about here]

Next, Figure 5b shows self-reported household cigarette consumption. As seen, while the mean smoking household consumes 22 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.[11]

Finally, Figure 6a shows annual cigarette expenditures for the CPS and Figure 6b shows quarterly cigarette expenditures for the CEX. The CPS and CEX tell a very similar story. The mean self-reported yearly household expenditures from the CPS and CEX are $1,254 and $928, respectively. Expenditures exhibit a strongly right-skewed distribution in both samples (Figure 6).

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

Estimating the Tax Pass-Through Rate

We now 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 that conditions on smoking households (DeCicca et al., 2013b). Columns (1) and (2) of Table 1 show the results. Each column represents one DD regression model and the models only differ by the inclusion of sets of covariates as indicated in the lower portion of the table. In our preferred specification, we find that taxes are

[10] 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.

[11] 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).

passed through to prices at a rate of 0.77. This pass-through rate is right in line with the recent literature (Harding et al., 2012).

[Insert Table 1 about here]

Cigarette Taxes and Cigarette Expenditures

Next, we estimate the effect of higher cigarette taxes on cigarette expenditures, which are conveyed through the average pass-through rate of 0.77. Appendix B1 shows that—across the entire time period from 2001 to 2011—the 7,552 smoking households in the CPS paid on average $3.56 for a pack of cigarettes, consumed 22 packs per month, and had annual expenditures of $1,254. However, Figure 5 also illustrates that the variation in all these key parameters is quite substantial.

We again employ Equation (4) and a DD model to estimate the tax effect on 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, an increase in the cigarette tax by $1 increases annual cigarette expenditures by $220 (Column (4)). Note that a simple static calculation based on the estimated tax pass-through rate would yield almost identical expenditure increases of $203 (12*22 packs times $0.77).

The expenditure estimates from the CEX (Columns (5) and (6)) show that a $1 tax increase would increase quarterly expenditures by $15 for the average smoking household. Note that the CEX estimates are based on retrospective expenditure self-reports concerning the last quarter prior to the interview. Thus, the expenditure estimate is certainly a lower bound because future price increases are not yet fully internalized in these self-reports. Even the CPS estimate in Column (4) likely represents a lower bound because it includes all short-term compensatory behaviors of smokers and all reductions in cigarette consumption that may result from increased taxes, e.g., stockpiling of cheap cigarettes or a temporary reduction in consumption.

In addition, the expenditure estimates are just mean increases. Remember 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.

Lastly, it is worthwhile mentioning that research in psychology, behavioral, and macroeconomics demonstrates that the *perceived* price increase of goods that are repeatedly purchased (e.g., gas, staple food, or cigarettes) is significantly larger than the actual price increase (cf. also "WeberFechner law") (Homburg et al., 2005; Monroe, 2007; Antonides, 2008; Bruine de Bruin et al., 2011).

5.2 Cigarette Taxes and Food Stamp Enrollment

5.2.1 The Compensation for Higher Cigarette 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 $157 per month—or $1,886 per year (Table D1)—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 1.

Second, Figure 7b shows the distribution of 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 per year. About 50% receive less than $100 per month in food stamp benefits. Recall that $100 is also the average monthly amount that low-income smoking households spend on tobacco (Tables B1 and D1).

[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 barriers that we describe in the model section (e.g., pecuniary and stigma costs). Our model suggests increases in cigarette taxes could be one of the triggers. Again, applying our estimated pass-through rate of 0.77, 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 a third of all SNAP households, the benefit value would just compensate for a $1 tax increase.

Figure 7b also shows nearly identical distributions of SNAP 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 implies that smoking households do not 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, we use administrative food stamp enrollment data from the Department of Agriculture (USDA)—the government agency that administers SNAP—to graphically link cigarette taxes and food stamp enrollment at the state level.

Figure 8 plots yearly state cigarette taxes (x-axis) against the share of the state population on food stamps (y-axis). 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 tax bin on the x-axis, illustrating a strong positive relationship on the state-year level. The graphs 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 (x-axis) against the share of the state population on food stamps (y-axis). While Figure 8 provides a pure correlation, the refined plot in Figure 9 yields already some 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. 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 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.[12]

[Insert Figures 8 to 10 about here]

Finally, Figure 10 links *changes* in state cigarette taxes to *changes* in food stamp enrollment. Note that the the raw plot in Figure 10a exhibits significant variation around the fitted line. The high variance due to outliers flattens the positive relationship between changes in taxes and enrollment substantially. However, increases in state cigarette taxes are nonetheless associated with increases in enrollment.

[12]Figures B1, C1 and D1 in the Appendix show the equivalent scatter plots for the CPS and CEX cross-sectional datasets used in our regressions models below. The just described pattern also hold with the CPS and CEX. The zero values on the y-axis indicate that, in the CPS and CEX, we do not observe people on food stamps in these states.

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 the DDD model in Equation (4) using the cross sectional CPS and CEX datasets. The dependent variable is *food stamp enrollment*—an indicator for whether the household is currently enrolled in food stamps.

The results are shown in Table 2. Table 2 follows our convention from above, with each column showing DDD models differing only by the sets of covariates included. Columns (1) through (3) use the CPS cross-sectional dataset, and Columns (4) through (6) use the CEX dataset.

[Insert Table 2 about here]

The main effect of interest is the interaction term between *State Cigarette Tax* and *Smoking Household*. It indicates the statistical relationship between cigarette tax increases of $1 and the probability to be on food stamps for smoking households.[13] As seen, after tax increases of $1, smoking households are between a highly significant 3.7 and 4.4ppt more likely to be enrolled in food stamps (Columns (1) to (3)). This mechanism holds up when exploiting the CEX in Columns (4) to (6). Here, in our preferred specification in Column (6) smoking households are 6.1ppt more likely to be enrolled in food stamps for each $1 increase in cigarette taxes. It is noteworthy that the coefficients of interest remain stable when we add sets of covariates stepwise to the models. This yields additional evidence that the identifying variation is exogenous.

The most convincing evidence against the notion of spurious correlations between cigarette tax increases and SNAP enrollment is represented by *State Cigarette Tax*, which yields the effect for the control group in these triple difference models: non-smoking households. Across all six model specifications, the magnitude of *State Cigarette Tax* is rather small, its sign ambiguous, and in no case is *State Cigarette Tax* statistically significant. 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. When we stratify the sample by smoking and nonsmoking households and estimate separate models, the results are nearly identical.

[13] 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.

It is also worth emphasizing that Columns (1) to (6) show that smoking households in general are significantly more likely to be on food stamps (approximately 5ppt). The effect increases when adding socio-demographics, reflecting the socio-demographic smoking gradient, but is otherwise stable.

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 DDD regression models as above, but employ the outcome variables as indicated in the column headers of Table 3. The main variable of interest is again *State Cigarette Tax*$\times$*Smoking Household*.

The binary dependent variable in Column (1) indicates whether at least one household member quit smoking. A household is defined to be a quitting household if at least one member reported that they smoked cigarettes one year ago but do not currently smoke cigarettes (see Appendix A for a detailed discussion of the sample generation). Note that households without current smokers and households with current smokers can both have members who quit smoking within the past year. Column (1) provides some evidence that a $1 increase in cigarette taxes is associated with a 0.9ppt (2.5%) increase in the probability that at least one household member quit smoking in the past year.[14]

Column (2) uses the self-reported amount of daily household cigarette consumption as the dependent variable. The precise point estimate implies that a $1 increase in cigarette taxes reduces in the number of daily cigarettes consumed by 2.7 cigarettes at the household level. Finally, Column (3) exploits a self-reported measure that indicates whether the household ran out of money for food within the last month. The interaction term yields a relatively large point estimate of 5% of the mean which is, however, imprecisely estimated.

[Insert Table 3 about here]

[14]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.

5.2.5 Evidence from Monthly Transitions Onto Food Stamps

Our last econometric model uses the CPS pseudo-panel as described in Section 3.1 and Appendix A. Here we exploit within-household variation in food stamp enrollment.[15] Note that the overall monthly transition rate is a mere 0.6% and that we employ the same rich DDD fixed effects model specifications as above—including month-year and state fixed effects as well as state time trends. Even though the statistical power 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.

The DDD models in Columns (1) to (4) again only differ by the inclusion of sets of covariates. The plain *State Cigarette Tax* coefficient shows that tax increases are not statistically related to food stamp enrollment for non-smoking households. The point estimates represent precisely estimated zeros and even carry negative signs. The interaction term *State Cigarette Tax*×*Smoking HH* yields the relationship between tax increases and food stamp take-up for smoking households. As seen, the coefficients are significant at the 1% level and are relatively large in size.[16] 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 and absorb 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 Cigarette Tax* coefficients for non-smoking households is small and the sign negative.

The findings in the first four columns let us conclude: 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 (5) and (6) 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

[15]Among other advantages such as being able to include household fixed effects, the panel structure permits estimation of dynamic models with lagged food stamp enrollment to consider state dependence. The results in Tables 4 are robust when we include lagged food stamp enrollment.

[16]The estimates slightly increase, albeit not in a statistically significant sense, when quitting households are excluded from the sample. As before, the results carry over to non-linear estimation as well, where the household fixed effects model is a conditional fixed-effects model.

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 covariates as before. Note that the at risk population is limited to the subset of households who are not enrolled in food stamps in the first month we observe them. The sample excludes households once they take-up, so the sample size of the duration analysis differs slightly from the other models. In other words, h_t is interpreted as the conditional probability of taking up food stamps at time t, conditional on not being enrolled in food stamps. For lack of space, we withhold further detail on the estimation strategy; see Van Den Berg (2001) for a comprehensive review.

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?) and we avoid issues surrounding the calculation of marginal effects of interaction terms in non-linear models.

For non-smoking households, the point estimate on tax 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. For example, 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 pseudo-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 C2). The fact that only smokers are "treated" by cigarette tax increases leads to non-smoking households serving as a useful counterfactual, just as in the DDD models.

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.[17] Figure 11 shows the event study graph. The x-axis indicates up to four months prior and post the increases, and the y-axis plots the share 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, among smoking households, whereas one does not observe any trend from months -4 to -2 before the tax increase, one observes a strong increase in food stamp participation starting at -2. The fact that the enrollment probability increases already before the actual implementation of the tax increase is plausible, given the typical pre-announcement of such tax measures by state legislatures and the known stockpiling of cigarettes before tax increases (Chiou and Muehlegger, 2014). We interpret this as an anticipation effect.

One would also expect the increase in enrollment to persist past month t_1 because 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

[17]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 (see Appendix A for detailed explanations).

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.

In summary, Figure 11 shows a nonparametrically identified 3ppt increase in the probability of enrolling in food stamps following a tax increase from a baseline probability of 25% for low-income smoking households. This is exactly the effect we identify in our rich parametric DDD models which bolsters the notion that tax increases are not systematically correlated with the covariates in the parametric models. In contrast, over the tax increase cycle, we observe flat enrollment for non-smoking households with almost no trend.

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 0.77 triggers an average increase in smoker household's yearly cigarette expenditures of about $220. However, we estimate that for a fifth of all low-income smoking households, expenditures increase by at least $400.

Exploiting variation in state cigarette taxes across US states over the first decade of the twenty-first century, we then show that cigarette tax increases are significantly associated with higher food stamp enrollment. We employ a difference-in-difference-in-differences model where nonsmokers in a state serve as an additional control group. Smokers are "treated" with cigarette taxes while nonsmokers are not. 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, we find that an increase in taxes by $1 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 for smoking households by 10 days. We find strong evidence that food stamp enrollment for nonsmoking households is unaffected by cigarette taxes.

The findings suggest that the recent expanded use of cigarette taxes to curb smoking has likely contributed to recent increases 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 to increase 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.

Our findings also suggest that there exist important spillover effects from state to federal policies. In particular, 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 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.

References

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

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

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

Aizer, A. (2007). Public Health Insurance, Program Take-Up, and Child Health. *Review of Economics and Statistics 89*(3), 400–415.

Antonides, G. (2008). How is Perceived Inflation Related to Actual Price Changes in the European Union? *Journal of Economic Psychology 29*(4), 417–432.

Bar, H. and D. Lillard (2012). Accounting for Heaping in Retrospectively Reported Event Data—A Mixture-Model Approach. *Statistics in Medicine 31*(27), 3347–3365.

Becker, G. and K. Murphy (1988). A Theory of Rational Addiction. *Journal of Political Economy 96*(4), 675–700.

Bernheim, B. and A. Rangel (2004). Addiction and Cue-Triggered Decision Processes. *American Economic Review 94*(5), 1558–1590.

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

Bishop, J. and S. Kang (1991). Applying for Entitlements: Employers and the Targeted Jobs Tax Credit. *Journal of Policy Analysis and Management 10*(1), 24–45.

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

Blundell, R. and L. Pistaferri (2003). Income Volatility and Household Consumption: The Impact of Food Assistance Programs. *Journal of Human Resources 38*, 1032–1050.

Broda, C. and J. A. Parker (2014). The Economic Stimulus Payments of 2008 and the Aggregate Demand for Consumption. *Journal of Monetary Economics 68*(S), S20–S36.

Bruine de Bruin, W., W. van der Klaauw, and G. Topa (2011). Expectations of Inflation: The Biasing Effect of Thoughts about Specific Prices. *Journal of Economic Psychology 32*(5), 834 – 845.

Burns, S. K. and J. P. Ziliak (2015). Identifying the Elasticity of Taxable Income. *Economic Journal*, forthcoming.

Chiou, L. and E. Muehlegger (2008). Crossing the Line: Direct Estimation of Cross-Border Cigarette Sales and the Effect on Tax Revenue. *B.E. Journal of Economic Analysis and Policy 8*(1).

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

CNBC (2015). The World's Most Expensive Cigarettes and Cigars. `http://www.cnbc.com/id/41650075/page/12`, last accessed on January, 11, 2015.

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

Daponte, B., S. Sanders, and L. Taylor (1999). Why Do Low-Income Households not Use Food Stamps? Evidence from an Experiment. *Journal of Human Resources 34*(3), 612–628.

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

DeCicca, P., D. Kenkel, and F. Liu (2013b). Who Pays Cigarette Taxes? The Impact of Consumer Price Search. *Review of Economics and Statistics 95*(2), 516–529.

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

DeCicca, P., D. Kenkel, and A. Mathios (2008). Cigarette Taxes and the Transition from Youth to Adult Smoking: Smoking Initiation, Cessation, and Participation. *Journal of Health Economics 27*(4), 904–917.

Dickert-Conlin, S. and A. Chandra (1999). Taxes and the Timing of Births. *Journal of Political Economy 107*(1), 161–177.

Dragone, D. (2009). A Rational Eating Model of Binges, Diets and Obesity. *Journal of Health Economics 28*(4), 799–804.

Duclos, J. (1995). Modelling the Take-Up of State Support. *Journal of Public Economics 58*(3), 391–415.

Fang, H. and D. Silverman (2009). Time-Inconsistency And Welfare Program Participation: Evidence From The NLSY. *International Economic Review 50*(4), 1043–1077.

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

Figlio, D., S. Hamersma, and J. Roth (2009). Does Prenatal WIC Participation Improve Birth Outcomes? New Evidence from Florida. *Journal of Public Economics 93*(12), 235–245.

Fraker, T. M., A. P. Martini, and J. C. Ohls (1995). The Effect of Food Stamp Cashout on Food Expenditures: An Assessment of the Findings from Four Demonstrations. *Journal of Human Resources 30*(4), 633–649.

Ganong, P. and J. B. Liebman (2013). The Decline, Rebound, and Further Rise in SNAP Enrollment: Disentangling Business Cycle Fluctuations and Policy Changes. Technical report. mimeo.

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

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

Gruber, J. and B. Kőszegi (2004). Tax Incidence when Individuals are Time-Inconsistent: The Case of Cigarette Excise Taxes. *Journal of Public Economics 88*(9-10), 1959–1987.

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

Gundersen, C. and B. Kreider (2008). Food Stamps and Food Insecurity: What Can Be Learned in the Presence of Nonclassical Measurement Error? *Journal of Human Resources 43*(2), 352–382.

Haavio, M. and K. Kotakorpi (2011). The Political Economy of Sin Taxes. *European Economic Review 55*(4), 575–594.

Hanratty, M. J. (2006). Has the Food Stamp Program Become More Accessible? Impacts of Recent Changes in Reporting Requirements and Asset Eligibility Limits. *Journal of Policy Analysis and Management 25*(3), 603–621.

Hansen, B., J. J. Sabia, and D. I. Rees (2015). Cigarette Taxes and Youth Smoking: Updated Estimates Using YRBS Data. NBER Working Paper 21311.

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

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

Heckman, J. and J. Smith (2004). The Determinants of Participation in a Social Program: Evidence from a Prototypical Job Training Program. *Journal of Labor Economics 22*(2), 243–298.

Homburg, C., W. Hoyer, and N. Koschate (2005). Do Satisfied Customers Really Pay More? A Study of the Relationship between Customer Satisfaction and Willingness to Pay. *Journal of the Academy of Marketing Science 33*(1), 36–49.

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

Hoynes, H. W. and D. W. Schanzenbach (2012). Work Incentives and the Food Stamp Program. *Journal of Public Economics 96*(1), 151–162.

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

Kaushal, N. and Q. Gao (2011). Food Stamp Program and Consumption Choices. In *Economic Aspects of Obesity*, NBER Chapters, pp. 223–247. National Bureau of Economic Research.

Kayser, H. and J. Frick (2000). Take It or Leave It: (Non-)Take-Up Behavior of Social Assistance in Germany. Discussion Papers of DIW Berlin 210, DIW Berlin, German Institute for Economic Research.

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

Kőszegi, B. (2005). On the Feasibility of Market Solutions to Self-Control Problems. *Swedish Economic Policy Review 12*(2), 71–94.

Kim, Y. (2003). Income Distribution and Equilibrium Multiplicity in a Stigma-Based Model of Tax Evasion. *Journal of Public Economics 87*(7-8), 1591–1616.

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

Leete, L. and N. Bania (2010). The Effect of Income Shocks on Food Insufficiency. *Review of Economics of the Household 8*(4), 505–526.

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

Lillard, D. R., E. Molloy, and A. Sfekas (2013). Smoking Initiation and the Iron Law of Demand. *Journal of Health Economics 32*(1), 114–127.

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

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

Merriman, D. (2010). The Micro-Geography of Tax Avoidance: Evidence from Littered Cigarette Packs in Chicago. *American Economic Journal: Economic Policy 2*(2), 61–84.

Meyer, B., W. Mok, and J. Sullivan (2009). The Under-Reporting of Transfers in Household Surveys: Its Nature and Consequences. NBER Working Paper 15181.

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

Moffitt, R. (1989). Estimating the Value of an In-Kind Transfer: The Case of Food Stamps. *Econometrica 57*(2), 385–409.

Monroe, K. B. (2007). *Pricing and Sales Promotion* (3rd ed.)., Chapter 24, pp. 668–671. Wiley.

O'Donoghue, T. and M. Rabin (2003). Studying Optimal Paternalism, Illustrated by a Model of Sin Taxes. *American Economic Review 93*(2), 186–191.

O'Donoghue, T. and M. Rabin (2006). Optimal Sin Taxes. *Journal of Public Economics 90*(10), 1825–1849.

Office of Management and Budget (2014). *Fiscal Year 2014: Budget of the US Government*. `www.whitehouse.gov/sites/default/files/omb/budget/fy2014/assets/budget.pdf`, last retrieved on January 19, 2014.

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

Pudney, S., M. Hernandez, and R. Hancock (2007). The Welfare Cost of Means-Testing: Pensioner Participation in Income Support. *Journal of Applied Econometrics 22*(3), 581–598.

Ranney, C. and J. Kushman (1987). Cash Equivalence, Welfare Stigma and Food Stamps. *Southern Economic Journal 53*(4), 1011–1027.

Sahm, C. R., M. D. Shapiro, and J. Slemrod (2012). Check in the Mail or More in the Paycheck: Does the Effectiveness of Fiscal Stimulus Depend on How It Is Delivered? *American Economic Journal: Economic Policy 4*(3), 216–50.

Shapiro, M. D. and J. Slemrod (2003). Consumer Response to Tax Rebates. *American Economic Review 93*(1), 381–396.

Stuber, J. and K. Kronebusch (2004). Stigma and Other Determinants of Participation in TANF and Medicaid. *Journal of Policy Analysis and Management 23*(3), 509–530.

Tax Burden on Tobacco (2012). Historical Compilation.

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

Topkis, D. (1998). *Supermodularity and Complementarity*. Princeton University Press.

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

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

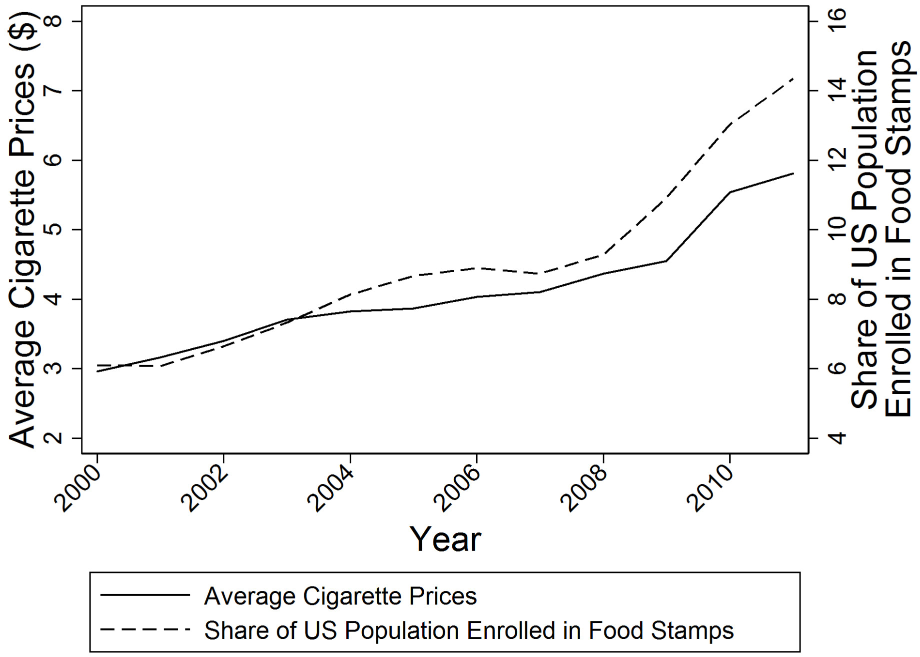
Ziliak, J. P. (2015b). Why Are So Many Americans on Food Stamps? The Role of the Economy, Policy, and Demographics. In J. Bartfeld, C. Gundersen, T. Smeeding, and J. P. Ziliak (Eds.), *SNAP Matters: How Food Stamps Affect Health and Well Being*. Stanford University Press.

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

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

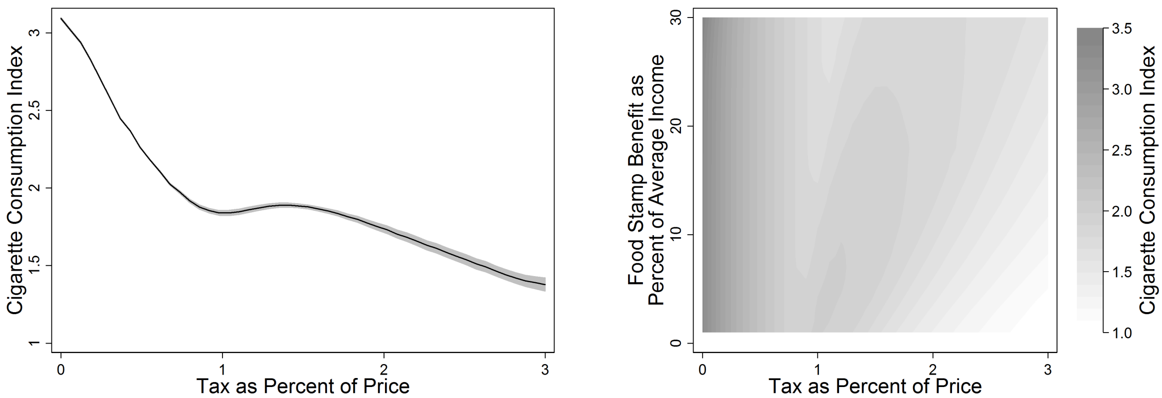
Figures and Tables

Figure 1: SNAP Enrollment in Relative Terms and Price



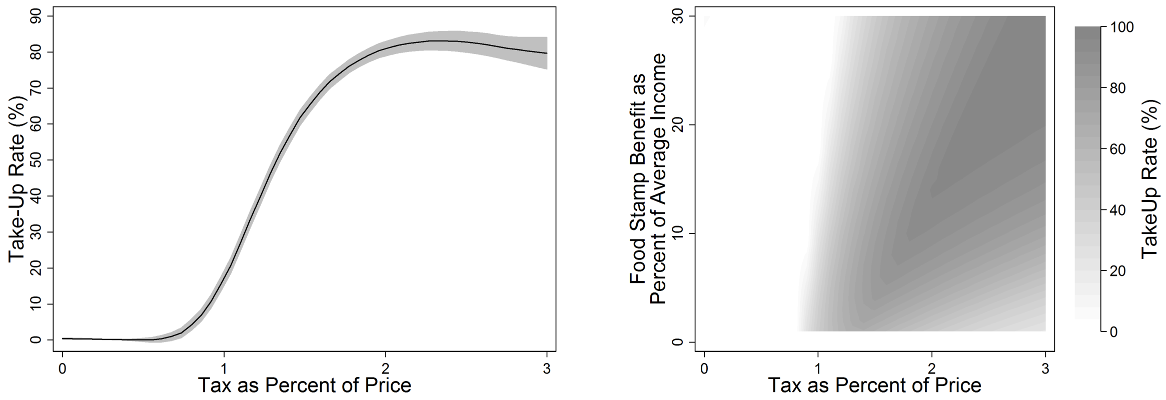
Source: Tax Burden on Tobacco (for average cigarette prices), and the official yearly statistics from the Department of Agriculture (for food stamp enrollment) and Census Bureau (for population), own illustration.

Figure 2: Simulated Cigarette Consumption Over (a) Cigarette Taxes, and (b) Food Stamp Benefits



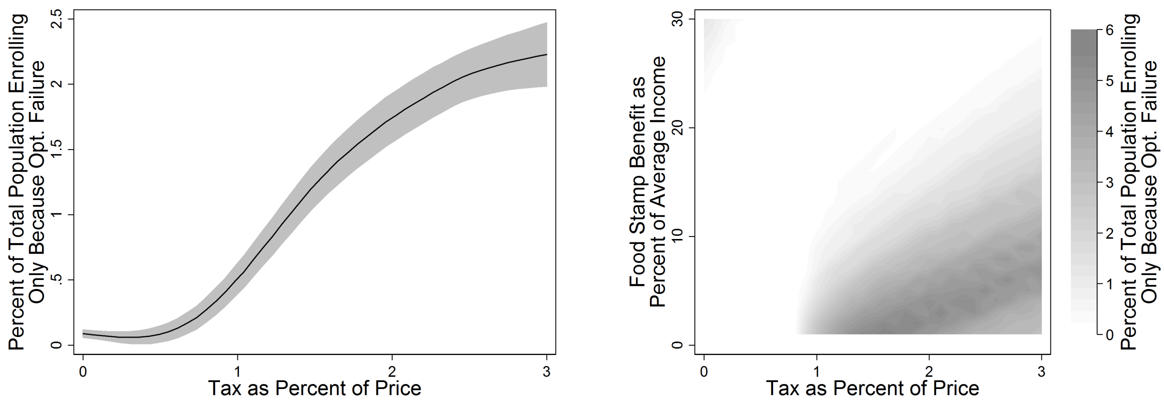
Source: Own simulation. The Cigarette Consumption Index is calculated by dividing the aggregate cigarette consumption under the given policy regime by aggregate cigarette consumption that would have occurred without either cigarette taxes or food stamp benefits.

Figure 3: Simulated Food Stamp Take-Up Rate Over (a) Cigarette Taxes, and (b) Food Stamp Benefits



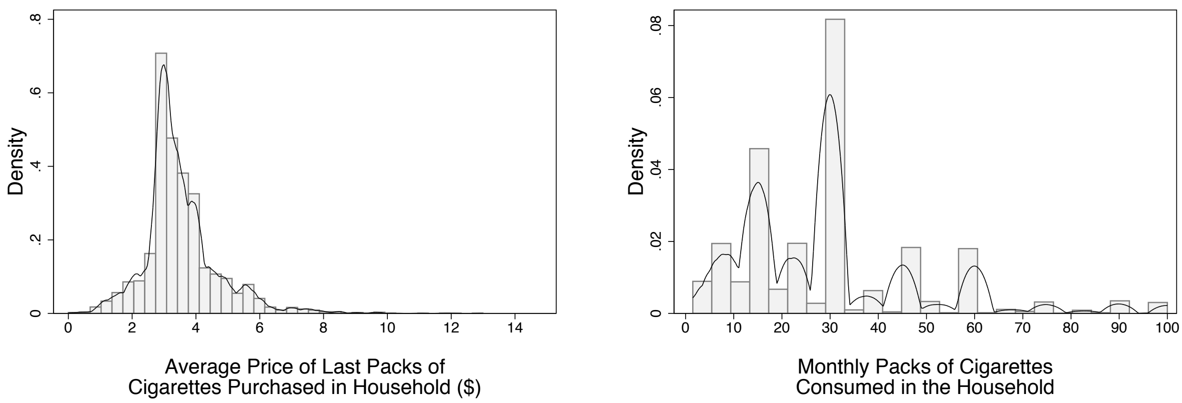
Source: Own simulation.

Figure 4: Simulated Food Stamp Take-Up Rate Due to Optimization Failure Over (a) Cigarette Taxes, and (b) Food Stamp Benefits



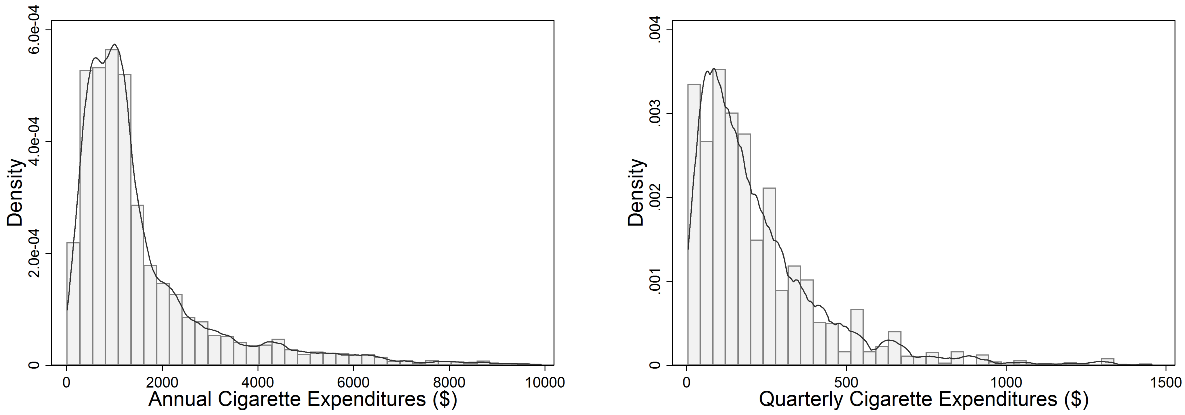
Source: Own simulation.

Figure 5: (a) Cigarette Prices Paid, and (b) Cigarette Consumption (Packs per Month)



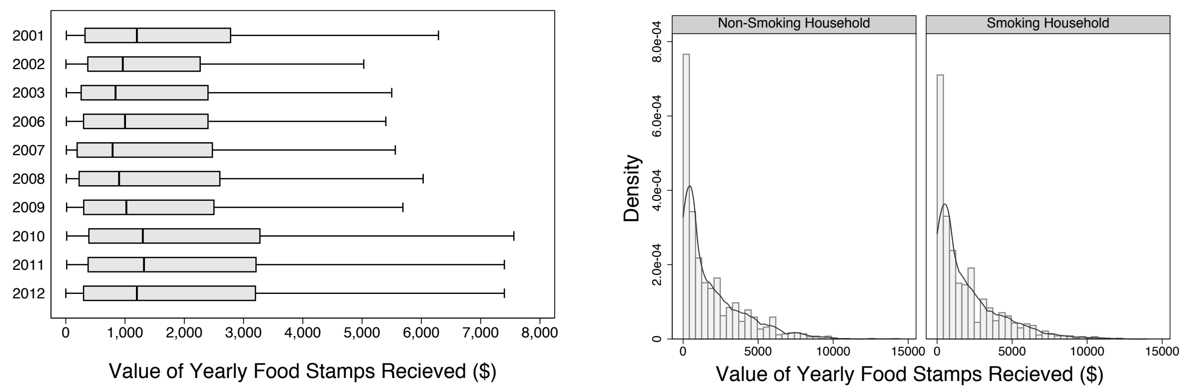
Source: CPS, FSS merged with TUS, own illustration.

Figure 6: (a) Annual Cigarette Expenditures in the CPS, and (b) Quarterly Expenditures in the CEX



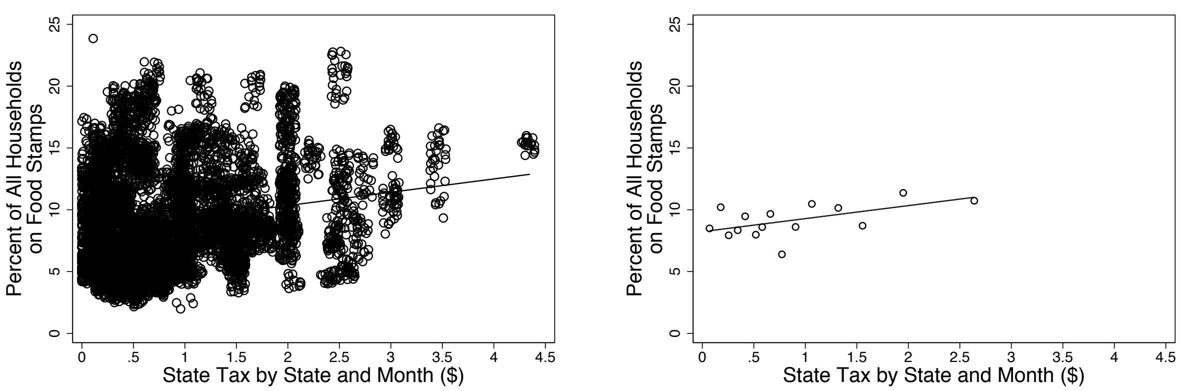
Source: Left: CPS, FSS merged with TUS, own illustration; Right: CEX, own illustration.

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



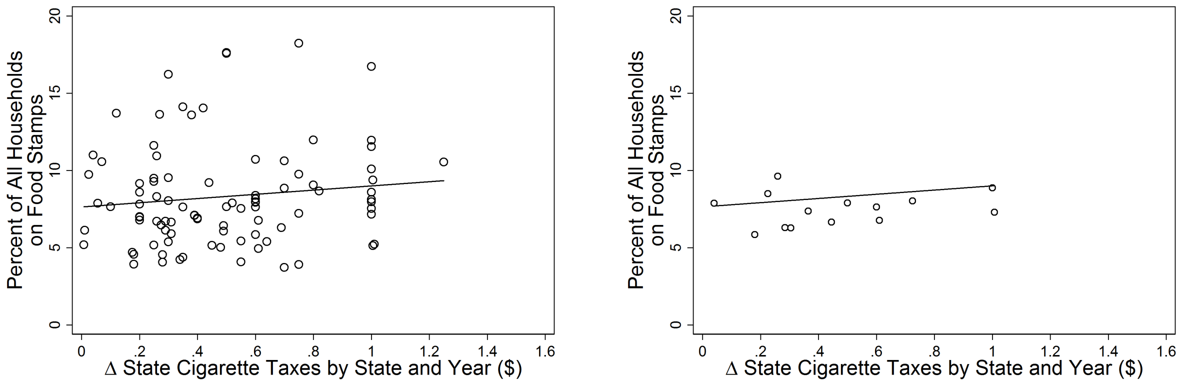
Source: CEX, own illustration.

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



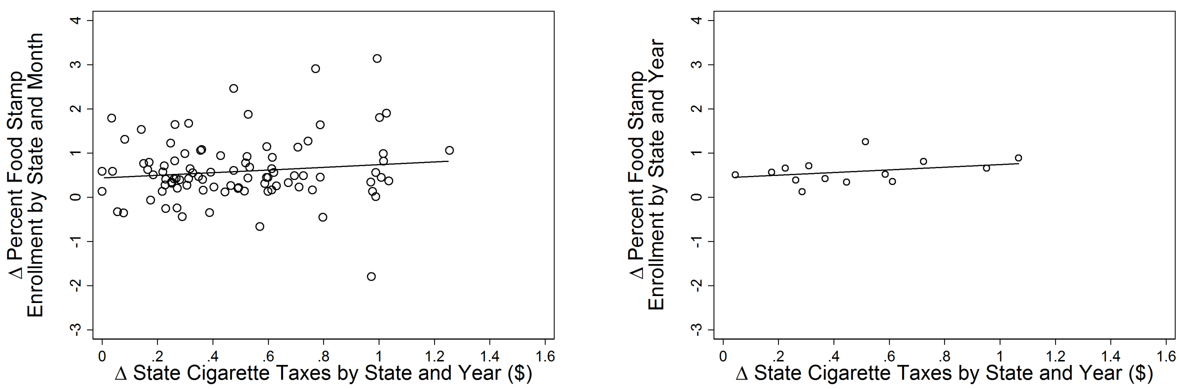
Source: Administrative data from Department of Agriculture, 2000 to 2012. The x-axis (cigarette taxes) of the left scatter plot is jittered to show the density of the distribution. The right scatter plot reports the mean share of the population on food stamps for each bin.

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



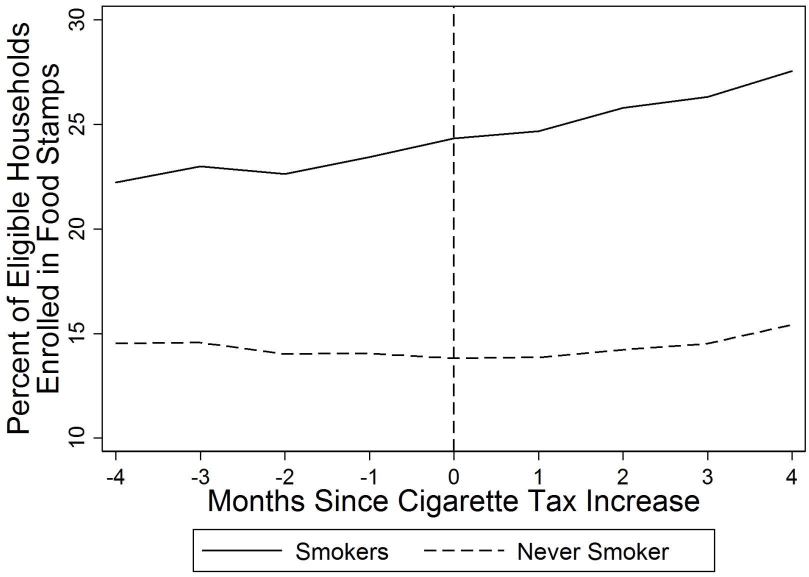
Source: Administrative data from Department of Agriculture, 2000 to 2012. The plots are conditional on positive changes in state cigarette taxes between year t_{-1} and t_0. The x-axis (cigarette taxes) of the left scatter plot is jittered to show the density of the distribution. The right scatter plot reports the mean share of the population on food stamps for each bin.

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 x-axis (cigarette taxes) of the left scatter plot is jittered to show the density of the distribution. The right scatter plot reports the mean share of the population on food stamps between year t_{-1} and t_0 for each bin.

Figure 11: Event Study—Food Stamp Enrollment and 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	0.8481***	0.7708***	61.6067	220.4998**	17.5482**	15.3488*
	(0.0978)	(0.1155)	(94.3731)	(106.5408)	(7.3712)	(7.7664)
Mean	3.56	3.56	1,253	1,253	231.81	231.81
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	7,552	7,552	7,552	7,552	5,740	5,740
R-squared	0.2629	0.2789	0.0175	0.3578	0.1450	0.1697

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. All samples condition on smoking households. Regressions are based on CPS and CEX cross sections as in Appendix B2 and D1. 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 cigarette expenditures in the last quarter prior to the interview, as reported by the household. *State Cigarette Tax* indicates the state cigarette tax level in 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)**
State Cigarette Tax×Smoking HH	0.0369***	0.0407***	0.0437***	0.0402***	0.0724***	0.0613***
	(0.0095)	(0.0094)	(0.0132)	(0.0114)	(0.0135)	(0.0123)
State Cigarette Tax	0.0125	-0.0146	-0.0140	0.0053	-0.0020	-0.0005
	(0.0113)	(0.0127)	(0.0132)	(0.0068)	(0.0105)	(0.0089)
Smoking Household	0.0389***	0.0335***	0.0525***	0.0672***	0.0380***	0.0524***
	(0.0077)	(0.0077)	(0.0153)	(0.0149)	(0.0044)	(0.0042)
Mean Smoking Households	0.1454	0.1454	0.1454	0.1972	0.1972	0.1972
Covariates employed						
Month FE	yes	no	no	yes	no	no
Year FE	yes	no	no	yes	no	no
Month×Year FE	no	yes	yes	no	yes	yes
State FE	no	yes	yes	no	yes	yes
State Time Trend	no	yes	yes	no	yes	yes
Socio-Demographics	no	no	yes	no	no	yes
Observations	26,729	26,729	26,729	24,729	24,729	24,729
R-squared	0.0648	0.0773	0.1888	0.0413	0.0641	0.1759

Source: Columns (1) to (3): 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 (4) 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. 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. All regressions include a full set of *Smoking Household*×*State Fixed Effects* to consider state differences in smoking household behavior. *State Cigarette Tax* 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×Smoking HH	0.0091***	-2.6664***	0.0147
	(0.0031)	(0.3594)	(0.0185)
State Cigarette Tax	0.0060	0.6383***	0.0153
	(0.0044)	(0.1966)	(0.0185)
Smoking Household	-0.0082***	18.2781***	0.0377***
	(0.0010)	(0.0846)	(0.0051)
Mean Smoking Households	0.3601	4.1173	0.3812
Covariates employed			
Month×Year FE	yes	yes	yes
State Fixed Effects	yes	yes	yes
State Time Trend	yes	yes	yes
Socio-Demographics	yes	yes	yes
Observations	26,729	26,729	26,729
R-squared	0.9366	0.4450	0.0818

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). All regressions include a full set of *Smoking Household*×*State Fixed Effects* to consider state differences in smoking household behavior. *State Cigarette Tax* 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 Cigarette Tax×Smoking HH	0.0219**	0.0214**	0.0313**	0.0305**		
	(0.0061)	(0.0061)	(0.0090)	(0.0089)		
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)
Mean Smoking Households	0.2465	0.2465	0.2465	0.2465		
Covariates employed						
Month×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
Observations	285,685	285,685	285,685	285,685	169,474	60,889
Within 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. Regressions are based on a pseudo-panel that makes use of the retrospective monthly information on household food stamp enrollment 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. The duration analysis sample differs from the other samples in that *(i)* it is limited to households who are initially not participating in food stamps in the first month in which we observe them, and in that *(ii)* it only includes households until the month they take-up food stamps or fall out of the sample (censored).

Appendix A: Merging the CPS-TUS and CPS-FSS to Construct (a) Cross-Sectional and (b) Pseudo-Panel Data

As mentioned in Section 3.1, 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. Each household is surveyed a maximum of one time in the TUS and FSS. For the years of our sample, the FSS is carried out each year in December and the TUS is carried out in periodic "waves" with three surveys per wave. The TUS waves we use are:

(a) June 2001, November 2001, and February 2002;

(b) February 2003, June 2003, and November 2003;

(c) May 2006, August 2006, and January 2007; and

(d) May 2010, August 2010, and January 2011.

We match households who appear in both the FSS and the TUS. 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.

Cross-Sectional Dataset. The cross-sectional dataset uses TUS information on household demographics, cigarette consumption, and prices paid for the last pack or carton of cigarettes purchased. 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.

Using the TUS survey as the reference date, we merge the household's food stamp enrollment information from the FSS that overlaps with the precise month the TUS was conducted. This is possible because the FSS asks about food stamp enrollment in the month of the survey as well as in the 11 preceding months. If one of those 11 preceding months was the month in which the household also participated in the TUS, we can match the food stamp enrollment status from the FSS to the cigarette information from the TUS.

It is important to note that this merging strategy isolates the smoking status of each household member and food stamp enrollment in the same month of the calendar year. We do not project the smoking or SNAP status forward or backward in time. That is, our sample does not include households for whom we observe smoking status in month t and food stamp enrollment in month $t + 1$, or vice versa.

It is also important to note that we use all household demographics from the TUS because this is the month in which we observe cigarette information as well as food stamp information (merged from the FSS). However, the results do not change significantly if we use demographics from the FSS.

Pseudo-Panel Dataset. The TUS surveys the smoking status of all household members in the month of the interview as well as 12 months before the interview, i.e., one year ago. The specific questions are:

(a) "Do you [Does household member X] now smoke cigarettes every day, some days, or not at all?".

(b) "Around this time 12 MONTHS AGO, were you [did household member X smoke] smoking cigarettes every day, some days, or not at all?"

This means that we can identify the number of household members who:

1. smoked in the month of the TUS interview and 12 months before, i.e., "always smokers",
2. smoked in the month of the TUS interview but not 12 months before, i.e., "initiators",
3. did not smoke in the month of the TUS interview but 12 months before, i.e., "quitters",
4. did not smoke in the month of the TUS interview nor 12 months before, i.e., "never smokers."

We define a household as a smoking household if it contains at least one smoking household member.[18] The pseudo-panel merges this "smoking status panel" with the "food stamp enrollment panel." We can generate a "food stamp enrollment panel" because the FSS interview in December asks about the household's food stamp enrollment for each calendar months of the year separately. As in the cross-sectional dataset, we use all household demographics from the TUS but, again, the results do not change significantly if we use demographics from the FSS.

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 pseudo-panel follows households for 12 months when the TUS was conducted in

[18]If a household contains zero "always smokers" but at least one "quitter" or initiator, we drop these households in the pseudo-panel, because we do not observe the month these members quit or initiated. We do not exclude these households in the cross-sectional dataset. The choice to exclude these households arose out of a concern that we could missclassify smoking households. These households account for less than 5% of all households. The results do not change if we keep and classify them as either smoking or nonsmoking households.

January, i.e., from January to December of the previous survey year. We restrict the pseudo-panel to households with 11 or 12 months of food stamp enrollment information. In particular, we keep the households of the January 2007 and 2011 TUS matched with the December 2006 and 2010 FSS, where we follow each household for 12 months. We also keep the households of the November 2003 TUS matched with the December 2003 FSS, where we follow each households for 11 months. This explains why our pseudo-panel only includes observations from 2003, 2006, and 2010. The results, however, do not change substantially when we keep the entire sample.

Appendix B: Descriptive Statistics CPS Cross Section

Table B1: Descriptive Statistics CPS FSS-TUS Cross-Sectional Data

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Cigarette Price ($)	3.5643	1.8135	0	65	7,552
Annual Cigarette Expenditures ($)	1,253.57	1,953.21	0	48,180	7,552
Household Daily Cigarette Consumption (# cigarettes)	14.5726	14.5938	0	120	7,552
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
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)	0.4587	0.2378	0.025	1	5,513
# 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

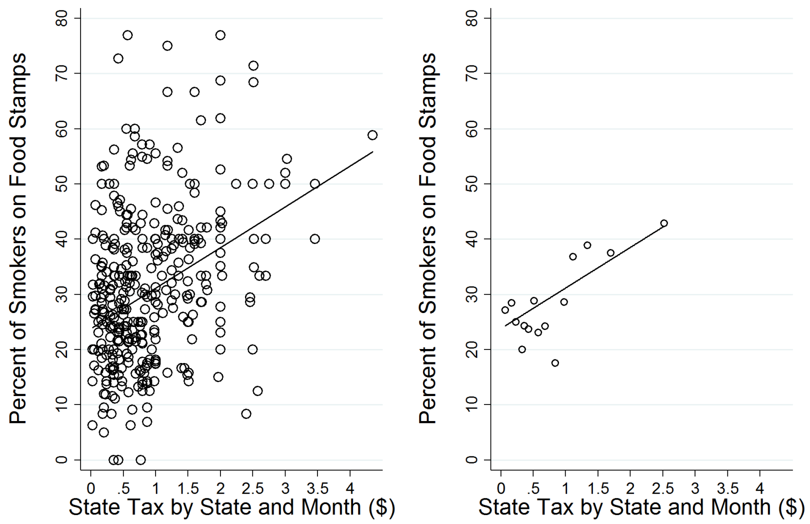
Source: CPS, FSS merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration. Note that cigarette price, consumption, and annual expenditures are reported for households which have at least one daily smoker.

Table B2: 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 B1: 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 C: Descriptive Statistics CPS Pseudo-Panel

Table C1: 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

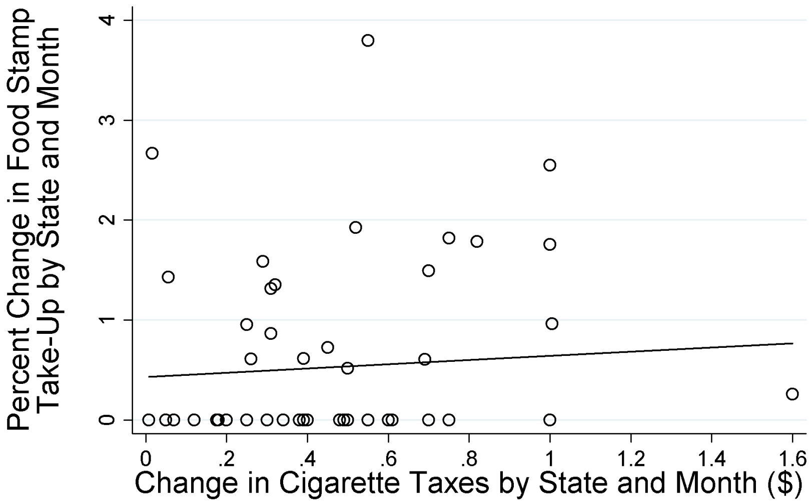
Source: CPS, FSS on last 12 month information merged with TUS and state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Table C2: 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 C1: 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 D: Descriptive Statistics CEX Cross Section

Table D1: Descriptive Statistics CEX

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Quarterly Cigarette Expenditure ($) (CEX Smoker Households Only)	231.8152	261.9108	4.3333	5,460	5,740
On Food Stamps in t_0	0.1796	0.3839	0	1	24,729
Value of Food Stamps ($) (Food Stamp Households Only)	1885.64	2072.03	1	14000	3,025
B. Covariates					
State Cigarette Tax in t_{-1}	0.8885	0.6601	0.025	4.3500	24,729
Change in State Cigarette Tax Between t_{-12} and t_0	0.5949	0.3869	0.008	1.6	3,493
Smoking Household	0.2321	0.4222	0	1	24,729
Rural Region	0.0121	0.1093	0	1	24,729
# Household Members	2.4533	1.621	1	16	24,729
# Male Household Members Over 16	0.8238	0.7059	0	8	24,729
Household Head White	0.7905	0.407	0	1	24,729
Household Head Black	0.1474	0.3545	0	1	24,729
Household Head Married	0.42	0.4936	0	1	24,729
Household Head Working	0.4675	0.499	0	1	24,729
Household Head No High School	0.2279	0.4195	0	1	24,729
Household Head Age	53.96	20.11	16	87	24,729
Household Head Male	0.4284	0.4949	0	1	24,729
Number of Household Earners	0.8611	0.8987	0	8	24,729
Annual Household Income Before Taxes	10,714	14,412	-97,672	97,524	24,729

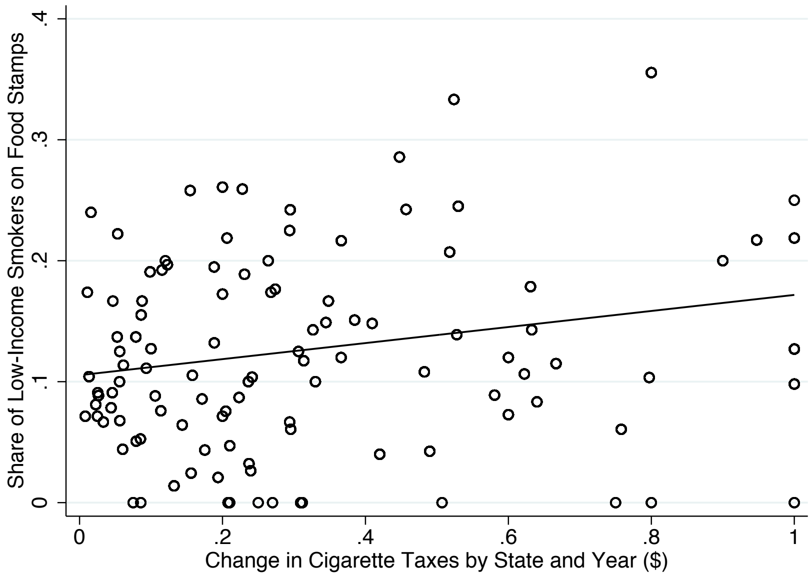
Source: CEX merged with state-month level cigarette tax information (Tax Burden on Tobacco, 2012), own illustration.

Table D2: CEX Cross-Sectional Observations Over Years and Months

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

Source: CEX, own illustration.

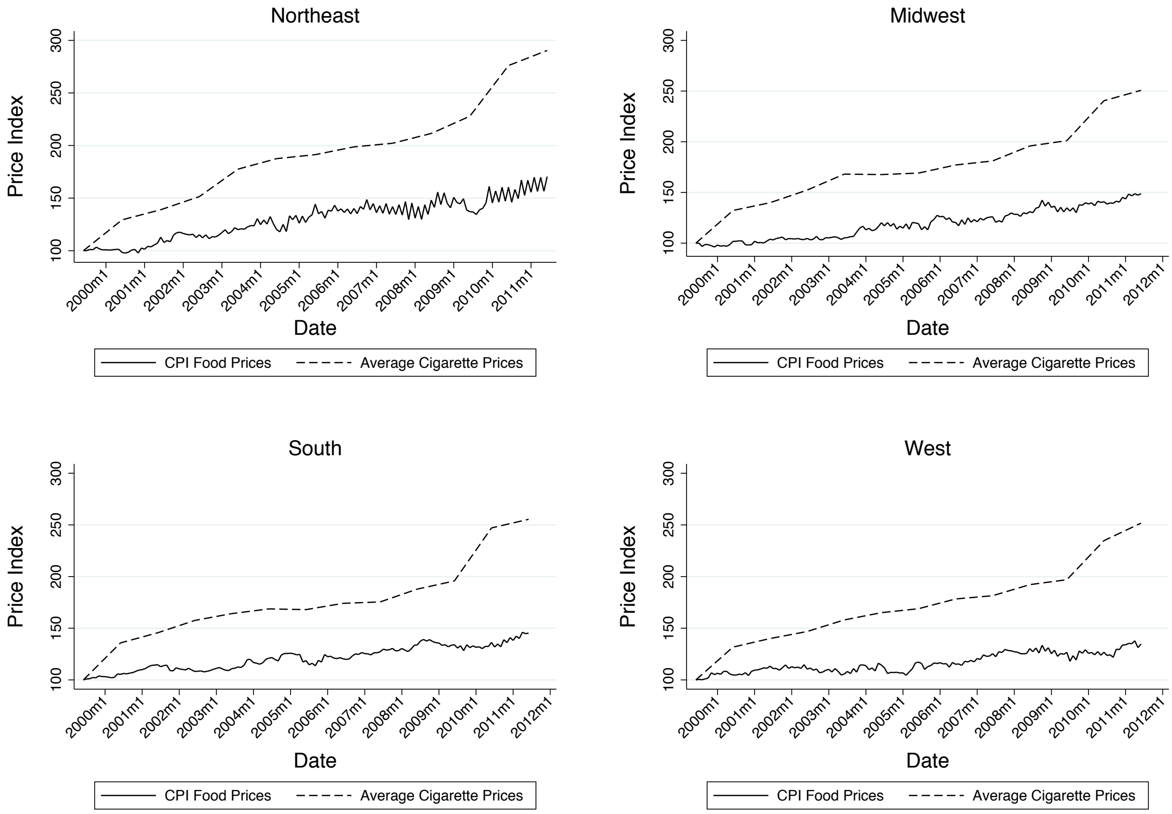
Figure D1: Yearly Change in State Cigarette Taxes and Share of Smokers on Food Stamps (CEX)



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

Appendix E: Cigarette Price and Food Price Inflation

Figure E1: Food Price and Cigarette Price Inflation



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