Smoking Initiation and the Iron Law of Demand *

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Abstract

We show, with three longitudinal datasets, that cigarette taxes and prices affect smoking initiation decisions. We resolve disagreements between empirical studies that use longitudinal and cross-sectional outcome data. The former mostly finds no correlation between price (tax) and the probability of initiation; the latter's evidence supports standard economic theory. This inconsistency is data driven. It arises when studies measure initiation differently or use samples that are small, cover periods with limited policy variation, or do not follow individuals over the full behavioral window. More generally, our analysis informs the modeling of initiation behaviors typically concentrated in a narrow chronological window.

Keywords: Smoking initiation; Cigarette price elasticity; cigarette tax elasticity; chronological behavioral windows; law of demand

*This research is supported by a grant from the National Cancer Institute (Award #1R01 CA 120338-01A1). We thank Kitt Carpenter, Phil DeCicca, Mike Grossman, Don Kenkel, Michael Lovenheim and participants at the 2010 PAA and ASHE conferences for comments and feedback.

1 Introduction

While economic theory clearly predicts that demand for a good falls when its price increases, empirical evidence sometimes fails to support the prediction. For example, in the case of starting to smoke, the extant empirical literature presents contradictory evidence. Studies based on cross-sectional data find that smoking prevalence among youth is lower when cigarettes cost more (Chaloupka and Warner (2000), Carpenter and Cook (2008)). Studies of smoking initiation that use longitudinal data to follow youth over this transition generally find no association between the initiation probability and changes in cigarette taxes (Douglas and Hariharan (1994), Douglas (1998), DeCicca, Kenkel, and Mathios (2002)). This evidence has caused economists to pause because longitudinal data are superior in many ways to cross-sectional data. The inconsistent evidence flowing from superior data has presented a puzzle to be explained.

It is important to resolve this empirical discrepancy for both scientific and policy reasons. From a scientific perspective it is interesting to understand if the "iron law of demand" applies at ages during which youths' brains are still developing. Available evidence suggests that the human brain is still developing during the ages when most people start to smoke.[1] That evidence suggests that youth deciding whether or not to smoke may respond differently to prices or taxes than they would if they face the same decision as adults. Such understanding will influence how economists model behavior over the life-cycle and may challenge the use of rational choice models for people of a particular age.[2] This type of understanding is also important because cigarette smoking is implicated in many aspects of health. As the production and maintenance of health often involves public monies,

[1] A large body of evidence supports the hypothesis that the frontal cortex and specifically the prefrontal cortex matures in the early to mid 20s (Sowell et al. 1999). Other evidence points to age variation in so-called white matter growth (Sowell et al. 2001) and neuron pruning (Giedd et al. 1999).

[2] Indeed Gruber and Koszegi (2001) propose hyperbolic discounting in part because smokers' behavior appears to be at odds with their stated satisfaction with smoking.

externalities, and/or public goods, it is important to know if youth respond to prices as demand theory predicts so that policy interventions are designed efficiently. Finally, when federal, state, and local governments levy cigarette taxes they often justify them to the electorate with claims that higher cigarette taxes will reduce the rate of smoking initiation among youth. Better evidence will inform such efforts.

DeCicca, Kenkel, and Mathios (2002) suggest that cross-sectional and longitudinal results might diverge because studies that use cross-sectional outcome data do not account for the fact that the probability of initiation at a given point in time is the accumulated result of the series of decisions not to start; that is it depends on the sequence of price and taxes an individual experiences up to that point. Because cross-sectional data do not measure an individual's transition to being a smoker, models that use cross-sectional price or tax variation miss this important behavior. However, to fit longitudinal models one needs data that are often hard to find. Available sources often cover only short calendar periods during which policies do not vary much.

Although we focus here on the role that prices and taxes play in smoking initiation, our investigation and evidence is relevant for the modelling of a much broader set of behaviors. Smoking initiation belongs to a class of behaviors in which a primary scientific or policy concern is the age at which people start to engage in the behavior. This class of behaviors is of interest because how people behave in the future often varies with the age they initiated the behavior. Another two well-recognized examples in this class are the initiation of sexual activity and initiation of alcohol consumption. Behaviors in this set share one main characteristic - most people initiate during a narrow chronological window. Because state governments often enact policies to try to affect these behaviors, the narrow behavioral window limits the inferential usefulness of model specifications that "throw away" policy variation – a (state) fixed-effect specification being the most popular example.

Here we explore general issues one confronts when modeling initiation behavior to shed light on the specific disagreement in the empirical literature on smoking initiation. We focus on the definition of a "start," the length of window over which behavior is tracked, and policy variation in the years included in sample periods.

In what follows we first review, in section 2, the main findings from studies that use cross-sectional data and review six studies that use longitudinal data. For each study, we focus on three aspects of the data and one aspect of model specification that we think critically affect what one can expect from empirical estimates. In section 3 we present the distribution of the age youth first try a cigarette and the age they start to smoke regularly. These distributions provide the first indication that differences in published results might arise from how smoking initiation is defined and from the window over which behavior is modeled. The length of the behavioral window is particularly relevant for models that use limited policy variation - e.g. state fixed effects models. To provide a context for the extent of variation that is available, we describe our policy data in section 4. Our data include a time series of cigarette prices and cigarette taxes that vary across states and over time. We show how cigarette taxes and cigarette prices varied over time, in observational windows of different length and for particular birth cohorts. In section 5 we describe our data. We use longitudinal data from the National Longitudinal Survey of Youth 1997 (NLSY97), the Panel Study of Income Dynamics (PSID), and the Tobacco Use Supplements to the Current Population Survey (TUS-CPS). These three data sets allow us to explore how the results vary with the available amount of price and tax variation, the length of the initiation window, and on economic factors that may affect a youth's disposable income. In this section we specify the equation we estimate. In section 6 we present results. In section 7 we explore the sensitivity of our results to different treatments of the data. Briefly we find:

1. Youth are less likely to start smoking when they face higher cigarette prices or taxes.
2. Price and tax reduce the probability of smoking one's first cigarette as well as the transition to smoking at least five cigarettes per day.

3. The point estimate on price and tax is generally larger for younger age groups and falls as one expands the age range.

4. The association is less precisely estimated when one restricts the sample to narrow age ranges because there is less variation in price and tax within states over the short behavioral windows.

5. Our estimated price elasticities of intiation range from -.11 to -2.68 centered around -.79 (all but the largest elasticity fall in the range reported in the literature).

6. Our estimated tax elasticities of initiation vary over a similar range - from -.04 to -.85

7. Across the three independently generated data sets results are suprisingly similar.

8. When we assume that people are geographically immobile, a common assumption in studies that use cross-sectional data, coefficients are attenuated towards zero by the measurement error that assumption introduces.

We discuss these results in more detail in section 6. To conclude, we discuss the limitations of our analysis and possible directions for future research.

2 Background

A large empirical literature uses cross-sectional data on aggregate cigarette sales or individual consumption to test whether cigarette demand responds to prices. Cross-sectional based evidence summarized by Chaloupka and Warner (2000) suggests that, on average, estimated price elasticities of cigarette demand range from -0.1 to -1.2 and that most estimates vary in a narrower range from -0.3 to -0.5. Gruber (2000) uses Monitoring the Future data to estimate that 12th grade students have a smoking participation elasticity of 0.67. Harris and Chan (1999) use data from the 1992-93 CPS

Tobacco Use Supplement to estimate a price elasticity of smoking participation that ranges from -0.83 for 15-17 year-olds to -0.095 for 27-29 year olds. More recently, Carpenter and Cook (2008) combine longitudinal data on prices and taxes with repeated cross-sectional data on smoking status to find statistically significant relationships between youth smoking participation, cigarette prices and cigarette taxes. Their estimates are somewhat lower. They range from -.05 to -.56. The evidence based on cross-sectional data suggests that if governments increase cigarette taxes, fewer youth will choose to smoke.

Other studies have produced contradictory evidence. This set of studies uses longitudinal data to follow non-smoking youths over the ages that most youths start to smoke. The use of longitudinal data better fits the theoretical world of the rational addiction model because one can estimate models of an individual's current consumption decision that capture the (net) effect of past prices. Consequently, there is a presumption that evidence based on longitudinal data on behavior is superior to evidence based on behavior observed at a single point in time.

In general the studies that use longitudinal data find little or no association between changes in cigarette taxes and the probability that a youth starts to smoke. To set the stage for our analysis below, we briefly review and summarize the main features of five studies that examine smoking initiation in a longitudinal framework.

Douglas and Hariharan (1994) use retrospectively reported data on smoking from the 1978 and 1979 waves of the National Health Interview Surveys (NHIS). Because of the price data available to them, they restrict their sample to cohorts born between 1940 and 1954. They assign two price measures to each individual: the price the individual would have faced at age 18 and the change in prices that the individual would have experienced between ages 15 and 18. They find that price has no measurable effect on the uptake of cigarette smoking. This study has two principal weaknesses. First, in the NHIS data, one only observes each respondent's state of residence at the time of the interview. Consequently the authors must assume a person never moved. This assumption means cross-state movers may be assigned the wrong price. The authors acknowledge that they assign a price that is measured with error. Second, their price measure eliminates all of the variation that each respondent may have experienced over the period during which he was deciding whether to start smoking.

Douglas (1998) uses retrospectively reported data on smoking from the 1987 NHIS to examine the effect of price on decisions to start and to stop smoking. He similarly restricts the sample to people born between 1942 and 1962. Because he uses NHIS data, Douglas must also asssume people were geographically immobile. He therefore assigns cigarette price to each respondent based on the state of residence observed in 1987 at the time of the interview. However, unlike Douglas and Hariharan (1994), he takes advantage of the full variation in the price time series. In particular he assigns a separate price for each year the individual was in the sample. Similar to Douglas and Hariharan (1994) he finds no correlation between cigarette price and the probability a youth starts to smoke.

DeCicca, Kenkel, and Mathios (2002) use data from the National Education Longitudinal Survey (NELS88) that are better than the NHIS data in several ways. First, because NELS88 follows a given grade cohort (respondents were in grade 8 in 1988) over five years, it identifes a state of residence in three years (1988, 1990, and 1992). Consequently, price is matched with less error.[3] DeCicca et al (2002) find that, although tax effects are strong in cross-sectional analyses, the association disappears in a model of the probability of initiation estimated with longitudinal data on individual behavior. Their key finding is that the estimated correlation disappears when one includes separate intercepts for people living in the same state (state fixed effects). In contrast to Douglas and Hariharan (1994) and Douglas (1998), the panel nature of the NELS88 data allows the authors to explore the sensitivity of the finding to alternative definitions of smoking initiation. Their findings are similar when they define smoking initiation by the age a person smoked at least one

[3]Individuals who moved across state lines in 1989 or 1991 faced a tax that might differ from the tax they faced in 1990 or 1992 but there are probably few people in this group.

cigarette and when they define “regular” smoking initiation (as smoking at least 10 cigarettes a day).

In a follow-up study, DeCicca, Kenkel, and Mathios (2008) extend their previous results to include an additional wave of the NELS: a survey conducted in 2000, eight years after respondents had graduated from high school. Their extension of the behavioral window is important because approximately half of all eventual smokers begin smoking after the age of 17. The extra wave, therefore, likely captures a large number of new smokers, though it does not pinpoint the initiation date to a particular year. The authors find that cigarette taxes in 2000 do not affect the probability of having initiated smoking after 1992. Most of the sample were born in 1974 and 1975, so they are 25 or 26 years old in 2000. The authors examine initiation that occurred inside an eight year window. We improve on their analysis by examining the price and tax responsiveness of initiation decisions over different behavioral windows and different time periods and by examining how the relationship varies with different assumptions that affect both the dependent and independent variables.

Liu (2009) uses one year retrospective information from the TUS-CPS to model how cigarette price and cigarette taxes affect smoking initiation probabilities. He uses data from 12 different waves of the TUS-CPS that span the period from September 1992 to February 2003 and focuses on smoking initiation of 15-24 year old respondents. Liu defines smoking initiation differently than the above studies. In particular, he uses a question in the TUS that asks whether a person was a smoker 12 months earlier. He defines a person to have started to smoke if he was not a smoker 12 months earlier but he reports being a smoker at the time he was interviewed. Similar to DeCicca et al. (2002), Liu (2009) finds a significant coefficient on cigarette price in a model without state fixed effects. Unlike DeCicca et al. (2002), the coefficient is larger in absolute value when Liu includes state fixed effects. Adding state fixed effects also causes the standard error to increase so the coefficient on cigarette price, while negative and large, is no longer statistically significant. However, this study is likely to be limited by the fact that it compared behavior in two adjacent time periods. That means that individual behavior is modeled only over a limited exposure (one year-on-year difference) to changes in price.

Cawley, Markowitz, and Tauras (2004) use data from the NLSY97 to investigate how smoking initiation varies with cigarette prices and body weight. While they find some evidence that higher prices deter males from starting to smoke, their results suggest that initiation decisions of girls are not significantly correlated with price. This result, however, is likely due to the sample period over which they restrict their analysis. They examine behavior in a short calendar window - from 1997 to 2000 - when the youngest respondents were 12 to 16 years old and the oldest respondents were 16 to 20. Further, they exclude information on initiation that occurred before 1997 because they focus on the role that lagged body weight plays and do not observe weight prior to 1997.

In a very recent study Nonnemaker and Farrelly (2011) use the NLSY97 to examine smoking initiation. Using the 1997-2006 surveys, they define initiation to have occured in the survey year a respondent reported smoking his first cigarette. They find that initiation probability is lower when both tax and price are higher but that the association is statistically significant only for price (the tax coefficient is marginally significant). They expand the age range over which they measure first cigarette smoking to include people age 5-25. They are unclear about how they assigned cigarette tax and cigarette price before 1997, the year the survey was first administered. Based on the results of their estimation, it appears they assume that youth are geographically immobile. If true, the authors assign some youth the wrong tax or price. We use similar data but use all available information on places of residence to impute states of residence in years before 1997, document that the geographic immobility assumption attenuates estimated tax and price effects, and show how responsiveness to taxes and price vary when one uses different measures of initiation.

The inconsistent evidence and usually insignificant price/tax effects reported in the above studies may be explained in several ways. It is possible that youth decide to smoke without regard to price or tax. Other social scientists and some economists conjecture that youth may start to smoke to rebel against parental authority and take risks (Burt et al. 2000), deal with anxiety (Patton et al. 1998), or to join a social group (Simons-Morton and Farhat 2010). While all of these explanations have some validity, the simpler explanation (if one thinks the law of demand holds) is that the above studies use less than perfect data, follow behavior over too short of a window, or use model specifications that demand too much of the available data. In what follows we explore these related issues.

3 The Behavioral Window of Initiation

It is quite important to describe what conditions must hold to consider a person to have "initiated" a given behavior. Often the object of policy interest is not in whether a person has ever engaged in a behavior but whether a person engages in that behavior regularly. For smoking, health is practically unaffected if a person smokes a single cigarette.[4] What matters is whether a person regularly smokes. Because the transition to regular smoking necessarily follows a first cigarette, many surveys ask respondents to report the age they were when they smoked their first cigarette. Other surveys ask respondents to report the age they began to smoke "regularly."[5]

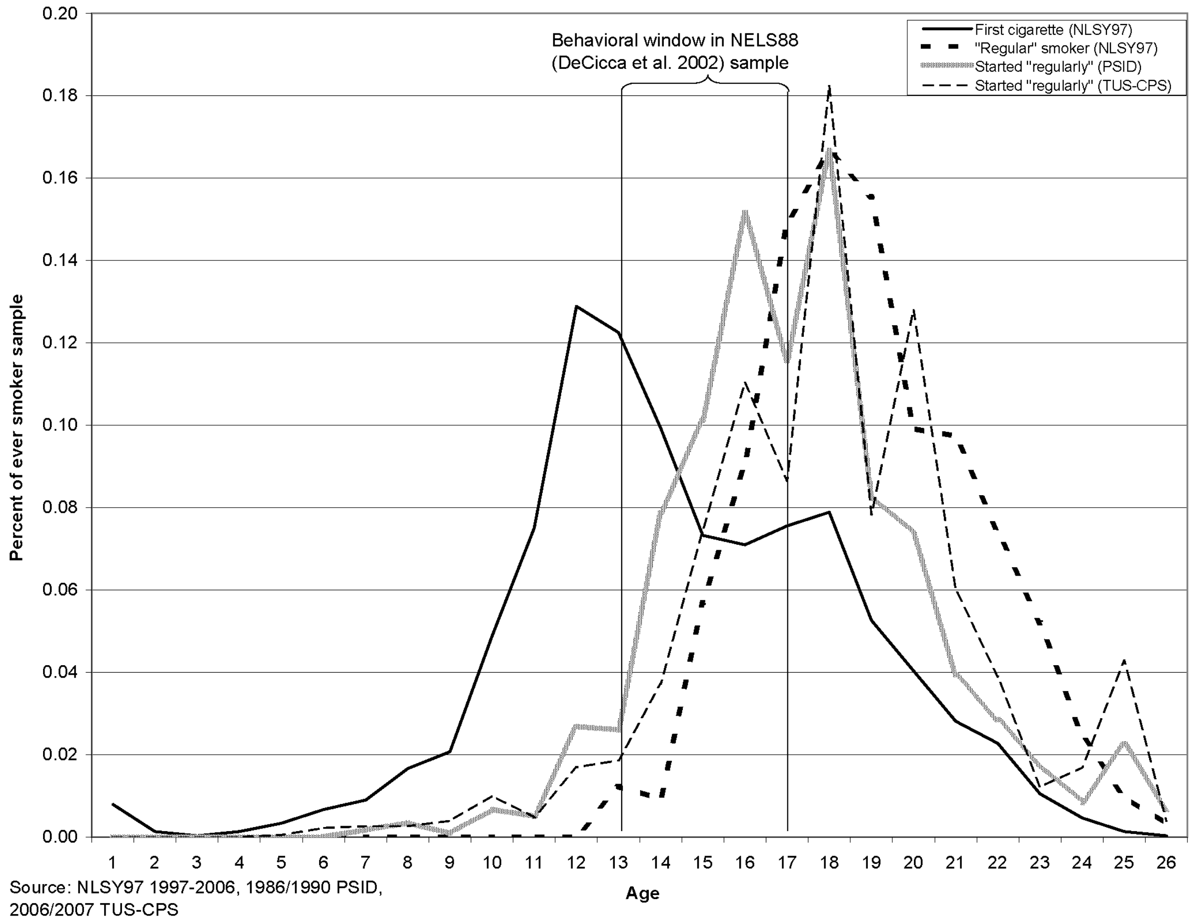
One of the more important design features of studies that use longitudinal data is the window over which one models behavior to have occurred. It is commonly recognized that the bulk of initiation occurs in a fairly narrow chronological age window that spans about 10 years. We use data from the NLSY97, the PSID, and the TUS-CPS to make this and two other points in Figure 1. Figure 1 shows that the two dependent variables used in

[4] Evidence suggests that cigarette smoke may trigger heart attacks (Pell et al. 2008). However, see Shetty et al (2011) for contrary evidence.

[5] The NHIS, TUS-CPS, and PSID collect data on the age a person began to smoke "regularly." The NLSY97 asks the age a person was when he smoked his first cigarette.

DeCicca et al. (2002) are distributed quite differently. It also show that the width of the behavioral window will partly dictate the amount of policy variation available to estimate coefficients of interest.

Figure 1: Distribution of Age Smoked First Cigarette and Age Smoked “Regularly”’



In Figure 1 we plot the distribution of the age NLSY97 respondents smoked their first cigarette, the age NLSY97 smokers first reported that they smoke 5 or more cigarettes on the average day, and the age that PSID and TUS-CPS smokers reported having started to smoke regularly. The second NLSY97 smoking measure is very similar to the “regular” smoking variable used in DeCicca et al. (2002). The PSID and TUS-CPS start age data were retrospectively reported. We use PSID data from all waves that collected smoking data (1986, 1990, 1999, 2001, 2003, 2005, and 2007) and TUS-CPS data from the 2001, 2002, 2003 and 2006/2007 surveys. In both cases, we only report the distribution up through age 26 - because this is the age of the oldest NLSY97 smoker. This age restriction does not eliminate much of the PSID and TUS-CPS samples. For example, of the 1,194 PSID respondents who said they currently or formerly smoked, only 4 percent reported having started after age 26. To underscore the idea that the length of the behavioral window matters, we highlight the age range (13 to 17 year olds) that is represented in the NELS88 sample used by DeCicca et al. (2002).

Figure 1 shows that youth try their first cigarette long before they become regular smokers. Of NLSY97 youth who ever smoked, the median youth tried his first cigarette at age 14. Of NLSY97 youth who ever smoked 10 or more cigarettes per day, the median youth became a "regular" smoker at age 18. Similarly, among PSID respondents who ever smoked, the median smoker started to smoke regularly at age 17. Thus, if one estimates an initiation model with data on smoking decisions only up to age 17, one will not model the start behavior of about half of all eventual initiators.

Figure 1 also shows that the behavioral window is approximately ten years long. Of all people who were ever "regular" smokers, the fraction that started between the ages of 13 and 22 was 91, 87, and 82 percent in the NLSY97, PSID, and TUS-CPS samples respectively.

Another feature in Figure 1 that we do not emphasize in what follows is the pattern of heaping in reported start ages when the data are retrospectively reported. The distribution of the age of initiation of regular smoking in the PSID and TUS-CPS samples has extra mass at age 16, 20, and 25. By contrast, regular smoking initiation ages are smoothly distributed over the full range in the NLSY97 sample. The most obvious reason is that the PSID and TUS-CPS data are retrospectively reported while the NLSY97 data are contemporaneously measured. Lillard et al (2011) use TUS-CPS data to show that, holding year of birth constant, as smokers age more of them report having started when they were older. Evidence from the PSID - which asks the same respondents to report intiation age up to seven different times - suggest that some of the heaping at older ages is because smokers temporarily quit and then report the age they **restarted** not their initial start age. The PSID evidence is only suggestive because the sample who report on both the 1986 survey and surveys from 1999 on is quite small. Taken together, the evidence suggest that the observed heaping in the TUS-CPS and PSID samples is recall bias and/or the result of ambiguous wording of survey questions. To control for the extra mass at these points of the start age distribution, we control for the age a person was when he was surveyed and the square of that age.

An immediate implication of modeling behavior over a longer window is that individuals in the sample are more likely to experience a change in cigarette tax or price. To give a general idea of how the expanded window taps into more variation, in Table 1 we measure changes in nominal cigarette tax and nominal cigarette price in a state over periods of one, five, and ten years starting in 1955 through 2009. We only measure a change if the nominal tax or nominal price in the current year differs from the tax or price 1, 5, or 10 years earlier. In any given year over this period 16 percent of states changed their nominal cigarette tax. Over any given five year period about 58 percent of states changed their cigarette tax. If one considers changes over all ten year periods, then 80 percent of states changed their tax at least once in any randomly chosen ten year window. Perhaps unsurprisingly, nominal cigarette prices change every year.

Table 1 also presents the average amount that real cigarette taxes and real cigarette prices changed in any given period of 1, 5, and 10 years. We present the absolute change and the change as a fraction of the real cigarette price. In any given year, real state cigarette taxes changed about 2 cents. If all of this tax increase was passed to smokers, the price they paid increased an average of .75 percent. By contrast, over any given year real cigarette prices changed twice as much - an average of 5 cents or 2.2 percent. Over any given 10 year period taxes and prices changed on average by 9 cents (4.5 percent) and 49 cents (23.5

percent) respectively.

Table 1: Variation in cigarette tax and price

	Tax			Price		
	1 year	5 years	10 years	1 year	5 years	10 years
Fraction states changing	0.16	0.57	0.79	0.99	1.00	1.00
Average change	0.02	0.07	0.09	0.05	0.25	0.49
Percent (of real price)	0.47	2.39	4.46	1.96	11.07	23.46
N (state-year)	2747	2717	2641	2703	2499	2244

Notes: Price and tax measured in January of each year. Change measured for states where nominal tax and nominal price in current and past year (1, 5, 10) differ. Reported change is average change in real tax/real price in a given state. Adjusted to 2008 dollars.

The choice of what one studies (first cigarette or regular smoking) and the behavioral window is dictated by the object of scientific or policy interest. For example, one may be specifically interested in understanding whether price or tax affects whether youth still living at home even experiment with cigarettes. In such a case one might model the probability a youth smokes his first cigarette and one might restrict the sample to youth less than 18 years old. Alternatively, one may be interested in understanding whether price affects the initiation of regular smoking, no matter at what age it might occur. One might, in such a case, also want to investigate whether and how price responsiveness varies with age. It is plausible that individuals who begin smoking after the ages of 17 or 18 may respond differently to price than individuals who begin smoking before 18. Indeed, evidence presented in DeCicca et al. (2008) shows this pattern (though their data do not allow them to establish during what ages the price sensitivity starts). Using cross-sectional outcome data from the TUS-CPS Harris and Chan (1999) report price elasticities of smoking participation that decline monotonically with age - from -.83 for youth ages 15-17 to -.095 for people ages 27-29. Notably, it is only in the middle age groups (18-20 and 21-23) that estimated elasticities are marginally different from zero.

More generally the hazard of initiating many behaviors declines sharply at some age. In the case of smoking, the hazard of initiation approaches zero after 26 or 27. This age defines the length of the window. More importantly, the length of the behavioral window has implications for the scope of policies to affect a behavior of interest. A policy lever that State governments frequently use to influence behavior is the state cigarette tax. If cigarette taxes change infrequently - say only every twenty years - then it will be more difficult to discern policy effects in any given longitudinal sample.

The length of the behavioral window affects the methods available to account for (potential) time-invariant heterogeneity that is thought to determine behavior. In particular, for behaviors that occur in very narrow chronological windows, one will not estimate precisely the effects of (state) policies if one specifies a model with state fixed-effects unless there is substantial policy variation over the short behavioral window. For many policies, such as state cigarette taxes in most periods, changes are rare. The coefficient on cigarette tax in DeCicca et al (2002) is statistically insignificant in their specifications with state fixed-effects. We argue this results in part from insufficient within-state variation in tax over the sample period available in their data. The short sample frame over which behavior is measured in the NELS88 data (five years) coupled with the paucity of within-state cigarette tax changes during the sample period combines to produce large standard errors. Indeed, DeCicca et al. recognize this issue as a potential explanation for the insignificant tax coefficient. The more general point is that the modeling of initiation behaviors requires that analysts pay special attention to the length of the behavioral window and underlying policy variation that each specification exploits.

4 State cigarette prices and taxes: levels, trends, and variation

To set up our analysis we next describe our data on cigarette prices and cigarette taxes. We describe the price and tax data to illuminate the variation that is available to estimate effects of price or tax on smoking initiation in models that use state fixed-effects.

Like all of the above studies, we draw our data on state cigarette prices and most of our data on state cigarette taxes from the *Tax Burden on Tobacco* (Orzechowski and Walker 2008).[6] We supplement the data on state cigarette taxes reported there with information on more recent tax changes that we got from state statutes listed on each state's website. We add the federal cigarette tax and the implicit tax associated with the Master Settlement Agreement (MSA) between 26 State Attorney's General and the 4 major tobacco companies. The MSA requires cigarette companies to pay states an amount that varies directly with the quantity of cigarettes they sell in each (participating) state. Viscusi and Hersch (2011) show that the payment acts as a tax. Our "full tax" measure that sums the state, federal, and MSA "tax."

Table 2 summarizes data on state cigarette prices and state and federal cigarette taxes for selected years between 1955 and 2005. The price data are measured in November of each year and represent the average cigarette price in each state. The tax data, measured down to the day that tax changes took effect, represent the average tax that was in force over the whole calendar year. We adjust both the price and tax data to be in constant 2008 dollars. We then average the data across all states. In our models below we measure the full tax

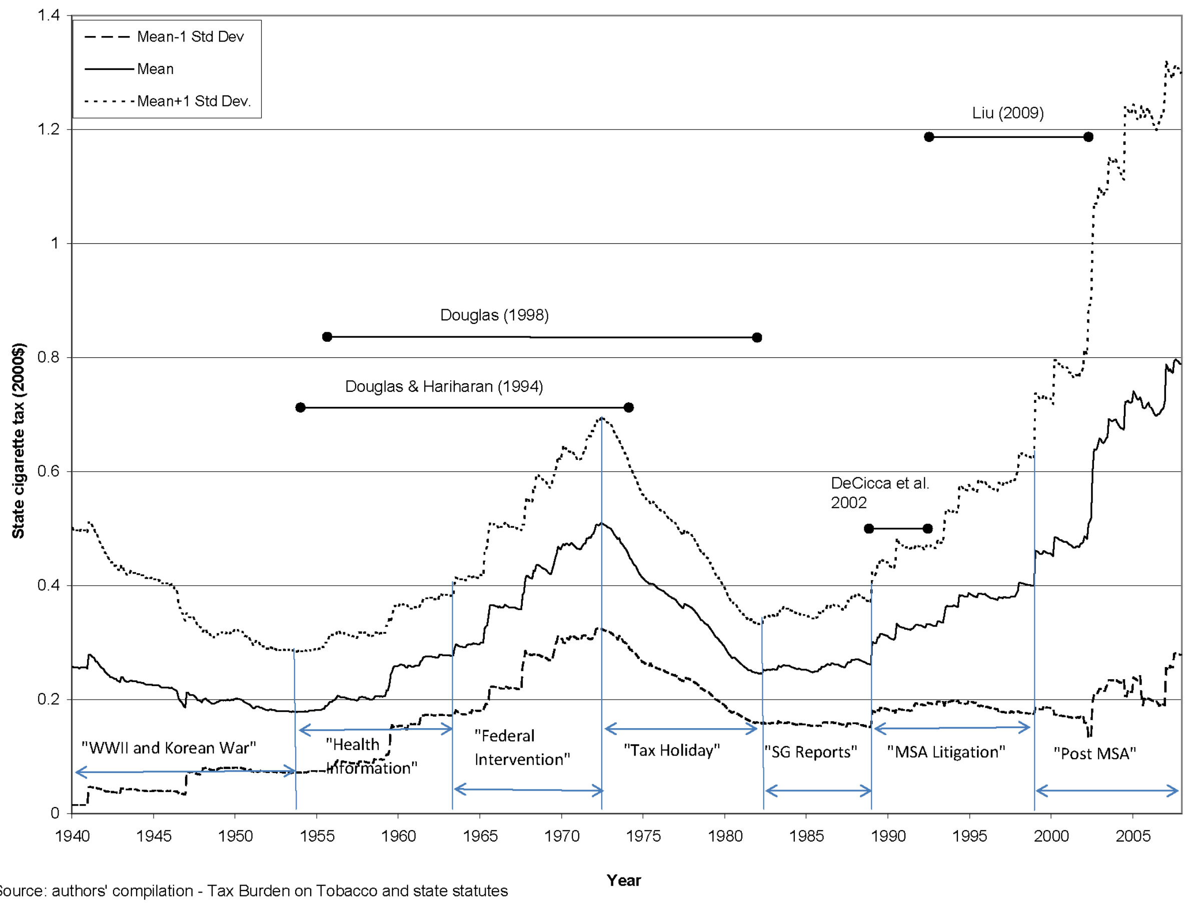
[6] There is no publicly available documentation that describes the collection of the data or construction of the cigarette price series reported in the *Tax Burden on Tobacco*. However, in private correspondence with Rob Walker of Orzechowski and Walker (3/4/2011) he confirmed for us that the TBOT price is measured in early November of each year. Based on that, we linearly interpolate prices between November of each year and average over the months in a calendar year.

that smokers pay. This tax is the sum of the state and federal tax and the implied per pack amount that states have collected each year since 1998 from the major cigarette companies under the terms of the Master Settlement Agreement.

To demonstrate the temporal variation in state cigarette tax, in Figure 2 we plot taxes from 1940 to 2007. We plot the trend in the tax in the average state, and the tax in the average state plus and minus one standard deviation. In Figure 2 we have also delineated nine time periods, each about 10 years long. Our choice of boundary years is partly data driven but mostly our choice was determined by external events that were associated with turning points in the trends shown in Figure 2. We briefly describe them but we do so only to provide some context that undergirds the trends we show. The labels we attach to each period are only for expository convenience.

In May 1921 Iowa became the first state to levy a state cigarette tax. Between 1921 and 1939 28 states adopted a cigarette tax. From 1940 to 1952, a period we label the "War Years," 14 more states enacted a tax. We label the period from 1953 to 1963 the "Health Information" period because during these years there were a growing number of scientific studies that were published that began to identify the health risk associated with smoking. In turn, staff science writers at consumer magazines, such as *Reader's Digest* and *Science News Letter*, wrote articles to communicate these findings to a wider audience. We label the period from 1964 to 1971 as the "Federal Intervention" period because these years saw the publication in 1964 of the Surgeon General's Report on Tobacco. This report was one of the first major and official statements of the US government that linked cigarette smoking to a range of negative health outcomes. The second major event occurred on January 2, 1971 when the 1970 federal "Public Health Cigarette Smoking Act" took effect. That act made it illegal for cigarette manufacturers to advertise cigarettes on radio and television. We label the years from 1972 to 1981 as the "Tax Holiday" period because so few states changed their cigarette tax in these years. Between 1972 and 1981 almost half of all states (24) did not change their cigarette tax at all. Another 21 states changed their tax

Figure 2: State Cigarette Tax 1940-2007 and Policy Windows Used in Four Studies



Source: authors' compilation - Tax Burden on Tobacco and state statutes

only once. Four states changed their tax twice and only two states changed their tax three times. For the average US resident, the real value of the cigarette tax fell during this period. We label the years from 1982 to 1988 as the "Surgeon Generals Reports" period because of the large number of reports on the health risks associated with smoking that the US Surgeon General issued. Starting with the end of this period, in 1989, cigarette taxes faced by the average US smoker began to steadily increase in real terms. We label the years from 1989 to 1998 as the "MSA Litigation" period because it was during these years that a series of lawsuits were filed against the tobacco manufacturers that ultimately led 26 States Attorneys General to file a lawsuit against the four biggest cigarette manufacturers. The Attorneys General sought to recover money their public health programs had spent to treat smokers. They argued that the tobacco firms should pay because they had deliberately misrepresented the health risks associated with smoking. That lawsuit was settled in 1998 under terms known as the "Master Settlement Agreement" (MSA). The MSA took effect in November 1998. We label the years from 1999 to 2008 the "Post-MSA" period.

5 Data and Methods

We use data from the National Longitudinal Survey of Youth 1997 (NLSY97), the Panel Study of Income Dynamics (PSID), and the Tobacco Use Supplement to the Current Population Survey (TUS-CPS) because these three data sets, individually and collectively, allow us to investigate the role that the above characteristics play in the estimation of price/tax effects on smoking initiation. The annually administered NLSY97 tracks individuals who were between the ages 12 and 16 at their first interview. Because the survey asks respondents the age they first smoked a cigarette, one can construct the variable that is comparable to one of the initiation measures used in DeCicca et al (2002). Further, the contemporaneous smoking information collected each year allows us to identify the age youth become regular smokers. The PSID and TUS-CPS surveys collect retrospectively reported data on whether individuals ever smoked and, if they said they did, on the age they began to smoke. By exploiting the retrospective data, we observe the age of initiation of anyone who ever smoked. These data are generated in the same way as the data used by Douglas and Hariharan (1994) and Douglas (1998). We use the relatively large sample size of the PSID to investigate how results change when one admits different number of cohorts into the analysis. Because we know or are able to impute a state of residence in each year of life for respondents to the NLSY97 and PSID, we use those data to investigate the attenuation bias that is introduced when researchers use data (e.g. the TUS-CPS or NHIS) that require one to assume that respondents never moved.

5.1 National Longitudinal Survey of Youth 1997

The NLSY97 is a nationally representative survey of approximately 9,000 individuals who were between the ages of 12 and 16 on December 31, 1996. Administered annually since 1997, the survey includes questions on work, education, demographics, cigarette use, places of residence, dates of moves, the identity of colleges and universities attended, and the month and year a person enrolled in each term he attended each university (available by contract with the Bureau of Labor Statistics). We describe how we construct our dependent variables after we describe unique characteristics of each data set.

We control for a standard set of demographic characteristics that includes parental education (separately for mother and father), sex, race, the highest grade a person ultimately completed, and a separate indicator to flag people who did not complete high school. Because we do not observe household income before 1997, we include observed income, averaged over all years it was available. We include this variable to control for unobserved family background and attitudes that are correlated with income. We drop observations if a person is missing data on parental education. Results do not change when we include those observations and a dummy variable that flags them.

Because individuals report the age they began to smoke, we use state of residence and each individual's month of birth to average the combined state, federal, and MSA cigarette tax and average state cigarette price over the 12 months he was a particular age (for price we use the interpolated monthly price mentioned above). Results are similar when we use price or tax averaged over a calendar year (but standard errors are slightly larger).

5.2 Tobacco Use Supplements to the Current Population Survey

The Tobacco Use Supplements to the Current Population Survey (TUS-CPS), sponsored by the National Cancer Institute and administered as part of the U.S. Census Bureau's continuing labor force survey, have been collected since 1955 (Haenszel, Shimkin, Miller 1956, Hartman et al. 2002). In the more recent TUS-CPS surveys, data on smoking behavior of a large, nationally representative sample of about 240,000 individuals 15 years of age and older is collected in a three-month survey cycle. These cycles were conducted in September 1992, January and May 1993; September 1995, January and May 1996; September 1998, January, and May 1999; June and November 2001 and February 2002; February, June, and November 2003; May and August 2006, and January 2007. Starting with the 2007 survey, the smoking data were only asked of respondents ages 18 and older.

The cross-sectional design of the TUS-CPS limits our analysis in two ways. First, like Douglas and Hariharan (1994), Douglas (1998), and Liu (2009), we must assume that nobody ever moved from birth until the survey year. Second, we have fewer demographic control variables. We include race and sex, an indicator for whether the respondent is a high school dropout and household income at the time of the survey.

An advantage of the TUS-CPS is that it yields an enormous analysis sample that is evenly distributed across multiple cohorts.

5.3 Panel Study of Income Dynamics

The PSID began in 1968 with a sample of 5,000 households, representing a disproportionate number of low-income individuals. All current PSID families contain at least one member who was either part of the original 5,000 families or born to a member of one of these families. Although the original sampling scheme disproportionately selected individuals from low-income families, a representative sample of the United States population can be obtained by excluding the original over-sample from the data or by applying sample weights.

In the 1986, 1999, 2001, 2003, 2005, and 2007 questionnaires, the survey asked all heads and “wives” (a PSID term designating the household member with whom the head has a “significant” relationship) to report a) if they had ever smoked cigarettes; b) the age they first smoked; c) the age they had last smoked regularly; and d) the average amount they smoke(d) per day. A special questionnaire administered in 1990 asked these questions of PSID household members over age 55. Because the PSID questions closely resemble the retrospective questions asked in the TUS-CPS we describe below how we construct the dependent variable in both data sets. The one difference is that we have multiple reported ages we might use. When multiple reports were available, we selected the youngest reported age.

We match US cigarette prices by year and state to PSID respondents by their state of residence in each year. In the appendix we describe how we assign states of residence in years before the PSID surveys people.

We include the same time-invariant demographic characteristics available to us in the other data sets (race, sex), whether a person (eventually) dropped out of high school, and household income averaged over all years it was available. For all data sets we control for age, state of residence, and calendar year.

5.4 Dependent variables

We construct two dependent variables - the probability a person smoked his first cigarette and the probability that he began to smoke regularly. The former variable is available only for the NLSY97. In both cases the variable equals “0” before a person smoked and equals

"1" in the year the initiation occurred (first cigarette or regular smoking). In the NLSY97 respondents reported the age they were when they first smoked (even one) a cigarette. At every interview date respondents who said they smoke also reported the number of cigarettes smoked on the average day. We code a person to have started to "regularly" smoke in the year he first reports he smokes 5 cigarettes on the average day.[7] In the TUS-CPS and PSID we use the retrospective reports to code a variable that indicates the year a person started to smoke "regularly." As we showed in Figure 1, for NLSY97, TUS-CPS, and PSID respondents this measure of regular smoking occurred at almost exactly the same frequency across the age distribution.

Because we model each initiation decision using a discrete time hazard model, we reshape the data into an event history format. We first create an observation for each year a person is alive. In this sample, a person contributes one observation for each year of life and so his age at the time of the survey determines how many observations he contributes to the raw data set. The dependent variable is "0" from birth until the year he turned the age that he was when he either smoked his first cigarette, first reported smoking 5 or more cigarettes on the average day, or reported that he began to smoke regularly. In that year, the corresponding dependent variable equals "1." In all subsequent years, the person contributes no observations. For people who do not start to smoke, we define several samples that restrict the behavioral window to end at age 17, 22, or 27.

5.5 Descriptive statistics

Table 3 reports summary statistics for all three samples. Means are roughly comparable across the samples. They have roughly equivalent numbers of initiators during each age window (13-17, 13-22, 13-27), and the mean initiation age is roughly the same, between 17 and 19. The TUS and PSID have a slightly higher percentage of female respondents than

[7] Results are similar when we define regular smoking as 10 or more cigarettes.

the NLSY97. The PSID has a higher percentage of black respondents than either of the other two surveys, due to its survey design.

The summary statistics also show that mean tax rates are similar across the samples, though mean price and tax are lower in the TUS and PSID because those samples include earlier time periods, when price and tax were lower.

5.6 Methods

We model observed initiation as a discrete time hazard model, in which the probability of initiation depends on an unobserved latent variable, which can be interpreted as the propensity to start smoking. We make the standard assumption that the latent variable is a linear function of observable and unobservable characteristics, including cigarette tax or cigarette price. Our model takes the form:

$$Pr_{it}(start = 1) = \delta_0 + \delta_1 P_{st} + X_{ist}\delta_2 + \omega_a + \tau_t + \nu_s + \epsilon_{ist} \tag{1}$$

where P_{st} is either the cigarette tax or cigarette price that varies across states and over time, X_{ist} is a vector of time-varying individual characteristics, ω, τ, ν capture differences in the probability of intiation that are fixed for people of a given age (a), in a given year (t) and in a specific state (s). ϵ_{ist} is an error term that is randomly distributed over individuals, states, and time. Individuals remain in the sample until the age-year they initiate, or until they reach a specific age (17, 22, or 27).

We estimate the above model using two different dependent variables and different samples from each dataset. Our first dependent variable uses the NLSY97 data to define initiation as having occurred at the age one smokes one's first cigarette. Using this dependent variable, we then vary the age range over which we track behavior. We start with samples that track smoking decisions from age 13-17, 13-22, and 13-27 because the lower bound of 13 was used in DeCicca et al. (2002). We then set the lower bound age at 7 and track smoking decisions from age 7-17, 7-22, and 7-27 because that is the lower bound age implied by the distribution shown in Figure 1. Our second dependent variable uses data from all three sources to define initiation as having occurred when people say they began to smoke regularly. For that outcome we vary the behavioral window over ages 13-17, 13-22, and 13-27 because Figure 1 suggest lower and upper bounds of 13 and 27. In our supplementary analyses we explore how results change when we limit the number of cohorts in the sample (PSID only), when we impose the assumption of geographic immobility (NLSY97 and PSID), and when we do not account for the heaping reported above (PSID and TUS-CPS).

For all three data sets we use retrospective reports of the age a person said he first smoked. In the NLSY97 respondents retrospectively report the age they smoked their first cigarette. In the TUS-CPS and PSID respondents report the age they began to smoke regularly. We use contemporaneously reported NLSY97 data on the amount people say they smoke on the average day to code up the "regular" smoke variable for that sample.

In all models we include age, year, and state fixed effects and the demographic control variables described above. We do not report results for those variables but interested readers should request them. In our tables of basic results, we use the coefficients to compute the tax and price elasticity evaluated at the mean initiation rate, tax, and price of each sample. We report those elasticities in Table 4 and Table 5.

6 Results

Table 4 reports coefficient estimates on tax and price for the model of the probability that a youth smokes his first cigarette. The left three columns set the lower bound age at 13. The right three columns set the lower bound age at 7. Results for the youngest sample are similar to those reported by DeCicca et al. (2002). Although the coefficients are negative in all cases, the results suggest that neither tax nor price affect the probability that youth under age 18 smoke their first cigarette. When one expands the age range there is stronger evidence that tax and price both matter. When one adds youth ages 18-22 (columns 2) standard errors fall, the absolute value of the coefficient rises in three of four cases, and the estimated relationship is statistically significant in two of four models and marginally significant (p-value .058) in a third and approaching significance in the fourth (the t-statistics on the tax coefficient in the sample of 13-22 year olds is 1.645). Expanding the behavioral window even further - to age 27 yields negative coefficients on tax and price that are statistically significant at conventional levels in three of four models and marginally significant in the fourth. Ignoring results for the 13-17 and 7-17 year old age group, the implied tax elasticities range from -.048 to -.154. Implied price elasticities range from -.344 to -.522.

In Table 5 we present results from models of the probability of regular smoking initiation using 13-17, 13-22, and 13-27 age ranges to select the samples. Results for these age groups are reported next to each other (reading left to right) using from the NLSY97, PSID, and TUS-CPS samples respectively. Results across all three samples are consistently negative, statistically significant, and show strikingly similar patterns. For the sample of 13-17 year olds in the NLSY97, the smallest sample, the coefficients on tax and price are statistically weaker with t-statistics of 1.84 and 1.77 respectively. However, the value of the coefficients estimated on the NLSY97 and PSID samples are similar, especially the price coefficients. In the other NLSY97 age groups and in all samples of the PSID and TUS-CPS the tax and price coefficients are negative and differ from zero with p-value less than .05.[8] Moreover, in all samples one observes the same pattern in estimated responsiveness by age group. Youth respond more to tax and price when they are young than when they are older.

[8]When we drop the "age at survey" and its square from the PSID and TUS-CPS models the coefficients are either unchanged (TUS-CPS) or slightly smaller (PSID) but always statistically significant with p-values less than .05.

The implied tax and price elasticities are quite consistent with those reported in the literature. Chaloupka and Warner (2000) report price elasticities of cigarette demand that range from -0.1 to -1.2. The price elasticies in Table 5 mostly fall in this range. Eight of the nine estimated price elasticities (of initiation) range from -.11 to -.97. The one that falls outside this range is for the 13-17 year olds in the NLSY97. Results imply that their decision to start regular smoking is very responsive to changes in price (elasticity of -2.68). The implied tax elasticities vary over a similar range - from -.04 to -.85. This range is very similar to the range of -.05 to -.56 that Carpenter and Cook (2008) report. The elasticities in Table 5 also follow the pattern predicted by theory - younger age groups are more tax and price sensitive than are younger groups.

It is perhaps unsurprising but nonetheless useful to point out that standard errors decrease consistently as one expands the behavioral window. Expanding the behavioral window simultaneously expands the sample size and brings more policy variation to bear.

Results in Table 4 and Table 5 point to the same consistent conclusion - decisions to try one's first cigarette and the decision to start regular smoking obey the "Iron Law of Demand." When it costs more, youth are less likely to start to smoke. At the same time, the results in Table 4 for the very youngest age groups, those age 13-17 or 7-17, suggest that young childrens' decision to smoke their first cigarette does not vary with changes in tax and price. This result is consistent with the findings of DeCicca et al. (2002) who find similarly insignificant effects for the probability of smoking one's first cigarette in a group of youth age 13-17. However, evaluated in a broader behavioral window (7-22, 7-27 and 13-27) both tax and price reduce the probability that youth try their first cigarette. Tax and price also operate on the decision to become a regular smoker in exactly the way price theory predicts. Youth who face higher taxes and higher prices are less likely to become regular smokers.

7 Delving Deeper

The elasticities reported in Table 5 are lowest in the TUS-CPS sample. One of the obvious differences between that sample and the NLSY97 and PSID samples is that we must assume that TUS-CPS respondents always lived in the state whether they were surveyed. We use the NLSY97 and PSID samples, where we observe (or impute) a state of residence in every year of life, to explore how estimated coefficients change when one assumes that people always lived in their last observed state of residence. We also use the PSID sample, which tracks a large number of smokers over states over the broadest range of policy years, to explore how coefficients vary when one uses fewer cohorts to estimate the models.

7.1 Geographic Immobility Assumption

As noted above, when one uses cross-sectional data (e.g. the NHIS or TUS-CPS) one must assume that everyone is geographically immobile to assign state cigarette tax or state cigarette price to respondents in every year of their lives. In both the NLSY97 and PSID we observe a person's state of residence in every year he participates in the survey. We use other survey information to impute a state of residence for all years that the survey does not report a person's state of residence.

We use this feature of those data to directly test whether the assumption of geographic immobility attenuates coefficient estimates towards zero. Theory and logic say it must. When one assumes a person always lived in only one state, one will assign incorrect values of the cigarette tax and cigarette price to people who move between states where tax and price differ at a point in time and over time. In Table 6 we present the basic result for each cohort from Table 5 next to results from a model where, in every year, we assign people the last state we observe them to occupy and then assign them that state's cigarette tax and cigarette price in every year of their lives.

Results in Table 6 show that the geographic immobility assumption introduces attenuation bias into the coefficients on cigarette tax and cigarette price. In the NLSY97 sample, all coefficients are much closer to zero when one assumes people are geographically immobile. For the youngest two age groups, the coefficients do not statistically differ from zero. In the 13-27 year old age group of NLYS97 respondents the coefficients on both tax and price statically differ from zero but their absolute value is 20 and 52 percent lower respectively than the coefficients one estimates with the sample that is followed across state lines over time.

The results are similar in the PSID sample. Under the assumption of geographic immobility, the tax and price coefficients respectively are 43.1 and 35.6 lower in the 13-17 year old age group, 28.6 and 19.8 percent lower in the 13-22 year old age group, and 19.9 and 7.2 percent lower in the 13-27 year old age group. This declining difference in the two samples as one adds older people is consistent with the findings of Lillard and Molloy (2008) who show that cross-state mobility drops rapidly after age 22. That evidence suggests that, as people age, their last observed state of residence is increasingly likely to be the state in which they decided whether or not to start smoking.

7.2 Sample Size - number of cohorts

In Table 7 we explore how results vary when one limits the number of cohorts that are included in the analysis sample. This exercise tries to understand whether and how results might vary if one uses data from a single cohort (like the NELS88 sample) or data that include a fairly small number of cohorts (like the NLSY97). We use the PSID sample because it tracks a large number of cohorts (and it follows them as the move across states). The full PSID sample tracks initiation decisions of up to 67 birth cohorts.

Our purpose here is not to track how responsiveness varies across different birth cohorts but to see if and how coefficients settle down as one adds more and more cohorts to the analysis. To add cohorts in a symmetric fashion over our sample period of 1954 to 2007, we start with the cohort that was born in 1975. This cohort is nearly but not exactly the middle cohort of our sample. However we also chose this cohort because it happens to be the birth cohort of the NELS88 sample (it turned 13 in 1992/1993).

As one proceeds down the rows of Table 7 each successive sample symmetrically adds cohorts from either side of 1975. For example, the sample that includes 5 cohorts selects birth years 1973-1977. The sample that includes 10 cohorts selects birth years 1971-1979 and so on. With each sample we track behavior over the same windows used in Table 5 (13-17, 13-22 and 13-27 year olds). Our outcome is the probability of regular smoking.

The first row of Table 7 repeats the PSID results from the full sample that are reported in Table 5. All other results are from estimation of the model using the data from the above samples. It is interesting that, for the 1975 birth cohort, the coefficients on tax and price are positive and statistically insignificant. But when one adds only four more cohorts, the coefficient turns negative and the point estimate is fairly close the final point estimate in the full sample. [9]

When one reads down a column in Table 7 one compares samples that add more cohorts while keeping the behavioral window constant. Adding more cohorts is, in this context, adding more potential policy variation over the same behavioral window. Reading across a row is similar to what we reported earlier, it expands the behavioral window over which given cohorts are followed. Both types of expansions reduce standard errors. In general, the younger the age group, the more sensitive they are to changes in tax and price (though

[9] This finding for the single 1975 birth cohort is very sensitive to whether or not one uses sample weights. When one uses sample weights, the coefficient on the tax variable is always negative, large in absolute value, but not statistically significant. As one adds more cohorts results do vary much when we use or do not use sample weights. The results in the full sample do not statistically differ when one uses or does not use sample weights.

this results is not uniformly true). Coefficient estimates start to settle down to the value observed in the full sample as the number of cohorts in the sample rises above 20.

These results highlight the unsurprising finding that, all else equal, standard errors will be larger in samples with fewer cohorts. At the same time, we showed above that we could estimate precisely the effects of tax and price in the NLSY97 sample, which only includes five birth cohorts. However, as Figure 2 illustrates, the full behavioral window of NLSY97 cohort members spanned a period during which state governments were aggressively raising cigarette taxes. Data sets with similarly few cohorts may not yield precisely estimated coefficients on price or tax if policies didn't change much during the behavioral window of those cohorts. [10]

8 Conclusion

In this study, we show that the Iron Law of Demand holds for the decision of youth to try cigarettes and to start to smoke regularly. When youth face higher taxes and higher prices, they are less likely to initiate. This result depends on how one measures initiation. We find that very young children ages 7-17 are not more or less likely to try a cigarette when tax and price are higher but that past age 17 demand curves (on the extensive margin) again slope downward even for one's first cigarette. More generally, when deciding whether or not to smoke regularly, people of all ages behave as predicted by neoclassical demand theory. As tax and price increase, they are less likely to start to smoke regularly.

[10] In some data sets with few cohorts it is not possible to estimate models with both age and year fixed effects. In such cases one might parametrize time trends. We note here as an aside that, when we estimated models with time trends, results were sensitive to the order of the polynomial. Results were particularly in the TUS-CPS and PSID samples because they cover a long calendar period. This finding suggests that, in samples that cover long periods, lower order polynomial time trends (below 3 or 4) do not sufficiently control for nationwide changes in smoking behavior over time.

We also show that the assumption of geographic immobility is critical when the behavioral window includes ages during which there is signficant cross-state mobility. The decision to smoke regularly occurs between the age of 13 and 27, a window that happens to coincide with the most cross-state mobility as people graduate from high school, attend college, or move to take early career jobs. Consequently, coefficients are attenuated towards zero when one uses data like the NHIS or the TUS-CPS where one must that people are geographically immobile. The large sample size afforded by the TUS-CPS compensates somewhat but estimates from those data should be treated as a lower bound of the true effect.

We also showed that the available policy variation matters. It is a truism that more variation is preferred but one should consider the policy variation afforded by a particular set of birth cohorts as well as the behavioral window of interest. When one is interested in a narrow behavioral window - say in the smoking experimentation of youth living at home - one may want to avoid model specifications that reduce the policy variation one can bring to bear to estimate a coefficient of interest. The primary example that is common in the empirical cigarette demand literature is the use of state-fixed effets models.

Our results show that expanding the behavioral window changes the point estimates of the effects of price and tax. The difference in point estimates is relatively large, although the estimates are within a 95 percent confidence interval of each other. Although we cannot rule out that the estimates are the same, their relative sizes would make a difference from a policy perspective.

Our results also shed some light on other issues related to smoking initiation. By comparing the initiation age distributions in the PSID and TUS to the distribution in the NLSY97, we show that "regular smoking" matches up fairly well to consumption of five or more cigarettes per day. Consumption of 10 or more cigarettes per day, on the other hand, occurs at a somewhat later age.

Finally, our findings and analysis has implications for the modeling of the class of initiation behaviors that occur in fairly narrow chronological windows. We noted before that initiation of sex and drinking share similar characteristics with the initiation of smoking. Indeed these behaviors occur around the same time in many societies. If policies aim to affect those behaviors, perhaps because the frequency or intensity of those behaviors later in life vary with the timing of the onset of the behavior, then analysts will confront many of the issues we raised and investigated here. In the end, there is much to be gained if analysts pay careful attention to the behavioral window, extent of policy variation, number of cohorts, and historical time period of the samples one uses. Of course such advice, like the Iron Law of Demand, applies everywhere and always.

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APPENDIX - Imputation of state of residence

We identify each respondent's state of residence using information from the public use files of the PSID and a special geocode file of the NLSY97 that is available by special arrangement with the Bureau of Labor Statistics. The NLSY97 geocode file also identifies the name and location of up to seven colleges that respondents attended. These files identify the state in which respondents lived at the time of each interview.

We impute a state of residence for each respondent in the years before the surveys began. In the NLSY97 we use different pieces of information available in the geocode files and in the public use data. In the PSID we use an algorithm developed by Lillard and Molloy (2008).

A PSID

The PSID algorithm uses all available information on places of residence to identify states in any given year. Lillard and Molly (2008) show that their algorithm more frequently assigns the correct state of residence than a "naive" rule that either assigns the current state of residence to all previous years or uses a combination of the current state of residence and the state of residence x years earlier (either one year or five years previous to the current year). The algorithm, applied to the PSID data uses information on the state in which each respondent was born, the state where respondents "grew up," and relationships between related family members. The algorithm also uses probabilistic matching to assign dates of moves inside of calendar periods within which a move is known to have occurred.

B NLSY97

To merge state level data for each year before 1997, we impute a person's state of residence. The base-year NLSY97 respondents report the state in which they lived longest since age 12. Unfortunately the question does not distinguish within-state from cross-state moves. If respondents lived in 1997 in the same state they had at age 12, we assume he lived in the same state in each intervening year. For those living in a different state at age 12 and in 1997, we must impute the date his family moved (the survey did not specifically ask about the timing of the moves). To minimize errors of assigning youth to the wrong state, we assume the date of the move coincided with the date of changes in the marital status of the respondent's parents. If a respondent's biological parents are not living together, we assume the move took place in the year the biological parents divorced or separated. If no divorce was reported, we assume that the move occurred in the year of any marriage that took place after the respondent was alive. If respondents live with both biological parents or when no marital history is available, we assume they moved in 1996. We also assume that families moved in June - at the end of a school year.[11]

[11] This algorithm assigns a person to the wrong state if he moved between two or more states between age 12 and 16. However, external evidence suggests that few people move across state lines more than once when young. In PSID data that tracks cross-state mobility, we find that only 1.7 percent of youth move across state lines more than once between the ages of 12 and 16. Although 10 percent do so between birth and age 12, relatively few youth tried their first cigarette in those years and we analyze initiation behavior from age 13 onwards.

Table 2: Cigarette Price and State and Federal Cigarette Taxes, selected years 1955-2005

	Price		State tax		Fed. tax		MSA "tax"		Full tax	
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1955	1.79	(0.16)	0.28	(0.24)	0.63	(0.00)	0.00	(0.00)	0.91	(0.24)
1960	1.85	(0.15)	0.33	(0.21)	0.57	(0.00)	0.00	(0.00)	0.90	(0.21)
1965	1.90	(0.17)	0.42	(0.20)	0.54	(0.00)	0.00	(0.00)	0.96	(0.20)
1970	2.03	(0.22)	0.54	(0.22)	0.45	(0.00)	0.00	(0.00)	0.99	(0.22)
1975	1.82	(0.19)	0.50	(0.24)	0.33	(0.00)	0.00	(0.00)	0.83	(0.24)
1980	1.64	(0.13)	0.37	(0.20)	0.22	(0.00)	0.00	(0.00)	0.58	(0.20)
1985	1.97	(0.15)	0.33	(0.18)	0.32	(0.00)	0.00	(0.00)	0.65	(0.18)
1990	2.41	(0.22)	0.37	(0.19)	0.27	(0.00)	0.00	(0.00)	0.63	(0.19)
1995	2.46	(0.33)	0.45	(0.25)	0.34	(0.00)	0.00	(0.00)	0.79	(0.25)
2000	3.63	(0.44)	0.52	(0.34)	0.37	(0.00)	0.56	(0.00)	1.45	(0.34)
2005	4.29	(0.75)	0.89	(0.59)	0.43	(0.00)	0.49	(0.00)	1.82	(0.59)

Notes: Price, state and federal tax data taken from Orzechowski and Walker (2008) supplemented by authors' compilation from state and federal tax statutes. MSA tax compiled by authors using formulas specified in the MSA. All figures are adjusted for inflation and reported in terms of 2008 dollars.

Table 3: Summary of variables

	Time-varying characteristics					
	NLSY97		PSID		TUS-CPS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Smoked first cigarette	0.09		n.a.		n.a.	
Began regular smoking	0.04		0.06		0.04	
Price	3.40	(0.90)	2.14	(0.59)	2.18	(0.56)
Tax	1.44	(0.72)	0.81	(0.32)	0.80	(0.27)
Age	17.19	(2.82)	16.89	(4.02)	17.03	(2.83)
Year	1999.21	(3.16)	1980.71	(11.56)	1981.00	(11.08)
N (person-year)	51619		113005		4096369	

	Time-invariant characteristics					
	NLSY97		PSID		TUS-CPS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Ever smoked	0.37		0.49		0.38	
Age smoked 1st cigarette	16.31	(2.85)	—		—	
Age smoked regularly	19.48	(2.81)	17.40	(3.74)	17.85	(3.91)
School dropout	0.17		0.21		0.11	
Female	0.50		0.54		0.52	
Black	0.22		0.34		0.09	
Hispanic	0.20		0.06		0.11	
Other race	0.01		0.01		0.06	
Household income ('0,000s)	7.00	(5.36)	6.18	(3.86)	5.49	(2.49)
Year of birth	1982.00	(1.40)	1963.70	(11.27)	1964.23	(11.05)
N (persons)	5779		14989		500548	

Notes: Means are for the 13-22 year old age group in each sample. Means for the other groups do not differ much (except for the age variables). Price, tax, and income in 2008 dollars.

Notes: Regular smoking in the NLSY97 identifies the year or age a respondent first smoked 5+ cigarettes on the average day. The second NLSY97 regular smoking measure is triggered the year or age he either smoked 10+ cigarettes or smoked on 20 of the past 30 days. Tax, price, and household income are in constant 2008 dollars.

Table 4: Effect of Cigarette Price & Tax on Probability of First Cigarette-NLSY97

	(1)	(2)	(3)	(1)	(2)	(3)
Tax	-0.0035	-0.0079	-0.0052*	-0.0029	-0.0066**	-0.0041**
	(0.0122)	(0.0048)	(0.0031)	(0.0062)	(0.0027)	(0.0017)
Elasticity	-0.032	-0.072	-0.048	-0.060	-0.154	-0.111
R2	0.034	0.026	0.032	0.081	0.062	0.061
Price	-0.0123	-0.0099*	-0.0082**	-0.0005	-0.0060**	-0.0049***
	(0.0162)	(0.0050)	(0.0035)	(0.0050)	(0.0025)	(0.0018)
Elasticity	-0.648	-0.522	-0.432	-0.032	-0.379	-0.344
R2	0.034	0.026	0.032	0.081	0.062	0.061
Age Range	13-17	13-22	13-27	7-17	7-22	7-27
N	23502	38504	45332	54582	69514	76324

Notes: Linear probability model coefficients. Robust standard errors in parentheses. Models include demographic controls and age, state, and year fixed-effects. Price in 2008 dollars. Coefficients that differ statistically from zero denoted by * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$)

Table 5: Effect of Cigarette Tax & Price on Probability of Regular Smoking

	NLSY97			PSID			TUS-CPS		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Tax	-0.0144*	-0.0084**	-0.0069**	-0.0305***	-0.0242***	-0.0170***	-0.0061***	-0.0035***	-0.0017***
	(0.0074)	(0.0039)	(0.0033)	(0.0078)	(0.0051)	(0.0036)	(0.0011)	(0.0008)	(0.0005)
Elasticity	-0.845	-0.353	-0.323	-0.375	-0.326	-0.290	-0.121	-0.072	-0.044
R2	0.030	0.030	0.026	0.047	0.050	0.054	0.016	0.016	0.021
Price	-0.0168*	-0.0099***	-0.0092***	-0.0227***	-0.0186***	-0.0127***	-0.0053***	-0.0030***	-0.0015***
	(0.0090)	(0.0030)	(0.0032)	(0.0064)	(0.0042)	(0.0029)	(0.0009)	(0.0006)	(0.0004)
Elasticity	-2.683	-0.968	-0.972	-0.702	-0.664	-0.583	-0.279	-0.168	-0.108
R2	0.030	0.030	0.026	0.047	0.050	0.054	0.016	0.016	0.021
Age Range	13-17	13-22	13-27	13-17	13-22	13-27	13-17	13-22	13-27
N	28254	51619	62791	67386	113005	148781	2352419	4096369	5495098

Notes: Linear probability model coefficients. Robust standard errors in parentheses. Models control for demographics, and dummy variables for age, state, and year. Tax and price in 2008 dollars. Coefficients that differ statistically from zero denoted by * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$)

Table 6: Coefficient on Tax and Price Under Assumption of Geographic Immobility

	NLSY97		PSID	
Variable	1	2	1	2
		Age 13-17		
Tax	-0.0144*	-0.0012	-0.0295***	-0.0168**
	(0.0074)	(0.0039)	(0.0087)	(0.0075)
R2	.030	.029	0.051	0.047
Price	-0.0168*	-0.0007	-0.0202***	-0.0130**
	(0.0090)	(.0033)	(0.0071)	(0.0061)
R2	.030	.029	0.051	0.047
N	28254		67386	
		Age 13-22		
Tax	-0.0084**	-0.0027	-0.0241***	-0.0172***
	(0.0039)	(.0039)	(0.0054)	(0.0048)
R2	.030	.030	0.0564	0.050
Price	-0.0099***	-0.0021	-0.0167***	-0.0134***
	(.0032)	(.0027)	(0.0041)	(0.0039)
R2	.030	.030	0.0563	0.050
N	51619		113005	
		Age 13-27		
Tax	-0.0069**	-0.0056**	-0.0166***	-0.0133***
	(0.0033)	(0.0025)	(0.0037)	(0.0034)
R2	.026	.026	0.0592	0.054
Price	-0.092***	-0.0045**	-0.0111***	-0.0103***
	(.0032)	(0.019)	(0.0026)	(0.0027)
R2	.026	.026	0.0592	0.054
N	62791		148781	
Assigned state	Actual	Last observed	Actual	Last observed

Notes: Coefficients from linear probability model of regular smoking. Robust standard errors (in parentheses). Models control for demographics, and dummy variables for age, state, and year. Tax and price in 2008 dollars. Coefficients that differ statistically from zero denoted by * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$)

Table 7: Change in Tax and Price Coefficient with Number of Cohorts in Sample

		Tax Coefficient			Price Coefficient		
Cohorts	Birth years	(1)	(2)	(3)	(1)	(2)	(3)
All	1927-1994	-0.0305***	-0.0242***	-0.0170***	-0.0227***	-0.0186***	-0.0127***
		(0.0078)	(0.0051)	(0.0036)	(0.0064)	(0.0042)	(0.0029)
1	1975	0.1327	0.0488	-0.0028	0.0382	0.0382	0.0041
		(0.0923)	(0.0468)	(0.0236)	(0.0623)	(0.0357)	(0.0196)
5	1973-1977	-0.0329	-0.0198	-0.0116	-0.0214	-0.0063	-0.0056
		(0.0387)	(0.0204)	(0.0102)	(0.0267)	(0.0154)	(0.0082)
10	1970-1979	-0.0040	-0.0119	-0.0098	-0.0003	-0.0067	-0.0066
		(0.0231)	(0.0125)	(0.0064)	(0.0167)	(0.0099)	(0.0052)
15	1967-1981	-0.0052	-0.0096	-0.0079	-0.0069	-0.0076	-0.0060
		(0.0170)	(0.0093)	(0.0051)	(0.0127)	(0.0075)	(0.0042)
20	1965-1984	-0.0152	-0.0161*	-0.0108*	-0.0117	-0.0112	-0.0078*
		(0.0127)	(0.0071)	(0.0045)	(0.0101)	(0.0058)	(0.0037)
25	1963-1987	-0.0352**	-0.0258***	-0.0167***	-0.0262**	-0.0187***	-0.0124***
		(0.0108)	(0.0063)	(0.0043)	(0.0087)	(0.0051)	(0.0035)
30	1960-1989	-0.0362***	-0.0260***	-0.0174***	-0.0249**	-0.0180***	-0.0124***
		(0.0099)	(0.0060)	(0.0041)	(0.0081)	(0.0049)	(0.0033)
35	1957-1991	-0.0295**	-0.0223***	-0.0148***	-0.0210**	-0.0157***	-0.0105**
		(0.0094)	(0.0057)	(0.0039)	(0.0078)	(0.0047)	(0.0033)
		Age 13-17	Age 13-22	Age 13-27	Age 13-17	Age 13-22	Age 13-27

Notes: Each coefficient and standard error (in parentheses) from separate regression. Estimated as linear probability model of probability of regular smoking. Models control for demographics, and dummy variables for age, state, and year. Tax and price in 2008 dollars. Coefficients that differ statistically from zero denoted by * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$) Sample sizes vary - available on request.