Unintended Consequences of Taxation: Cigarette Taxes and Food Stamp Take-Up*

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Abstract

This paper investigates previously unexplored compensating behavior in response to sin taxes: whether cigarette excise taxes increase the take-up of the Supplemental Nutrition Assistance Program (SNAP). First, we show theoretically that increases in cigarette taxes can induce non-enrolled eligible smoking households to enroll in SNAP. Second, we study these predictions empirically using the Current Population Survey (CPS) and the Consumer Expenditure Survey (CEX). A $1 increase in state cigarette taxes increases cigarette pack prices by $0.72 and smoker households' annual cigarette expenditures by $150 to $200. It increases food stamp take-up by about 15% among eligible smoking households.

Keywords: cigarette taxes, food stamp take-up, externalities, unintended consequences,

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

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1. Introduction

Sin taxes can be a powerful stick to curb behavior. Yet, they also have the potential to induce strategic behavior which may counteract their intended purpose. For instance, smokers may respond strategically to cigarette tax increases by switching to cigarettes that are higher in tar and nicotine (Farrelly et al., 2004), by extracting more nicotine per cigarette (Adda and Cornaglia, 2006, 2013), or by purchasing cigarettes in a nearby lower tax jurisdiction (Lovenheim, 2008; Goolsbee et al., 2010; DeCicca et al., 2010). Sin taxes can also interact with other public policies in a non-trivial way that can retard the potency the tax was intended to bestow. For example, Kenkel (1996) demonstrates that the optimal tax on alcohol is lower in places with tough drunk driving laws.

For low income smokers, high cigarette taxes can induce significant financial burdens, especially for highly addicted price inelastic smokers. As a result, higher cigarette taxes may crowd out other expenditures, e.g., for food or education.

Figure 1 illustrates how cigarette taxes have increased over time relative to minimum wages. It also illustrates how cigarette expenditures for a pack-a-day smoker have increased. In 2000, the average price for a pack of cigarettes was about $3, and the share of household income that a minimum wage earning a pack-a-day smoker had to spend on cigarettes was less than 4%. These numbers increased to about $10 for a pack of cigarettes and 10% of the household budget for an equivalent smoker in 2011. Because of the increasing share of household income devoted to cigarettes, the figure also strongly suggests that higher cigarette taxes have the potential to crowd-out food or non-food expenditures of low-income smoking households.

[Insert Figures 1 and 2 about here]

At the same time, since 2000, enrollment in the Supplemental Nutrition Assistance Program (SNAP)—commonly referred to as food stamps—has almost tripled from 17.2 to 47.6 million households (Figure 2). The share of the population on food stamps has more than doubled from 6.1% to 15.1%. As of 2014, SNAP is the largest near cash welfare program in the US with total yearly costs amounting to almost $80 billion (USDA, 2014).

In this article, we first study a model of cigarette taxes and take-up of public assistance programs. The model shows that increases in taxes on addictive goods can lead non-participating but eligible individuals to take-up public assistance programs. One interpretation of the model predictions is that access to governmental programs can partly neutralize the effect of sin taxes on discouraging bad behavior. A more conservative interpretation of the model predictions is that taxing addictive goods can have spillover effects by way of higher enrollment rates in public assistance programs.

We then empirically test the model's predictions using merged information from the Tobacco Use Supplements (TUS) and the Food Security Supplements (FSS) of the CPS along with monthly state-level cigarette tax data. In a first step we show that an increase in cigarette taxes by $1 leads to an increase in cigarette prices by $0.72 and higher annual cigarette expenditures of $150 to $200 for a smoking household. We also provide suggestive, imprecise, evidence that annual food expenditures decrease by about the same amount. Our main results show that for every $1 cigarette tax increase the probability of food stamp take-up among eligible households increases by about 15%.

These findings shed light on unexamined (and unintended) consequences of using sin taxes to discourage unhealthy behavior. Moreover, the findings suggest that inefficiencies in the current structure of the SNAP program may be reduced by considering the smoking status of eligible households. Finally, the findings also help explain the staggering increase in food stamp enrollment rates as illustrated in Figure 2 (Wilde, 2012).

The paper contributes to the literature on group differences in behavioral responses to governmental programs, including informational programs and imperfect optimization (Chetty et al., 2009, 2013; Liebman and Zeckhauser, 2004). In addition, our analysis builds to the literature on optimal sin taxes (O'Donoghue and Rabin, 2006). The findings suggest that the optimal sin tax likely strikes a balance between reducing substance use on the one hand and efficiency gains on the other, which may both depend on the structuring of other public policies. Rather than viewing the welfare implications of cigarette tax increases in a vacuum, our findings suggest that governments should probe into how well the taxes reach the subpopulation to which they are aimed.

The organization of this article is as follows. Section 2 develops a simple model of food stamp take-up to motivate 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. Model

To fix ideas, we present a simple static model of consumption and food stamp take-up. We first analyze whether increases in cigarette taxes can lead to take-up of food stamps under a standard utility maximizing framework and then again after relaxing some of its assumptions.[1] The relaxation of standard model assumptions incorporates one aspect of optimization failures from the behavioral economics literature, but the intuition holds more generally under a handful of other standard behavioral modifications to the consumer problem (Congdon et al., 2011). Even though the behavioral mechanism we exploit to drive behavior is specific, in the empirical section we do not seek to isolate the mechanism at work. Conditional on observing smokers with an inelastic demand for cigarettes, which can result from various optimization failures, the model takes an agnostic stance as to why demand is inelastic and simply applies existing models to examine the interaction between cigarette taxes and the public assistance take-up decisions.[2]

The standard utility model exploited relies on the following three main assumptions: First, agents must satisfy their true budget constraint regardless of any optimization failures

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[1] We ignore pecuniary costs of taking up food stamps such as the time spent on paperwork or travel. Even though the these costs might be relatively high—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)—these application costs can simply be thought of as transaction costs that essentially subtract from the monetary food stamp benefit, and can be modeled as such.

[2] The main critique of this approach to modeling argues that researchers should not simply modify how to model preferences in order to explain anomaly empirical patterns (Stigler and Becker, 1977).

due to behavioral or other issues related to addiction. Second, SNAP is modelled as a cash transfer program. Third, enrolling in public assistance programs entails costs in form of stigma. Since Moffitt's (1983) seminal paper on welfare stigma, most standard utility maximization models with optimizing agents consuming goods and choosing to participate in public assistance programs acknowledge a disutility from stigma, that is, most take-up models include a distaste or non-pecuniary cost arising from enrollment in the program per se.[3] Note that we will not directly empirically test the existence of stigma or attempting to estimate the effect size of stigma on take-up.

A great deal of analytical work documented the existence of stigma (Weisbrod, 1970; Horan and Austin, 1974; Rainwater, 1979), and empirical evidence suggests that stigma plays a role in take-up decisions (Currie 2004; Stuber and Kronebusch 2004; Currie and Groger 2000; Perry et al., 2000; Shrup-tine et al., 1998; Moffitt 1983). Conditional on stigma playing a role in a household's decision to take up a public assistance program, the model analyzes the effect of cigarette prices on take-up and includes stigma to represent the trade-offs we expect consumers to be experiencing.

[3] Social scientist even break stigma down into two forms, one capturing how individuals view themselves and another capturing how others view and treat recipients of public assistance programs. For instance, potential recipients might themselves adopt the social belief that public assistance recipients are undeserving (Cook and Barrett, 1992; Gilens, 1999), and those who take-up are lazy, having a lacking in ambition, "shift-less, dishonest, aggressive seekers of unearned rewards, morally weak, and bad parents" (Hochschild, 1996; Klugel and Smith, 1985). Moreover, even without one's own negative beliefs, recipients might have reservations for taking up public assistance because many recipients explain their experiences of seeking public benefits as a hostile and unpleasant environment (Auleta, 1982; Goodban, 1985; Piven and Cloward, 1993).

2.1 The Consumer Problem under a Standard Rational Utility Model

Suppose that the utility of an agent depends on cigarettes *c*, a composite food good, *x* (normalized to one), and the social stigma of enrolling in food stamps, *S*. Assume that the agent's income, *W*, is low enough such that the agent is eligible for food stamps, and that food stamps is a cash transfer program. The agent faces a standard budget constraint, and decides the consumption levels of cigarettes *c* and food *x*. The agent also decides whether to take-up food stamps that pays *FS* at a utility cost of $\phi(S)$. The problem of the agent is

$$max_{c,x,S}\, u(c,x) - \phi(S)\{FS > 0\} \quad \textit{subject to}$$

$$W + FS \geq pc + x$$

where *p* is the price of a pack of cigarettes. We assume the agents' utility function is separable in consumption and stigma, and follow the general consensus that stigma mainly comes in the form of a flat amount arising from enrollment (Ranney and Kushman, 1987). That is, we model stigma as a disutility shock, i.e., there is no marginal stigma that varies with the size of the benefit.[4] Choosing not to enroll means *FS* = 0.

The decision problem can be thought of as the agent choosing *c* and *x* and then enrolling if the utility in the food stamp state is higher than the utility in the non-food stamp state. That is, the problem can be reduced to the choice over two states:

[4] As Ranney and Kushman (1987) note, "[i]t seems reasonable to assume no marginal stigma associated with food stamp use because households can adjust their shopping behavior and make all their food purchases with stamps on one shopping trip."

$$max\{u(c(p, W + FS), x(p, W + FS)) - \phi(S),\; u(c(p, W), x(p, W))\} \quad (I)$$

Suppose that agents vary along S according to a uniform distribution. For simplicity, we allow social stigma to act to scale down the total utility from consuming everything else by defining $\phi(S) = S$. Then the agent with the marginal stigma is indifferent between enrolling and not enrolling if:

$$\phi(S) = S \leq u(c(p, W + FS), x(p, W + FS)) - u(c(p, W), x(p, W))$$

To determine how the marginal stigma of the last agent enrolling in food stamps changes with p, taking a total derivative, we obtain:

$$\frac{dS}{dp} = \frac{\partial u(c(p, W + FS), x(p, W + FS))}{\partial x(p, W + FS)} \frac{\partial x(p, W + FS)}{\partial p} + \frac{\partial u(c(p, W + FS), x(p, W + FS))}{\partial c(p, W + FS)} \frac{\partial c(p, W + FS)}{\partial p}$$

$$- \frac{\partial u(c(p, W), x(p, W))}{\partial x(p, W)} \frac{\partial x(p, W)}{\partial p} - \frac{\partial u(c(p, W), x(p, W))}{\partial c(p, W)} \frac{\partial c(p, W)}{\partial p}$$

Notice that deriving the sign of how the agent of marginal stigma enrolling changes with p depends on the functional form of the utility function. In a standard rational utility framework, the magnitude of the increase in marginal utility from x (by an increase in δx due to an increase in δp) relative to the decrease in marginal utility of c (by a decrease in δc due to an increase in δp) is unknown. Under certain conditions they would be equal, which would imply $\partial S \backslash \partial p = 0$. In words, this would mean that the marginal stigma of the last agent enrolling in food stamps does not change when the price of cigarettes increase in the standard rational utility framework.

2.2 Relaxing the Standard Rational Utility Model Assumptions and Introducing Addiction

We now follow Bernheim and Rangel (2004) to relax some of the assumptions in the standard model above, leading to the prediction that cigarette taxes can increase food stamp take-up.[5] Bernheim and Rangel (2004) introduced a "cue-triggered" type of addiction, where the consumer 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.

Ignoring how the hot state is exactly triggered and how past cigarette consumption levels impact entering the hot state, the question here is: what happens to the marginal stigma when individuals *are* in the hot state. In the hot state, addicted consumers consume a particular amount of the addiction good c^*, irrespective of underlying preferences and the price of cigarettes p[6], implying that

[5] Other behavioral assumptions lead to the same predictions such as in the Becker and Murphy's (1988) seminal *Theory of Rational Addiction* model, the Gruber and Koszegi's (2001) addiction model, or a more recent model in Dragone (2009). The latter assumes that any change in cigarette consumption, whether due to increase in cigarette taxes or otherwise, is costly to the agent.

[6] Note that consumer care about stigma and preferences in the cold state even though they do not care about them when in a hot state due to addiction. The reason is that addicted consumers only care about preferences *after* they made the cigarette purchasing decisions, when they are in the cold state again.

$\frac{\partial c(p,W)}{\partial p} = 0 \ \forall p.$[7]

As mentioned, we assume that smokers must satisfy their true budget constraint. Thus, if they consumes c^* units of cigarettes, their consumption of x will directly depend on the price of cigarettes p:

$$\frac{\partial x(p, W + FS)}{\partial p} = \frac{\partial x(p, W)}{\partial p} = -\frac{1}{p} \qquad (II)$$

In other words, every extra dollar smokers spends to consume the same amount of cigarettes from an increase in cigarette prices decreases the consumption of x one for one. Thus, the change in marginal stigma for a change in cigarette price reduces to:

$$\frac{dS}{dp} = -\frac{1}{p}\left[\frac{\partial u(c^*, x(p, W + FS))}{\partial x(p, W + FS)} - \frac{\partial u(c^*, x(p, W))}{\partial x(p, W)}\right]$$

Inside the parentheses, the first term represents the change in utility for an additional unit of food x when we are at an income of $W + FS$. It is the marginal utility of consuming good x when $x = W + FS - pc^*$. The second term is the marginal utility of consuming good x when $x = W - pc^*$.

[7] Capturing this type of inelastic supply is not specific to the functional form in Bernheim and Rangel (2004). There are multiple other ways to model addiction and inelastic demand for cigarettes due to "los[t] self-control outright due to addiction" (Congdon, Kling, and Mullainathan, 2011). For instance, one could assume that agents live under a "vail of addiction ignorance" in that they make consumption choices about cigarettes. Such a dynamic model would be along the lines of the models in Camerer et al. (1997) and Loewenstein (1996), where one could essentially treat cigarette consumption, other forms of consumption and welfare program enrollment as a distinct decision-making processes. Agents consider cigarette expenditures as sunk costs just as in the Bernheim and Rangel (2004). We follow Bernheim and Rangel (2004) because it is more tractable than the dynamic models. Yet, any of the previously mentioned models would only involve a small departure from the standard rational utility framework.

Under the standard assumption of decreasing marginal utility, the above equation implies that the first partial derivative is less than the second, because c^* does not change and by definition $W + FS - pc^* > W - pc^*$. As such, the sign inside the brackets is negative, and the change in marginal stigma becomes positive:

$$\frac{dS}{dp} = \frac{\Delta MU(x \rightarrow x')}{p} > 0 \qquad (III)$$

The above equation shows that under inelastic demand due to addiction, a cigarette tax increase increases the stigma that the marginal consumer is willing to accept when enrolling in food stamps. Thus an increase in cigarette taxes leads to a higher food-stamp take-up.

To summarize and in plain words: A time t_0 smokers are not on food stamps due to stigma and cigarette taxes are at their baseline level. At t_1 cigarette taxes increase, as do prices, but smokers nevertheless buy them since they are addicted and in a "hot state." At t_2 smokers fall back to the cold state again and now realize their binding budget constraint and that they spent too much on cigarettes. Hence marginal smokers, whose stigma tolerance has increased due to the price increase, now rationally enroll in food stamps.

3. Datasets

3.1. CPS: Food Security (FSS) and Tobacco Use Supplement (TUS) Merged with Taxes

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

Our main dataset combines the Tobacco Use Supplements (TUS) and the Food Security Supplements (FSS) of the CPS from 2001 to 2011. Each household is surveyed a maximum of one time in the TUS and FSS and, for the years we use, they are carried out in different months of the year: the FSS each year in December and the TUS in periodic "waves" with three surveys per wave.[8] We match households who appear in both the FSS and the TUS. For example, we matched households in the January 2007 TUS with the same households in the December 2006 FSS.[9]

Matching households who participated in both the TUS and FSS, we construct two datasets. *(i)* a cross sectional dataset, and *(ii)* a pseudo-panel dataset. We are able to construct a pseudo panel because the FSS surveys the monthly food stamp enrollment information separately in each of 12 months prior to the survey. As such,

[8] (1) June 2001, November 2001, and February 2002; (2) February 2003, June 2003, and November 2003; (3) May 2006, August 2006, and January 2007; and (4) May 2010, August 2010, and January 2011.

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

we can use each monthly food stamp enrollment information for each household as a separate observation.[10]

In the interest of clarity, we will define what we mean by two terms that we will use use throughout the rest of the paper. First, we define food stamp *enrollment* to be whether or whether or not a household received food stamp benefits in a given month. Second, we define define food stamp *take-up* in a given month when a household *transitioned on* food stamps in stamps in that month.[11]

Cross-Sectional Dataset. We exploit TUS information on socio-demographics, the current cigarette consumption, and prices paid for the last pack or carton of cigarettes purchased.[12] Then we merge the FSS food stamp enrollment information that overlaps with the month the TUS was conducted.

Our target population is low income households who are eligible for food stamps. Hence we restrict our sample to households below the 185% Federal Poverty Line (FPL) as indicated by the CPS[13] and we discard observations with missings on their observables. Because we use the

[10] We refer to the panel as a pseudo-panel because the socio-demographics are time-invariant.

[11] Note that because we observe at most 12 months of food stamp enrollment, we at most have 11 months of take-up information on a household.

[12] Note that the 2001-2002 TUS did not ask respondents about the price of last cigarette purchased. For these years we imputed missing self-reported cigarette price information with official state-year level price information from the *Tax Burden on Tobacco (2013)*.

[13]In reality, eligibility depends on a gross income test, a net income test, and an asset test. These income tests use the household's income in the previous month, which we do not obverse. However, the FSS (in December) estimates whether the household is under 185% of the poverty line, and only asks food stamp enrollment questions to these households. We follow this convention and use this CPS filter question as a proxy for food stamp eligibility. This more expanded view on eligibility (e.g., 185% of the poverty line) allows for some expected fluctuations in household incomes for low income households throughout the year.

cross-section data mainly to assess the impact of higher cigarette taxes on cigarette pack prices paid and annual cigarette expenditures, we also restrict the sample to smoking households in the cross sectional analysis. This leaves us with 10,888 household-month-year observations, where the reference month is the month of the TUS. [14] Table 1 shows that the observations span across 10 different year-months between 2001 and 2011.

[Insert Tables 1 and 2 about here]

Pseudo-Panel Dataset. Using the implicit panel structure of the FSS (the month-month food stamp enrollment information) and the implicit panel structure of the TUS, we generate a monthly household pseudo-panel with at most 12 observations per household.[15] Due to the variation in monthly timing of the TUS—and since the FSS is always carried out in December—the pseudo panel follows households for different lengths of time. For instance, the panel follows households for twelve months when the TUS was conducted in January, e.g., from January of the previous calendar year to December of the previous survey year; the panel follows households for eleven months when the TUS was conducted in November, e.g., from January of the current calendar

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

[15] We restrict the data to households with more than 6 months of food stamp enrollment information in the data.

year to the month of the TUS survey, and so on. [16] Here, we rely on demographic information in the FSS.

As above with the cross-section, we restrict the data to households under 185% of the of the FPL and disregard households with missing information on their observables.[17] Because Because we use the pseudo-panel mainly to estimate the impact of higher cigarette taxes on taxes on food stamp take-up, we restrict the sample to households without members who quit smoking within a year of the TUS survey for the reason that higher taxes may induce people to quit smoking (DeCicca et al., 2002, 2008).[18] Table 2 shows the distribution of the 345,665 monthly household observations between 2002 and 2011. As above, the years 2004, 2005, 2008, and 2009 do not carry observations, but—besides that the panel structure allow us to study actual take-up decisions—one main advantage of this dataset is that observations are almost evenly distributed across all months of the year. For almost every month of the calendar year, we have about 30,000 household observations that we exploit empirically.

Merging in State-Month Tax Data. The public version of CPS includes state identifiers. The century month and state in the two final datasets is used as the reference to which we merge monthly data on state cigarette taxes from *The Tax Burden on Tobacco (2013*).

[16] In 2007 and 2011, TUS was conducted in December and in 2001 and 2003 in November.

[17] Because we recent unemployment may dwarf effects of cigarette taxes on take-up decisions, we drop households where the head of household is unemployed. Unemployment could be an unobserved third factor that is correlated with both tax increases and food stamp take-up.

[18] The TUS asks the smoking status of each household member at the time of the survey and one year before the survey. These two variables allowed us to establish the smoking status of each member of the household in the time frame of the FSS for households who were surveyed in the TUS in months following when they were surveyed in the FSS. The results are robust to including households with quitters.

Dependent Variables. Descriptive statistics for the cross sectional and pseudo-panel datasets are in Tables A1 and B1 of the Appendix. Panel A of Tables A1 and B1 show the main dependent variables of interest in the corresponding datasets.

With regard to Table A1 and the CPS cross-section, the first dependent variable is price paid for the last pack or carton of cigarettes.[19] As seen, in the decade from 2001 the average nominal price was $3.66 but varied from 0 to $50.[20]The second dependent variable in Table A1 contains the annual household cigarette expenditures. We calculate these expenditures by using the number of daily cigarettes smoked per household member and the (last) cigarette pack price per smoker to generate a yearly household expenditures.[21] The average smoking household with 1.3 average smokers spends $1,640 per year for cigarettes, or $137 per month[22] (Table A1), which on average equals14% of the *earned* household income (not shown).

With regard to the pseudo-panel in Table B2, the two dependent are indicator variables for food stamp enrollment and the take-up of food stamps. Among eligible poor households in our pseudo-panel, on average 16% are on food stamps in a given

[19] If the respondent reported purchasing a carton of cigarettes, the price was established by dividing the reported carton price by 10 (because there are 10 pacsk of cigarettes per carton). If the household has more than one smoker, we take the smoker-average cigarette price, i.e., we do not weight by the number of cigarettes smoked per household member.

[21] This variable is $expenditures$ = $365 \sum_{m=1}^{M} p_m c_m$for smoker member *m* of total household smoking members

cigarettes smoked of member *m*. Note that this calculation uses the last pack's price paid and then extrapolating over the rest of the year. We underestimate expenditures in case of irregular cross-border shopping, i.e., if a household residing in New York purchased their last pack of cigarettes for $5 in New Jersey. We also underestimate expenditures in case of future price increases in the course of the year. In contrast, we overestimate expenditures if the price of the last pack was whatever reason (unusually) high or if the smoker reduces consumption in the course of the year.

[22] This equals 39 cigarette packs consumed per month and household (not shown in Table A1).

month.[23] The take-up rate is naturally much smaller than the enrollment rate, amounting to an average of 0.7%, i.e., each month 0.7% of our sample—2,455 households in total—transition on food stamps. Along with the monthly state-level tax variation, these households provide the identifying variation for our empirical analysis.

Covariates. Our main independent variable of interest is the state cigarette tax in a in a given month. In the empirical models, we employ the state tax in the month prior to the to the interview and food stamp take-up because of the time lag between applying for food food stamps and officially enrolling.[24] Table A1 in the Appendix shows that the average state excise tax is $0.76, 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 states and over time. Note that we do not include city or county taxes such as in New York City and Cook County (Chicago). The average monthly increase in taxes is $0.0034. However, the distribution of this variable is highly skewed; conditional on a tax increase, the increase was on average $0.36 between 2001 and 2011.

Finally, we adjust the already relatively homogenous samples for the following socio-economic characteristics as Panel B of Table A1 shows: the average household has 2.7 members and $18,850 as earned annual income. Roughly half of all heads of the household are male; the

[23]This is higher than the official food stamp enrollment during that time frame (see Figure 2), which is because we condition on households below 185% of the FPL. It has also been documented that the CPS underreports food stamp participation (Meyer and George, 2011) which is probably why the mean among poor households is not as high as one would expect. We rerun the analysis using different definitions of eligibility such as 100% of the FPL and the results do not significantly change.

[24] We manually impute state-month tax information for the first months we observe a household to not lose these observations.

household head is on average 45 years old, most likely white and not married. Almost 30% have no high school degree. About 50% of the household heads are employed and the other half are not in the labor force.

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.[25]

We focus on the BLS-provided family files with food stamp information from 2002 to 2012. Those files contain income, expenditure, and housing information at the CU level. The information mainly stems from the IS; however, detailed expenditure information from the DS are already merged into the family files by the BLS. Similarly,

[25] The expenditure information collected in the IS focuses on larger expenditures that occur in bigger time intervals such as expenditures for rent, automobiles, and major durable goods (BLS, 2014). The main purpose of the DS, by contrast, is to focus on smaller expenditures that cannot be easily recalled over longer time periods, e.g., detailed food, tobacco, and prescription drug expenditures. The DS is carried out in a diary form over two consecutive periods of one week each.

the family files contain aggregated information from the separate member files.

As we use the public version of the CEX, only a subset of observations is available with clean unambiguous state identifiers (BLS, 2014). We use the state identifiers to merge in the monthly tax information in a given state as provided by the *The Tax Burden on Tobacco (2013*). We then restrict our sample to CUs with complete income information and also restrict the sample to the second interview and smoking households.

Dependent Variables. We specifically employ the CEX in addition to the CPS for three reasons: *(a)* to check for the consistency of our results, *(b)* to exploit a representative sample that spans observations more evenly across calendar months and years (as demonstrated in Table 3), and *(c)* to better exploit the expenditure information provided in the CEX. We present evidence from the CEX regarding how increased cigarette expenditures may crowd out food expenditures.

Thus, we make use of the CU cigarette as well as food expenditure information in the last quarter.[26] As seen in Panel A of Table C1, the retrospective CEX information yields quarterly cigarette expenditures of about $250, which are significantly lower as compared to the calculated prospective expenditures in the CPS. This may be (partly) due to differences in sample selection. Average food at home expenditures are $800 per quarter and average food

[26] Note that CEX cigarette expenditures are self-reported retrospective information, whereas the expenditure information in the CPS is manually calculated based on current prices and consumption of each household member.

away from home expenditures are $330. About 11% of all 9,456 observed smoker households are on food stamps.[27]

Covariates. Because, in contrast to the CPS, we do not restrict the CEX to poor households, the sample characteristics as indicated by socio-economics differ slightly. In the CEX, we have on average 2.8 members per household where less than half of them are male but 1.6 are active in the labor market. The average income after taxes is almost $53K and almost all households live in urban regions. Half or all household heads are male and married; 84% of them are white and 10% black (see Table C1 in the Appendix).

[Insert Table 3 about here]

4. Empirical Approach and Identification

Our research design relies on two sources of variation. The first is monthly state-level cigarette tax changes. The second is the households who take-up food stamps during the time frame observed in the data.

4.1 Empirical Approach

The first econometric specification, using cross-sectional CPS and CEX data, is as follows:

[27] Note that the figure for the CPS cross sectional sample would be 29%. The difference may be due to several reasons. The main is certainly that, while both samples condition on smoking households, we do not restrict the CEX data to poor households. Another could be that both data are unweighted. However, weights do not matter a lot here since applying BLS provided CU weights to the CEX data yields a food stamp enrollment rate of 11.51% instead of 11.09%: In contrast, when we restrict the CEX sample to CUs with an annual income after taxes of less than $35K, we obtain a similar average household income as in the CPS of about $18.8K and the CEX food stamp enrollment rate jumps up to 21.6%.

$$y_{imt} = \alpha + \beta CigaretteTax_{smt_{-1}} + X_{imt}\gamma + \delta_t \times \phi_m + \xi_s + \epsilon_{it} \quad (1)$$

where y_{imt} is a dependent variable that measures either *(i)* the price of the last cigarette cigarette pack bought, *(ii)* cigarette expenditures, *(iii)* food expenditures, or *(iv)* whether household *i* is enrolled in food stamps in month *m* in year *t*. The specification also includes includes month-year fixed effects $\delta_t \times \phi_m$ as well as state fixed effects ξ_s. In some specifications, we additionally include state time trends. In addition, we adjust the sample for a set of socio-economic covariates, X_{imt}, as described in more detail above. Standard errors are routinely clustered on the state level.

The second econometric specification is also as in equation (1), but exploits the pseudo-panel dimension of the CPS by using the *change* in food stamp enrollment between month m_{-1} and m_0 as dependent variable – what we refer to as take-up. More specifically, the dependent variable Δy_{imt}t takes a value of one if household *i* transitioned on food stamps between m_{-1} and m_0 and is otherwise zero.

4.2 Identification

In principle, there is a consensus in the economics literature that (changes in) state-level taxes are exogenous to individuals. However, it may be that people move or chose their state of residence based on preferences, among them taxes. 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 exclude that migration based on tax changes biases our results. However, given the story of this paper, one would need to assume that moving out of state due to higher cigarette taxes induces lower costs than food stamp take-up, which is unlikely to be the case. Empirically, residential sorting based on cigarette tax increases should be negligible.

Consequently, all estimates ought to be interpreted as intend-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—actually study—compensatory behavior of smokers as a reaction to higher taxes, such as cross-border shopping, tax evasion, switching to cheaper or higher nicotine content cigarettes, or becoming a more efficient smoker. We expect all these behaviors to reduce the probability that smokers take-up food stamps, given stigma, as a response to higher cigarette prices. In this sense, we expect our estimates to underestimate the "true" cigarette tax-food stamp relationship.

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

Finally, it is worthwhile to mention that we do not only link these changes in state-month level cigarette taxes to the probability of participating in the food stamp program in that particular state in that particular month, but also link it to the probability that households *transition* on food stamps. Using the pseudo-panel structure of the CPS data, we show that the results are robust in size and significance when we employ changes in food stamp enrollment as dependent variable.

5. Empirical Results

5.1. Descriptive Findings

Referring back to the introduction, Figures 1 and 2 show staggering increases in cigarette taxes and potential spending among smokers on the one hand, and food stamp enrollment on the other. The question is whether both developments are causally related in some way. Figures 3 and 4 link tax levels (Figure 3) and changes in tax levels (Figure 4) to food stamp enrollment on the state level.

Figure 3 is based on the cross sectional CPS dataset and plots yearly state cigarette taxes and the share of smokers on food stamps at the state level. One observes a clear positive correlation albeit the picture exhibits some noise around the plotted linear line.[28] Figure 4 is based on the cross sectional CEX dataset and plots *changes* in state cigarette taxes between year $t_{-1}$and t_0 along with the share of smokers on food stamps in that given state. While Figure 3 provides a pure correlation, the refined picture in Figure 4 yields already more evidence for a causal association. While it is imaginable that unobservable factors exist that correlate both

[28] We obtain a very similar scatterplot when using the CEX as underlying dataset with the same variables.

with the level of taxes and food stamp enrollment , relating changes in taxes and food stamp enrollment provides more sophisticated evidence that unobserved factors are not likely the driving force.

Figure 4 can also be interpreted as the graphical equivalent to a state fixed effects regression model whose identification is based on changes in taxes from one year to the next in a given state. Figure 4 let us conclude the following: *(a)* Not surprisingly, as compared to Figure 3, the tax variation is significantly reduced which might reduce the statistical power of our regression models. *(b)* In terms of size, there is a lot of variation in state cigarette tax increases. We observe a lot of changes at around or even below $0.2, but also many tax increases of size $0.5 or even above $0.8. *(c)* Because the number of respondents in some (smaller) states is fairly low, we have to deal with noise, e.g., we observe some states without *any* respondent on food stamps which is clearly a data artifact. *(d)* Again, one observes an unambiguously positive association between yearly changes in cigarette state-level taxes and the share of smokers on food stamps.

[Insert Figures 3 to 6 about here]

Finally, using the CPS pseudo-panel, we link changes in monthly state cigarette taxes to *changes* in food stamp enrollment, i.e., food stamp take-up. As already discussed in Section 3.1 and seen in Table B1, while SNAP enrollment is on average 16.4% in the pseudo-panel, the average take-up rate in any given month is only 0.7%.

However, the average take-up rate is still based on a total of 2,455 households who transitioned onto food stamps during the time frame we observe them.

Figure 5 plots changes in food stamp enrollment against monthly changes in state cigarette taxes. Note that Figure 5 is aggregated on the month-state level, implying that *(a)* the empirical variation is further reduced, *(b)* noise increases further, and *(c)* we observe many state-month observations without any respondent transitioning onto food stamps. However, we still observe a clearly positive association between increases in monthly cigarette taxes and increases in food stamp enrollment. Also note that the graph artificially reduces the true variation exploited in the econometric models because the estimates are *not* based on state-level aggregates but rather the 2,455 households transitioning onto food stamps.

Lastly, Figure 6 shows an event study graph. The x-axis indicates up to five months before and after the tax increases and the y-axis plots the percent of eligible households on food stamps. The graph differentiates by smoking and non-smoking households. The share of non-smoking households is remarkably stable over time and exhibits almost to trend.[29] In contrast, exactly around the time of the tax increase, one observes a simultaneous strong increase in food stamp participation among smoking households. In combination with the graphs above, this yields strong suggestive evidence for a causal link between cigarette tax increases and food stamp take-up.

[29] In the pseudo-panel, we do not observe a complete year of food stamp enrollment information. As such, as we move from months since cigarette tax increase (*t* = 0), the individuals in some states drop out of the sample. Thus, the increase in food stamp enrollment among non-smoking households beyond month t=3 since the cigarette tax increase could be due to sample composition changes.

5.2. Regression Results

Pass-Through Rate of Cigarette Taxes to Prices

In a very first step, we estimate the extent to which excise tax increases are passed through to cigarette prices. For this exercise we employ a regression model as in equation (1), our first cross-sectional CPS dataset, and the self-reported prices of the last pack of cigarettes bought as dependent variable. Recall that the right hand side variable of interest, state cigarette taxes in a given month, are lagged to allow some time for the pass-through process and to account for the fact that some respondents reported prices before the tax increase. This is a standard tax incidence regression.

The first three columns of Table 4 show the results. Each column represents one regression model and the models only differ by the inclusion of sets of covariates as indicated in the lower portion of the table. The first model in column (1) solely nets out month-year fixed effects and finds that prices increase by $0.95 for every $1 increase in taxes. Column (2) includes socio-demographic covariates (as described in Section 3.1), and Column (3) further includes state fixed effects. Combing state fixed effects with month-year fixed effects allows us to focus on *changes* in state taxes after netting out average tax rates in that particular month and year. Models (2) and (3) yield a slightly lower, albeit still large, and highly significant pass-through rate of $0.72 for every $1 increase in taxes. This is absolutely in line with the recent literature (Harding et al. 2012). Note the high R-squared in column (3) that explains 20% of the variation in cigarette prices paid.

[Insert Table 4 about here]

Effect of Higher Cigarette Taxes on Cigarette Expenditures

Next, we estimate the effect of higher cigarette taxes on cigarette expenditures, which are triggered through the pass-through rate of about 0.7. Appendix A1 shows that—across our entire time period from 2001 to 2011—smoker households counted on average 1.3 smokers, paid $3.67 for a pack of cigarettes, and had annual expenditures of $1,640.

Columns (4) to (6) of Table 4 estimate the effects of cigarette taxes on cigarette expenditures. The model setup is the same as in the first three columns. When adjusting the sample for socio-economics, the effect of a $1 cigarette tax increase on annual expenditures increases from a significant $131 to a significant $178. Although this increase is not statistically significant, it suggests that household composition, income, and education are relevant factors in the households' cigarette purchasing decisions. Netting out persistent differences across states further increases the effect of a $1 tax increase on annual cigarette expenditures to $202. This point estimate is significant at the 5% level.

Note that this $202 estimate is the increase in cigarette expenditures *in addition to* all other compensating behaviors of smokers and all reductions in cigarette consumption that may result from increased taxes.[30] That is, even after smoking households may have reduced consumption (DeCicca et al., 2008), switched to cigarettes that are higher in tar and nicotine (Farrelly et al., 2004), extracted more nicotine per cigarette (Adda and Cornaglia, 2006 2013), or

[30] Note that this number can be easily calculated from the means directly: smoking households buy on average 280 cigarette packs with the higher price which triggers the expenditure increase—by definition according to our definition of the dependent variable (see Section 3.1).

purchased cigarettes in a nearby lower tax jurisdiction (Lovenheim, 2008; Goolsbee et al. 2010; DeCicca et al., 2010), smoking households are still on average spending $202 more on cigarettes per year. To put this in perspective, this amounts to a reduction in earned income of 1% (cf. Table A1).

State Cigarette Taxes and Food Stamp Take-Up

In the next step, we make use of our CPS pseudo-panel dataset and relate the change in state cigarette taxes to food stamp enrollment and take-up. Table 5 still follows our convention from above, with each column showing one model as in equation (1), and the models differing only by the sets of covariates. All models routinely control for month and year fixed effects. The first four columns use the binary indicator of whether the household receives food stamps in a particular month as dependent variable. Column (1) adds state fixed effects, column (2) additionally corrects for socio-demographics, column (3) employs month-year fixed effects instead of year and month fixed effects, and column (4) employs linear state time trends instead of the state fixed effects.

[Insert Table 5 about here]

As seen, despite these very rich specifications with month-year and state fixed effects or state time trends, the results are very robust. Accordingly, a $1 increase in state cigarette taxes increases the probability that a household is enrolled in food stamps by between 1.9 and 2.4ppt, or 11.3 and 14.5%.

The next econometric model in columns (5) to (8) exploits variation in whether households *transition* onto food stamps after an increase in taxes. The dependent variable here is an indicator that takes a value of one if respondents are new on food stamps between month t_{-1} and t_0 after a tax increase in t_{-1}. This is certainly the most sophisticated specification, given that the overall transition rate is solely 0.7% and given that we employ the same models specifications as above in the four models, including month-year and state fixed effects as well as state time trends. However, albeit the statistical power of our models is clearly reduced as compared to the first model, recall that we still rely on 2,455 transitioning households in the decade between 2002 and 2011. Nevertheless, we find effects of tax increases on the probability to transition onto food stamps which are estimated with great precision, given their small size.

The coefficient estimates are also surprisingly robust in terms of size across the specifications. In column (5) where we employ year, month, and state fixed effects, we find that a $1 cigarette tax increase increases the probability that a household transitions onto food stamps by 0.1ppt. Related to the baseline transition rate of 0.7% this represents an increase of 13.3%. The coefficient estimates in columns (6) to (8) are 0.09ppt, significant on the 10% or even 5% level, and all translate into percent changes of about 13%.[31]

[31]We also estimated hazard models using the event study research design previously discussed. The results are in line with the present results, but are not included here to save on space. In the specifications, we define the hazard rate as having a baseline hazard for smoking versus nonsmoking households taking up food stamps at any event time, where the "at risk" population is the subset of un-enrolled households as of a given event time. The households who take-up food stamps are no longer at risk so drop out of sample. Thus, the hazard rate can be interpreted as the conditional probability of household taking up food stamps in a given month, conditional on not already taken-up. In the hazard model, we do not include cigarette taxes; rather, because we allow being a smoker to vary non-parametrically in each period, we can implicitly estimate changes in hazard rate at $t = 0$, i.e., when cigarette taxes are increased. See online appendix for a further discussion of the model and the results.

We conclude: *(a)* Even if one employs the very low SNAP take-up rate of 0.7% in our monthly pseudo-panel as the dependent variable, one consistently finds positive and statistically significant effects of tax increases on take-up. *(b)* This holds even for very rich model specifications with month, year, and state fixed effects as well as state time trends. *(c)* The estimates are very small in size, very precise, and very robust across the model specifications. *(d)* The estimated relationship between a $1 tax increase and the increase in the probability to transition onto food stamps is reasonable (13%). *(e)* The strength of the estimated relationship is almost identical to the strength of the relationship estimated in the first four columns of Table 5 according to which a $1 tax increase increases the probability to be on food stamps by about 12%.

Falsifying the Estimates Using the CEX

As a last step, we employ the CEX to *(a)* test the consistency of our results and *(b)* exploit the expenditure information provided in the CEX. Table 3 reports the findings. The models employed are again as in equation (1). All models condition on smoking households.

Columns (1) and (2) use as dependent variable the CU cigarette expenditures in the last quarter, as reported by the CU members and aggregated by the BLS. We find that increases in cigarette taxes are associated with significantly higher CU cigarette expenditures, which is in line with the CPS results seen in Table 4. However, there are two notable differences between the CEX and the CPS results. First, when controlling for socio-demographics and state fixed effects, quarterly expenditures slightly *decrease* from $39 to $25. Second, when converting the increase in quarterly expenditures in column (2) to yearly expenditures (i.e., multiplying the estimates by four), they are only about half as large as in the CPS models.

There are several potential explanations for these differences. *(a)*The CEX does not restrict households to those potentially eligible for food stamps. As such, the CEX data include households with higher income than in the CPS data. If households with different socio-demographics such as income and education respond differently to increases in cigarette taxes, the observed differences could be due to sample differences *(b)* Because the CEX does not ask about past smoking status, the CEX includes households where members may have quit in the past, which could lead a decrease in cigarette expenditures. *(c)* In contrast to the CPS, the CEX expenditure information refers to the last quarter and we only employ tax rates with one monthly lag which certainly downward biases the association found. This is confirmed when we include a lag of five instead of one month, which increases the coefficient in column (2) to a highly significant $37 or $148 per year. *(d)* The expenditure information is collected in different ways. While the CEX asks specifically about expenditures, our CPS expenditure data is self-generated based on the self-reported information on the number of daily cigarettes typically smoked by each household member and the price paid for the lack pack. *(e)* The sampling procedure of the CPS differs from the CEX. For example, we can only consider individuals who participated in the TUS and FSS, so the CPS samples lack data from the years 2008 and 2009 that are included in the CEX. The great recession alone may have an impact that explains the differences. Also, as Tables 2 and 3 demonstrates, the sampling of participating households is by far not as evenly distributed in the CPS as it is in the CEX.

[Insert Table 6 about here]

Columns (3) and (4) of Table 6 use last quarter's expenditures for food at home and food away from home as explanatory variables. According to our theory in Section 3, the underlying mechanism at work, and as shown in equation (2), higher cigarette taxes lead to higher cigarette expenditures and crowd-out expenditures for other consumption good among smoking households.

We already provided empirical evidence for this relationship and found that smoking households have to spend between $150 and $200 more per year for cigarettes following a tax increase of §1. Although imprecisely estimated, columns (3) and (4) of Table 6 now show that, among smoker households, cigarette tax increases are associated with decreases in food expenditures of about 2.5% or $30 per quarter. This fits nicely with the found $25-40 increase in expenses for cigarettes in columns (1) and (2). We interpret the findings in columns (3) and (4) as suggestive evidence not only that higher cigarette taxes lead to higher cigarette expenditures but also that that these expenditures crowd-out food expenditures.

Columns (5) and (6) of Table 6 now replicate the first two columns in Table 5 using CEX data. In line with Table 5, we find that a $1 cigarette tax increase leads to a 2-3ppt higher probability that a household is on food stamps in a given state and month, after netting out persistent differences across states, months, years, and differences in socio-demographics. However, because the baseline level of households enrolled in food stamps is higher in the CPS sample relative to the CEX sample (16% vs. 11%), the percent change would be even higher in the CEX. Explanations for these differences have already been extensively discussed above.

Despite some minor differences in the size of the coefficient estimates, one can conclude: estimating essentially the same econometric models using CEX and CPS data yields very similar and statistically significant relationships between cigarette taxes and cigarette expenditures as well as food stamp enrollment.

6. Discussion and Conclusion

This paper investigates whether low income smoking households respond to sin taxes by accepting government transfers. First, we show theoretically—applying features of addiction models and incorporating disutility from social stigma when receiving public welfare transfers—that cigarette taxes may induce budget constraint addictive smoker to take-up food stamps. Second, using the CPS as well as the CEX matched with monthly cigarette tax information, we make the following empirical observations: We find for each $1 of cigarette tax increases *(a)* a pass-through rate of about 0.7, which *(b)* increases annual household cigarette expenditures by between $150 and $200, and *(c)* increases the probability that a household takes up food stamps by between 10 and 15%.

An optimal sin tax on cigarettes would take into account how resulting increases in cigarette expenditures may trigger compensating behavior or crowd out consumption of other goods such as food or education. A potential crowding out of food expenditures may in turn lead to an increase in food stamp enrollment as shown by this paper. Hence financial strains imposed on low income households by higher taxes on additive goods may construct an environment that promotes individuals to seek out governmental assistance.

Given the recent expanded use of cigarette taxes to curb smoking, our results show that higher taxes may partly explain the recent staggering increase in food stamp enrollment. The findings also suggest that sin taxes may be a less effective stick for low income populations with access to means-tested governmental programs, which may be used for tax avoidance and prevent affected individuals from fully internalizing the extent of the sin taxes.

Access to and accepting governmental transfers adds to the list of second order influences that modify how the optimal sin tax should be calculated. Failing to take into account such second-order effects in the setting of cigarette taxes might therefore lead to inefficient, non-optimal tax rates. Fascinating avenues for future research would be to peel back all the different layers of smoker's strategic responses to cigarette taxes in an attempt to determine the optimal level of taxation.

7. Literature

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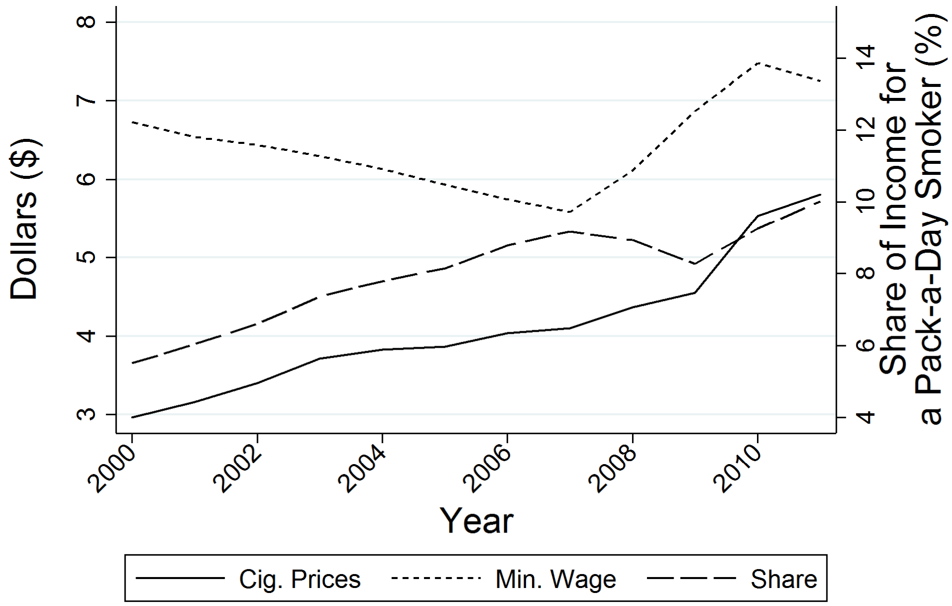
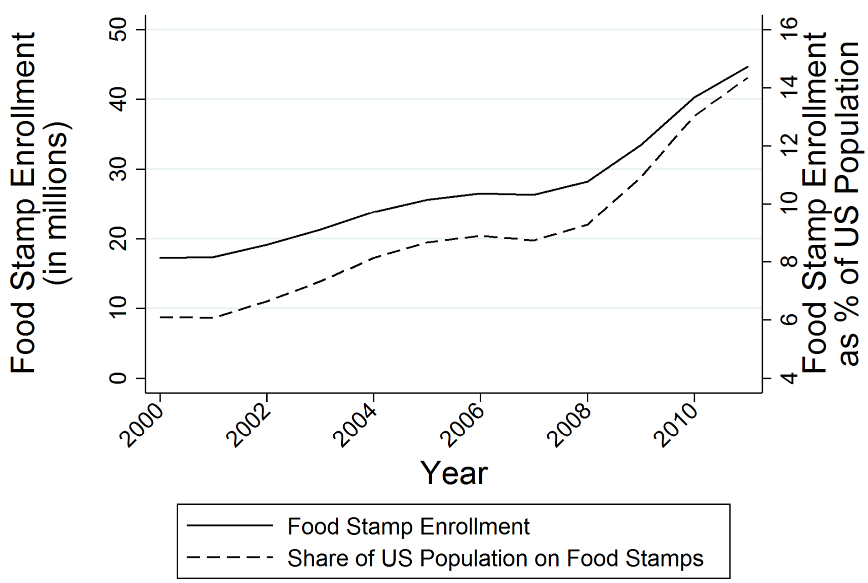
Figures and Tables

Figure 1: Development of Cigarette Prices, Minimum Wages, and Share of Minimum Wage Earners Income Spent on Cigarettes (2000-2011)



Source: Authors graph using Tax Burden on Tobacco (cigarette price) and BLS (for the average minimum wage)
Note: Adjusted by CPI to 2011 dollars

Figure 2: SNAP Enrollment in Absolute and Relative Terms (2000-2011)

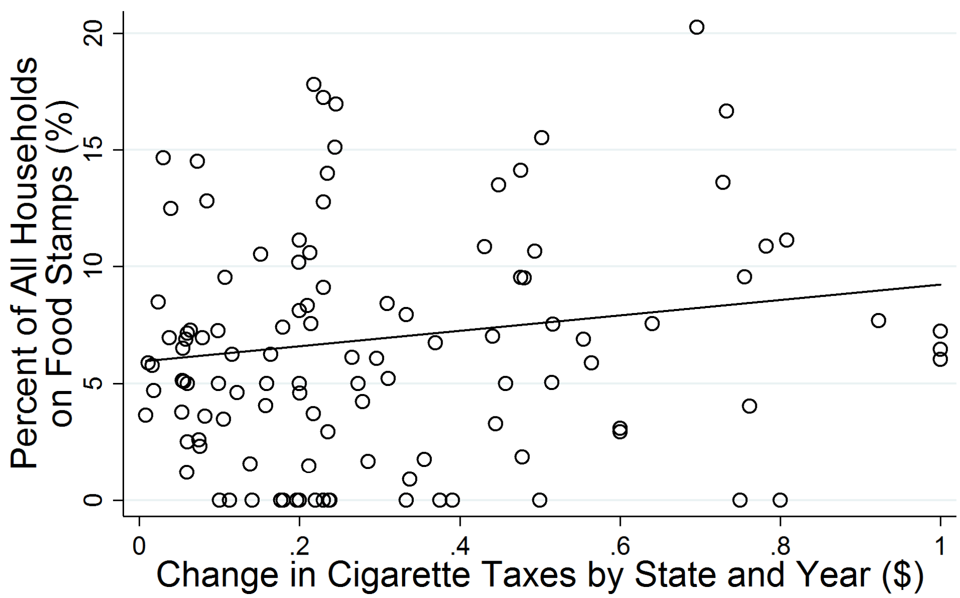


Source: Authors graph using official yearly statistics from the Department of Agriculture.

Figure 3: State Cigarette Taxes & Share of Smokers on Food Stamps (CPS): 2001-2011

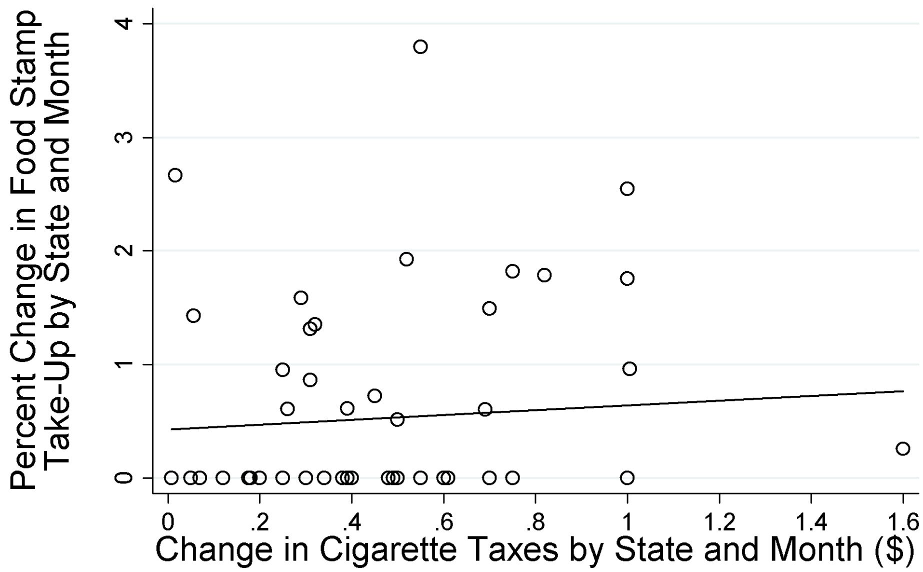
Source: CPS 2001-2011
Note: Right figure uses mean percent of smokers on food stamps for each bin reported

Figure 4: Yearly Change in State Cigarette Taxes and Share of Smokers on Food Stamps (CEX): 2002-2012



Source: CEX 2002-2011
Note: Graph is conditional on positive changes in state cigarette tax rates between year t_{-1} and t_0

Figure 5: Monthly Change in State Cigarette Taxes and Change in Food Stamp Enrollment (CPS): 2002-2011



Source: CPS 2001-2011
Note: Graph is conditional on positive changes in state cigarette tax rates between year t_{-1} and t_0

Figure 6: Event Study: Food Stamp Enrollment in States with Cigarette Tax Increases (CPS): 2002-2003; 2005-2006; 2010-2011

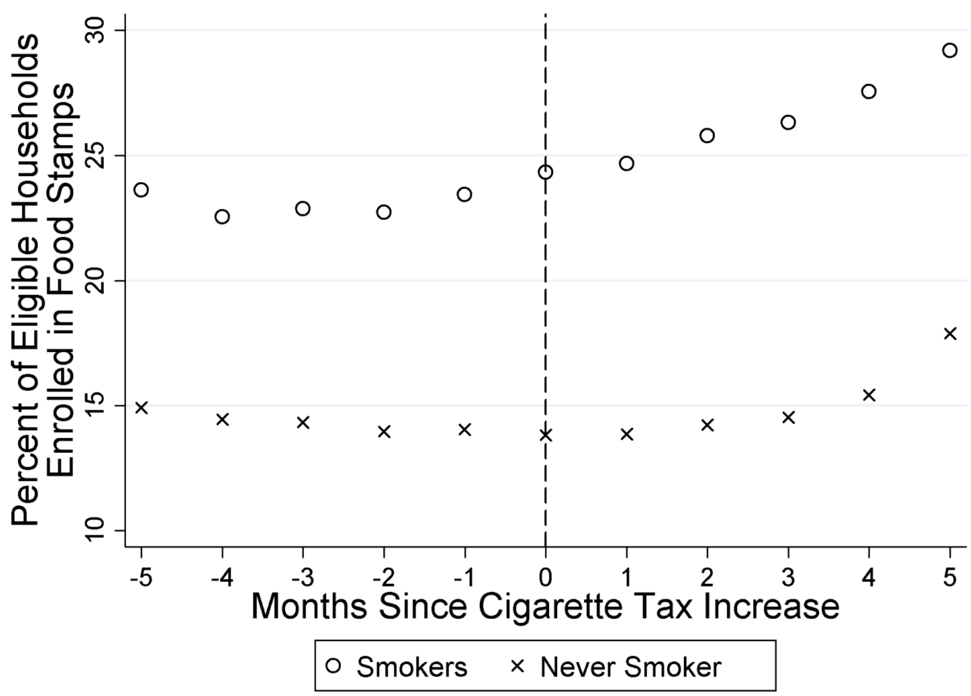


Table 1: Distribution of CPS FSS-TUS Cross Sectional Observations Over Month-Years 2003-2011[32]

Variable	Frequency	Percent	Cumulative
Feb 2001	771	7.08	7.08
Nov 2001	2,725	25.03	32.11
Feb 2002	720	6.61	38.72
Nov 2002	388	3.56	42.29
Feb 2003	211	1.94	44.22
Nov 2003	1,590	14.60	58.83
Jan 2006	1,494	13.72	72.55
Jan 2007	681	6.25	78.80
Jan 2010	1,635	15.02	93.82
Jan 2011	673	6.18	100.00
Total	10,888	100.00	

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

Table 2: Distribution of CPS FSS-TUS Pseudo-Panel Observations Over Month-Years: 2002-2011

Variable	Frequency	Percent		Frequency	Percent
2002	48,799	14.12	Jan	15,095	4.37
2003	85,855	24.84	Feb	29,280	8.47
2006	96,846	28.02	Mar	30,471	8.82
2007	2,839	0.82	Apr	30,471	8.82
2010	108,372	31.35	May	30,471	8.82
2011	2,954	0.85	June	30,471	8.82
			July	30,471	8.82
			Aug	30,471	8.82
			Sept	30,471	8.82
			Oct	30,471	9.49
			Nov	32,794	7.15
			Dec	24,728	7.15
Total	345,665	100.00	345,665	100.00	

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

Table 3: Distribution of CEX Cross Sectional Observations Over Years and Months: 2002-2012

Variable	Frequency	Percent		Frequency	Percent
2001	1,110	11.74	Jan	800	8.46
2002	1,183	12.51	Feb	812	8.59
2003	1,154	12.20	Mar	775	8.20
2006	1,072	11.34	Apr	768	8.12
2007	897	9.49	May	840	8.88
2008	814	8.61	June	811	8.58
2009	900	9.52	July	803	8.49
2010	809	8.56	Aug	794	8.40
2011	788	8.33	Sept	791	8.37
2012	729	7.71	Oct	762	8.06
			Nov	748	7.91
			Dec	752	7.95
Total	9,456	100.00	9,456	100.00	

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

Table 4: State Cigarette Taxes and Food Stamp Take-Up (CPS)[33]

	Price of Last Cigarette Pack Bought			*Annual Cigarette Expenditures*		
Variable	**Month-Year FE (1)**	**+ Covariates (2)**	**+ State FE (3)**	**Month-Year FE (4)**	**+ Covariates (5)**	**+ State FE (6)**
State cigarette tax	0.952***	0.731***	0.719***	131.13*	178.59*	201.54**
	(0.0916)	(0.129)	(0.128)	(72.98)	(100.08)	(91.54)
Mean	3.66	3.66	3.66	1640	1640	1640
in%	25.9	19.9	19.6	7.9	10.9	12.3
Covariates employed						
Month-Year FE	yes	yes	yes	yes	yes	yes
Socio-Demographics	no	yes	yes	no	yes	yes
State FE	no	no	yes	no	no	yes
Observations	10,888	10,888	10,888	10,888	10,888	10,888
R-squared	0.1800	0.1926	0.1988	0.0191	0.0284	0.0752

Source: CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (The Tax Burden on Tobacco, 2012), own calculation and illustration; * $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors are in parentheses and clustered at the state level. Regressions are based on cross sections. Each column represents one regression as in equation (1). The dependent variable in the first three models is the average price of the last cigarette pack paid by the smokers in the household. The dependent variable in the last three models measures the annual cigarette expenditures, based on the current price and consumption information by the household. The variable of interest indicates the state cigarette tax level in month t_{-1}.

Table 5: State Cigarette Taxes and Food Stamp Take-Up (CPS)

Variable	*On Food Stamps This Month*				*New On Food Stamps This Month*			
	Year + State FE (1)	**+ Covariates (2)**	**+ State Time Trend (3)**	**+ Month-Year FE (4)**	**Year + State FE (5)**	**+ Covariates (6)**	**+ State Time Trend (7)**	**+ Month-Year FE (8)**
State cigarette tax	0.0238***	0.0222***	0.0186**	0.0219***	0.0010**	0.0009**	0.0009*	0.0009**
	(0.0079)	(0.0075)	(0.0075)	(0.0075)	(0.0004)	(0.0004)	(0.0005)	(0.0004)
Mean	0.1641	0.1641	0.1641	0.1641	0.007	0.007	0.007	0.007
in%	14.5	13.5	12.6	11.3	13.3	13.2	12.9	13.1
Covariates employed								
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
State FE	yes	yes	no	yes	yes	yes	no	yes
Socio-Demographics	no	yes	yes	yes	no	yes	yes	yes
State time trend	no	no	yes	yes	no	no	yes	yes
Month-Year FE	no	no	no	yes	no	no	yes	yes
Observations	345,665	345,665	345,665	345,665	345,665	345,665	345,665	345,665
R-squared	0.0225	0.1940	0.1942	0.1941	0.0075	0.0118	0.0118	0.0121

Source: CPS Food Security Supplement (FSS) and Tobacco Use Supplement (TUS) 2001-2011 merged with state-month level cigarette tax information (The Tax Burden on Tobacco, 2012), own calculation and illustration; * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Regressions are based on a pseudo-panel that makes use of the retrospective monthly information on household food stamp take-up in the FSS. Each column represents one regression as in equation (1). The binary dependent variable in the first four models simply indicates whether the household is on food stamps in the current month, t_0. The binary dependent variable in the last four models indicates food stamp take up in between the previous and the current month (t_0 -t_{-1}) . The variable of interest indicates the state cigarette tax level in month t_{-1}.

Table 6: State Cigarette Taxes, Cigarette and Food Expenditures, and Food Stamp Take-Up (CEX)

Variable	*Tobacco Exp. Last Quarter*		*Food at Home Exp.* Last Quarter	*Food Away Exp.* Last Quarter	*On Food Stamps This Month*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
State cigarette tax	39.19***	25.41***	-23.65	-8.29	0.0239**	0.0311***
	(7.70)	(8.61)	(14.86)	(14.71)	(0.0099)	(0.0113)
Mean	248	248	799	330	0.1109	0.1109
in%	15.8	10.2	2.9	2.5	21.6	28.0
Covariates employed						
Month FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
State FE	no	yes	yes	yes	no	yes
Socio-Demographics	no	yes	yes	yes	no	yes
Observations	9,456	9,456	9,456	9,456	9,456	9,456
R-squared	0.1233	0.1549	0.4555	0.1781	0.0258	0.1906

Source: CEX 2001-2012 merged with state-month level cigarette tax information (The Tax Burden on Tobacco, 2012), own calculation and illustration; * p<0.1, ** p<0.05, *** p<0.01; standard errors are in parentheses and clustered at the state level. Each column represents one regression as in equation (1). The binary dependent variable in the first two columns measures the households' tobacco expenditures in the last quarter, while columns (3) and (4) measure food at home and food away expenditures in the last quarter. The last two columns indicate whether the household is on food stamps in the current month, t_0. The variable of interest indicates the state cigarette tax level in month t_{-1}.

Appendix: Descriptive Statistics

Table A1: Descriptive Statistics March CPS FSS-TUS Cross Sectional Data 2001-2011

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Price of last pack cigarettes bought	3.6688	2.2872	0	50	10,888
Annual Tobacco Expenditures	1639.5668	2384.961	0	89527.2031	10,888
B. Covariates					
State cigarette tax in t_{-1}	0.7578	0.6255	0.025	4.3500	10,888
Change in state cigarette tax between t_{-1} and t_0	0.0034	0.0547	0	1.6	10,888
# Household Members	2.7724	1.6091	1	8	10,888
# Smoking Household Members	1.3029	0.5476	1	6	10888
Earned Family Income	18,449	12,227	2,500	87,500	10,888
# Male Household Members	1.3325	1.0635	0	10	10,888
# White Household Members	2.2649	1.7557	0	12	10,888
# Black Household Members	0.3035	0.9997	0	12	10,888
# Asian Household Members	0.0472	0.4392	0	15	10,888
Household Head Employed	0.4873	0.4999	0	1	10,888
Household Head No High School	0.2711	0.4446	0	1	10,888
Age of Household Head	45.1979	15.9302	14	90	10,888
Household Head Married	0.3621	0.4806	0	1	10,888

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

Table B1: Descriptive Statistics March CPS FSS-TUS Pseudo-Panel Data 2002-2011

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
On food stamps in t_0	0.1642	0.3705	0	1	345,665
Food stamp take-up btw. t_{-1} and t_0	0.0071	0.0837	0	1	345,665
B. Covariates					
State cigarette tax in t_{-1}	0.9494	0.7155	0.025	4.3500	345,665
Change in state cigarette tax between t_{-1} and t_0	0.0085	0.0825	0	1.6	345,665
# Household Members	2.5935	1.6515	1	8	345,665
# Male Household Members	1.1997	1.0854	0	12	345,665
# White Household Members	2.0044	1.781	0	15	345,665
# Black Household Members	0.3816	1.1055	0	12	345,665
# Asian Household Members	0.0809	0.5670	0	16	345,665
Earned Family Income	18,343	11,687	2,500	87,500	345,665
Household Head Employed	0.4376	0.4961	0	1	345,665
Household Head No High School	0.2654	0.4415	0	1	345,665
Age of Household Head	50.0162	19.0727	14	85	345,665
Household Head Married	0.3773	0.4847	0	1	345,665

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

Table C1: Descriptive Statistics CEX 2002-2012

Variable	Mean	Std. Dev.	Min.	Max.	N
A. Outcome Variables					
Tobacco Exp. lq	248.4169	296.2568	4.3333	8450	9,456
Food at home Exp. lq	799.7367	655.7827	0	7410	9,456
Food away from home Exp. lq	330.2369	557.3779	0	21477	9,456
On food stamps in t_0	0.1109	0.3141	0	1	9,456
B. Covariates					
State cigarette tax in t_{-1}	0.8468	0.6326	0.025	4.3500	9,456
Change in state cigarette tax between t_{-1} and t_0	0.1456	0.2923	0	1.87	9,456
Age of Household Head	40.5398	10.8054	18	59	9,456
Rural region	0.0144	0.1191	0	1	9,456
# Household Members	2.8066	1.5801	1	16	9,456
# Male Household Members over 16	1.0567	0.7141	0	8	9,456
Household Head White	0.8351	0.3711	0	1	9,456
Household Head Black	0.1036	0.3048	0	1	9,456
Household Head Married	0.4753	0.4994	0	1	9,456
Household Head Male	0.5067	0.5	0	1	9,456
Number of Household Earners	1.6046	0.9133	0	8	9,456
Income After Taxes	52656.6305	46533.2570	-91636	694670	9,456

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