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THE BEHAVIORAL DYNAMICS OF YOUTH SMOKING

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ABSTRACT

While individual smoking behavior persists over time, it is unknown whether this repeated behavior is due to addiction or individual propensities to smoke. To address this issue, we develop a dynamic empirical model of smoking decisions which explicitly accounts for the impact of previous smoking behavior and allows for unobserved individual heterogeneity. The model is estimated using longitudinal data on a representative sample of teens from all 50 United States from 1988 to 1992. We find that current smokers are both more likely to continue smoking and are less price sensitive than current non-smokers. For example, smoking in 8th grade (as opposed to not smoking) increased the probability of smoking two years later three fold, while smoking participation rates are double four years later. The estimated price sensitivities of previous non-smokers and previous smokers are -0.32 and 0.08, respectively. This suggests that a cigarette price increase will have a larger aggregate effect in the long run than in the short run as more individuals accumulate in the price-sensitive non-smoking group. In total, a dollar increase in cigarette prices reduces (age 18) smoking participation predictions by four percentage points more when unobserved individual heterogeneity and behavior modification associated with previous price changes are taken into account than when they are ignored.

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Smoking remains one of the primary public health concerns in the U.S. The case for government intervention has recently grown stronger with new evidence of negative externalities such as the effects of second hand smoke. Although individual states are experimenting with different ways to reduce smoking, the most common policy tool remains federal and state cigarette taxation.

One important element in assessing the effectiveness of tax policies is the role of smoking dynamics. Individuals who smoked in the past are several times more likely to smoke today relative to previous non-smokers. For example, using data from the National Education Longitudinal Study, we see that 75% of youth aged 14 to 18 who smoked in the past continue to smoke; only 10% of non-smokers begin smoking. Previous smoking intensity also seems to matter; 31% of light smokers quit smoking while less than 13% of heavy smokers quit. There is also movement toward higher levels of smoking in the future among those who were moderate or heavy smokers in the past. Most importantly, while individuals under age 18 consume only 2% of the total amount of cigarettes smoked in a year in the U.S., there are long-term dynamic implications because youth smoking behavior appears to persist into adulthood.[1]

The effectiveness of cigarette taxes as a smoking deterrence depends on the source of smoking persistence. It could be that previous smoking behavior influences the future marginal benefit of smoking through such channels as addiction or habituation.[2] For example, the utility of not smoking today might be relatively low for an individual who was a long-time or high-quantity smoker in the past. Under this explanation, tax or price increases have a larger effect on previous non-smokers than on previous smokers. Tax policies are quite powerful in this case: by discouraging some individuals from smoking today, they will increase the proportion of relatively more price sensitive non-smokers in the future. This compositional change produces a multiplier effect as future taxes become more effective at reducing aggregate smoking rates. Alternatively, the intertemporal smoking correlation could simply reflect an individual propensity to smoke that is persistent over time. This propensity is likely to result from both observed and unobserved individual factors. In this case tax policy is unlikely to significantly influence smoking patterns which are driven by individual heterogeneity.

[1]In addition, smoking is initiated at an early age: almost 42% of current or former adult smokers started before age 16 and 75% started before age 19 (Gruber and Zinman, 2000).

[2]Addiction refers to the pharmacological effect of smoking while habituation indicates a psychological effect that alters one's habits. As economists we make no attempt to measure the precise source of behavior modification and use these terms interchangeably.

This paper provides the first estimates of price/tax sensitivity based on a dynamic behavioral model of smoking using longitudinal data on a representative sample of individuals from all 50 United States. The theoretical model considers the decisions of forward-looking individuals whose smoking history might influence the value of smoking today. We estimate an approximation to the theoretical model that allows previous smokers to have different price sensitivity than non-smokers. These estimates also include controls for observed and unobserved individual heterogeneity. Our approach allows us to simulate both the immediate and long-run effects of a tax change. As we discuss in more detail in the next sections, the results depend crucially on whether smoking history is treated as exogenous and whether unobserved heterogeneity is controlled.

We focus on the smoking behavior of teens using restricted use data from the National Education Longitudinal Survey (NELS:88) which follows a representative sample of 8th graders in two year waves beginning in 1988. These data contain detailed individual demographic information as well as parent, school, and community characteristics. Unlike most school-based surveys, dropouts are followed providing a better representation of all youth in the U.S. Also, because the survey reinterviews participants each wave, our data do not suffer from retrospective bias. In general, we find that price sensitivity decreases over time and non-smokers are more price sensitive than smokers (with price elasticities of -0.32 and 0.08, respectively). We provide additional evidence of the behavioral modifying (i.e., "addictive" or "habitual") nature of smoking even after controlling for observed and unobserved individual differences. For example, smoking in 8th grade (as opposed to not smoking) increases the probability of smoking two years later three fold, while smoking participation rates are double four years later. Modeling unobserved individual heterogeneity and accounting for the behavior modification associated with previous price changes produces significantly different predictions of smoking behavior than when these components are ignored.

In the next section we review the relevant smoking literature and highlight the new contributions of our paper. In Section 2 we introduce a general theoretical model of smoking decisions over time which serves as the basis of our empirical model of individual smoking behavior. Having introduced the data used in estimation in Section 3, we describe in detail the set of equations to be jointly estimated in Section 4. We motivate our empirical model with comparisons to those in the recent literature, and discuss the main results and several policy simulations in Section 5. Section 6 concludes.

1 Introduction

1.1 Review of the Literature

Most papers in the empirical literature on smoking ignore dynamic issues regarding endogenous past cigarette consumption, rely on aggregate state data or cross-sectional individual data, and treat cigarette prices (or state taxes) as exogenous.[3] Among the few papers focusing on behavioral dynamics, none address the limitations of previous work in a single model.[4] Chaloupka (1991) and Gruber and Zinman (2000) investigate the role of smoking dynamics using data on individuals.[5] Chaloupka (1991) considers the effect of smoking history on current smoking decisions of adults within the context of a rational addiction model. To account for the endogeneity of previous behavior, he uses instrumental variables to form predictions of past consumption levels. While Chaloupka is the first to estimate the effect of smoking history using individual data, his data are somewhat limited. Because he uses retrospective data, he has only limited and inaccurate measures of previous cigarette use. Additionally, he has little information on current or lagged individual demographics, cannot accurately identify the prices individuals faced in the past due to lack of knowledge of residence, and does not control for the potential endogeneity of prices.[6] Our results demonstrate that the latter omission imparts a significant negative bias on price parameters.

Gruber and Zinman (2000) consider how a proxy for previous smoking behavior — the average of state cigarette tax rates when one was 14-17 years old — influences the smoking participation of pregnant women. However, it is difficult to assess the appropriateness of their instrument without formally modeling smoking behavior over time. For example, they do not interact the teen tax with the individual's age. The tax proxy reflects a recent smoking history for young women and an earlier history for older women. More importantly, because they do not estimate the quantitative relationship

[3] See Chaloupka and Warner (forthcoming) for an excellent summary of previous work.

[4] The theoretical "rational addiction" literature considers the relationship between cigarette consumption in consecutive periods, but most empirical tests of such adjacent complementarity are based on state aggregate data (see Becker, Grossman, and Murphy, 1994).

[5] Douglas (1998) estimates hazards for smoking initiation and quitting. While he implicitly considers behavioral dynamics by allowing for a non-monotonic hazard, his empirical implementation suffers from the same data limitations as Chaloupka (1991) discussed in the text.

[6] Because Chaloupka estimates least squares models of total smoking consumption which ignores the censored nature of his dependent variable (and significant mass at zero consumption), modeling enhancements such as separately estimating smoking participation and conditional consumption and using different techniques to control for the endogeneity of past use may improve our understanding of individual smoking behavior.

between smoking history and current behavior, their results cannot be used to perform the dynamic policy simulations which are a focus of our paper.[7]

Tauras and Chaloupka (1999a and 1999b) and DeCicca et al. (1999) are the only authors who use panel data on individuals. Tauras and Chaloupka (1999b) use longitudinal observations on young adults to allow permanent unobserved heterogeneity to influence the smoking decision (via individual fixed effects), but do not control for previous smoking behavior. Tauras and Chaloupka (1999a) estimate smoking cessation hazards, but only consider the minority of individuals who are smoking in 12th grade and do not fully control for differences in previous smoking behavior such as smoking intensity. DeCicca et al. (1999) study the smoking behavior of youth and estimate both cross-sectional and longitudinal models. However, like Tauras and Chaloupka (1999a), they do not fully control for differences in previous smoking behavior.

In general, the available estimates of the price sensitivity of individual smoking decisions suffer from two deficiencies. First, none of the estimates are based on a dynamic behavioral model using panel data. That is, the current literature has not adequately considered previous behavior or has simply included previous behavior as an exogenous explanatory variable. Our work distinguishes between the immediate and long-run impact of a price change by correctly modeling the effects of past behavior on current and future decisions. Second, only three papers (Chaloupka and Grossman, 1996; DeCicca et al., 1999; and Gruber, 2000) study the smoking behavior of youths prior to 12th grade. Each of these studies examines youth from data sources that do not follow the same individual over time or, if panel data are available, the authors do not examine the dynamic participation and consumption decisions jointly.[8] We improve upon these initial studies of youth behavior by modeling the endogeneity of past use and generating both immediate and long-run elasticities that better predict the influence of policy changes on youth.

[7]The implication of their demonstration, that past cigarette consumption significantly influences current behavior, can be verified and formally modeled in our work. Additionally, we improve the measurement of this effect by using individual observations from a nationally representative sample of youth over time. Gruber and Zinman (2000) find their result using a very select cross section of individuals (pregnant women) and aggregating observations into cells.

[8]These authors do consider the effect of non-price tobacco control regulations such as restrictions on youth access. In general, they find that these have a small (and often insignificant) impact on youth smoking. To maintain focus, we study the price sensitivity of youth. In addition, the Synar Amendment which penalizes states that do not enforce youth access laws was not enacted until after the last year of our sample (1992).

1.2 New Contributions

We provide a more refined estimate of youth price sensitivity by making methodological contributions which can all be extended to populations beyond the teens we consider here. Our first contribution is to explicitly estimate the dynamic nature of smoking decisions. That is, based on a dynamic theoretical model of optimizing behavior, we empirically evaluate how an individual's smoking history influences his choices over time. The framework allows smokers with different levels of use and non-smokers to have different price sensitivities, an important generalization given the possibility of cigarette addiction and habit formation. Models that do not capture dynamic behavior provide estimates which are difficult to interpret and cannot be used to accurately evaluate the effect of a policy (price) change. For example, if smokers and non-smokers have different price sensitivities and different baseline probabilities of smoking in the future, they will respond differently to price increases. A price increase can have a much larger aggregate effect in the long run than in the short run by influencing the future composition of the population. By inducing individuals not to smoke today, there will be more non-smokers in the future who may be more price sensitive. It is not possible to assess the importance of such a feed-forward effect without estimating a dynamic behavioral model. Non-behavioral models estimate the average price effect based on the current percentage of smokers and non-smokers (i.e., the immediate effect). To the extent that smokers are less price sensitive than non-smokers, the non-behavioral models now in use will understate the long-run reduction in smokers from a price increase.

Second, we recognize that individual smoking behavior can be explained by both observed and unobserved characteristics. The NELS:88 data allow us to control for many more observables than are available in other datasets, and we find dramatic differences in the smoking behavior of observably different youth using these data. For example, among kids who have dropped out of school after 8th or 10th grade, almost 50% smoke compared to only 17.5% of those (16 to 18 years old) who are in school. More interestingly, only 8% of those who stay in school were smoking previously while over 32% of those who eventually drop out were smokers. While being a dropout may influence behavior (due to a potentially different set of peers or responsibilities), it is possible that something unobserved about these individuals has led them to have different schooling and smoking behavior. Similarly, although it appears that youth smoking is a strong determinant of adult smoking, causality (or addiction) is not obvious; there could be something unobserved that makes an individual likely to smoke both as a child and as an adult. Therefore, we not only control for observed individual-specific differences, but also any remaining unobserved differences such as attitudes toward smoking and self-esteem. We show that ignoring unobserved heterogeneity overstates the persistence of smoking behavior and understates the price sensitivity of non-smokers.[9]

2 Dynamic Smoking Behavior

In our theoretical model of smoking behavior we consider a dynamic framework that accounts for decisions made in the past as well as expectations of the future.[10] There are several avenues through which past smoking behavior might influence current smoking decisions. First, current utility or preferences might differ depending on whether one smoked previously and the amount smoked (addictive or habitual effects). Similarly, the utility (or disutility) of choosing not to smoke might be quite different for heavy smokers versus light smokers and might depend on the length of time someone has been smoking (withdrawal effects). Second, current and past behavior are likely to influence expectations of what the future holds. For example, the probability of reduced health next period is higher for a smoker than a non-smoker. Individuals may also make forecasts about pecuniary costs of smoking in the future (i.e., prices of cigarettes next period) by using current and lagged prices to form these expectations. Each of these aspects of the decision making problem rely on past behavior or previous information.

Let J define the set of smoking alternatives available in period t where $j = 0$ indicates no smoking and $j = 1, \ldots, J$ are increasing levels of smoking (e.g., the number of cigarettes smoked per day). An indicator of the mutually exclusive smoking alternatives is d_t^j where $d_t^j = 1$ if alternative j is chosen in period t and $d_t^j = 0$ otherwise.[11] Smoking behavior today depends on the current utility

[9]We also account for the possibility that unobserved "social norms" within a state influence both youth smoking behavior and state tax rates. Ignoring these characteristics is clearly inappropriate since states with less tolerant social norms (or strong anti-smoking sentiment) will have higher tax rates and (irrespective of the tax rate) lower smoking rates. Without controls for this state-level heterogeneity the price elasticity will be over-estimated since part of the measured price effect reflects the social norm. That is, failing to control for the potential endogeneity of tax policy produces a spurious negative correlation between prices and smoking participation.

[10]The model is general enough to apply to youths or adults with minor reinterpretations of variables. For example, because the health effects of smoking are likely to differ at different ages, measures of health could be defined to reflect health events relevant to different cohorts. We have suppressed individual (n) and state of residence (s) subscripts throughout unless distinction is necessary.

[11]Other important decisions (e.g., exercise, pregnancy, medical care consumption, and savings) may directly or indirectly influence smoking behavior. These are omitted from the theoretical model because our empirical

of each alternative as well as the expected future discounted value of all possible smoking alternatives in the future. These values are likely to differ depending on a person's smoking behavior prior to the current decision making period. We assume that previous behavior consists of one's smoking level last period ($\mathbf{d}_{t-1} = (d^0_{t-1}, \ldots, d^J_{t-1})$) and the total number of periods that the individual has smoked up to period t (D_t) where duration increases by one each period that the individual chooses to smoke.[12] A vector of exogenous individual, social, and environmental variables is denoted $\mathbf{X}_t$.

The current period utility associated with health state h_t during period t is $U(h_t, c_t, \mathbf{d}_t, \mathbf{z}_t, \mathbf{X}_t, u_t)$ where c_t is consumption of a composite commodity, $\mathbf{d}_t$ is the vector of current smoking indicators, $\mathbf{z}_t = (\mathbf{d}_{t-1}, D_t, \mathbf{X}_{t-1})$ is the vector of state variables upon entering period t, and u_t is a vector of period t utility shocks that depend on health and smoking behavior. The dependence of utility on the observed smoking history is intended to capture the effects of habit, tolerance, and withdrawal which may be a function of the smoking history. For example, the utility of smoking today (or marginal utility of an additional cigarette) is allowed to differ depending on whether the individual smoked last period or not as well as his duration and past levels of smoking. Similarly, choosing not to smoke may create disutility for someone who smoked last period and no disutility if he never smoked. This disutility may decrease as the duration of cessation increases.[13] We also admit the possibility that permanent unobserved individual heterogeneity influences smoking decisions by allowing correlation in u_t across time.

Our policy variable of interest is the state-imposed tax rate (per unit) on cigarettes and is denoted τ_{st}. The pre-tax price of cigarettes (per unit), which includes federal taxes, is p_{st}; thus, the consumer price of cigarettes in state s at time t is $q_{st} = p_{st} + \tau_{st}$. Composite consumption is defined by the per-period budget constraint such that $c_t = y_t(h_t, \mathbf{X}_t) - m_t(h_t, \mathbf{z}_t, \mathbf{X}_t) - q_{st} \cdot j$ where y_t is income, m_t is medical care expenditures, and j measures the quantity (units) of cigarettes consumed.

model does not include the joint estimation of these endogenous behaviors. While these additional behaviors are determined simultaneously with smoking decisions, their omission does not influence the relationship between smoking and prices in the model. We do, however, jointly model the decision to drop out of school in the empirical model and allow prices to differently affect the smoking behavior of dropouts and non-dropouts.

[12]Other relevant variables describing an individual's smoking history include the number of attempts to quit smoking and durations of cessation. The importance of particular variables describing one's history (i.e., their influence on utility or health transitions) is likely to differ as the individual ages. Because we focus on youth (where attempts to quit smoking and duration of cessation are less variable) and because our data do not contain information on attempts to quit, we limit the variables describing one's smoking history to previous intensity and duration.

[13]Such adjacent complementarity is discussed more fully in the rational addiction literature of Chaloupka (1991) and Becker, Grossman, and Murphy (1994).

While employment and medical care consumption are not choice variables in this simple model, we assume that health affects income (either through its effect on wages or its effect on hours of work) and medical care expenditures (either through price per service or the quantity of services consumed).

Assuming that current period exogenous variables, cigarette prices, health, and utility shocks are revealed prior to making smoking choices, the lifetime value of a particular smoking alternative j in period t is

$$V_j(\mathbf{z}_t, \mathbf{X}_t, q_{st}, h_t, u_t) = U(h_t, c_t, \mathbf{d}_t, \mathbf{z}_t, \mathbf{X}_t, u_t) + \beta V(\mathbf{z}_{t+1}, \mathbf{X}_{t+1}),\ \forall t \tag{1}$$

where β is the discount factor and $V(\mathbf{z}_{t+1}, \mathbf{X}_{t+1}) = E_t \max_{j \in J} [V_j(\mathbf{z}_{t+1}, \mathbf{X}_{t+1}, q_{st+1}, h_{t+1}, u_{t+1})]$ is the period t expectation of the maximal value of lifetime utility at period $t+1$ conditional on the updated state.[14] Optimal behavior in each period is characterized by the alternative that gives the highest value of lifetime utility (current utility plus discounted expected future utility).

Our general model of optimal behavior contains two important features — namely that cigarette prices affect smoking behavior and that previous smoking history influences current smoking decisions. The focus of this paper is the empirical work and thus the mathematical derivations of sufficient conditions for the following implications are not provided. First, prices, or cigarette taxes, influence smoking propensity.[15] Second, our assumptions also allow previous smoking behavior to influence current smoking probabilities. That is, individuals who smoked last period are more likely to smoke today than non-smokers or former smokers if a recent history of smoking increases the utility of smoking today. Additionally, current smokers will continue to smoke if the addictive or habitual effects outweigh the withdrawal effects. Finally, smokers and non-smokers have different price sensitivities. These predictions are empirically testable by including previous smoking behavior (which is endogenous) in the empirical specification. We detail an empirical approximation to the theoretical model in Section 4 after describing the data in the next section.

[14] The expectation at t is over the distribution of all future unknowns such as cigarette prices, health, and utility shocks. Additionally, income and medical care expenditures may not be known with perfect foresight. Individuals use current and lagged information, summarized by the updated state vector $\mathbf{z}_{t+1}$, to forecast these future values.

[15] A typical assumption is that prices negatively affect smoking. However, a positive effect is also possible if there is a "forbidden fruit" effect (i.e., a higher utility of smoking when price increases are interpreted as a social distaste for smoking).

3 Description of the Data

The individual data used in estimation are from the National Education Longitudinal Study of 1988 (NELS:88), a continuing study sponsored by the U.S. Department of Education's National Center for Education Statistics. The study began in 1988 with the specific purpose of collecting information on educational, vocational, and personal development of a nationally representative sample of 8th graders as they transition from middle school into high school, through high school, and into postsecondary institutions and the work force. Approximately 24,500 8th graders in more than 1,000 public and private schools in all 50 states participated in the first wave of the study. In addition to the student questionnaires, supplementary questionnaires were administered to the students' parents, teachers, and school principals and provide a wealth of information on the early social environment of the students. Through special agreement with the U.S. Department of Education, we obtained access to restricted-use NELS:88 data that include geographic information. These data, supplemented with state-level data (Tobacco Institute, 1997) and measures of inflation, allow us to determine the appropriate real cigarette price and state tax rate for all individuals in each year.

The first follow-up, administered in the spring of 1990, includes responses from approximately 17,500 of the students from the first wave, while the second follow-up, administered in the spring of 1992, includes approximately 16,500 students from the original cohort.[16] One of the many unique features of the NELS:88 data is that youth who leave high school prior to graduation continue to be interviewed throughout the longitudinal study and are asked the same questions pertaining to smoking behavior. It is therefore possible to examine the smoking behavior of dropouts who are not represented in other national school-based surveys.

The NELS:88 data contain information on the student's background, upbringing, early family environment, early school environment, and other behaviors. Many variables that have been found to be significant risk factors for smoking can be constructed from these surveys including school performance, religious affiliation, family structure and living arrangement, and parental education. Since parents are surveyed in the base year and second follow-up, it is possible to obtain time-varying information on family background and socioeconomic characteristics that the student would not be as informed about. In the first and second follow-up, school principals and teachers continue to be

[16]A third follow-up was administered in 1994 but does not contain information on smoking behavior. A fourth follow-up was administered in the spring of 1998, but will not likely be available until after 2000.

surveyed, making it possible to control for important school environmental characteristics as well. We model the behavior of youths who are observed in each year (1988, 1990, and 1992) of the survey; we do not model attrition from the full sample. We keep only those youth who were on grade during the sample period or who were permanent dropouts (12,954 youth). We are forced to drop 2237 kids for whom smoking behavior is unobserved. Because prices differ by state, another 270 are dropped if we cannot identify the state in which they live or go to school, and 196 are dropped if they do not reside in the same state in all three waves.[17] After deleting 18 individuals for which other important variables are missing, our sample consists of three years of observations on 4755 males and 5478 females.

Information on smoking behavior is collected in each wave of the survey. In each year, youths are asked, "How many cigarettes do you currently smoke in a day?" Responses are limited to the following categories: do not smoke, smoke less than 1 cigarette a day, smoke 1 to 5 cigarettes, smoke about a half pack (6-10), smoke more than half a pack but less than 2 packs (11-39), and smoke 2 packs or more (40+). Table 1 reveals that 4.6% of youths reported smoking in the 8th grade (1988), while 22.7% of these same youths reported smoking in the second follow-up (1992). The dramatic increase in smoking rates is not surprising given that smoking initiation typically occurs during the late teens. We also form indicators of the quantity smoked conditional on being a smoker.[18] Table 1 indicates that smokers appear to be smoking larger quantities over time. The summary statistics also reveal that dropouts are more likely to smoke and to smoke heavily than those youth who remain in school.

The dependence of current smoking behavior on past consumption is described in Table 2. Despite the increased proportion of smokers in 1990 and 1992, the proportion of non-smoking youth who take up smoking is constant after 1988.[19] Similarly, the proportion of light smokers (1-5 cigarettes per day) who quit smoking is constant at 32%. However, the probability of quitting if one was a moderate or heavy smoker decreases dramatically as these youth age. Smokers who continue to smoke

[17] We do not have a state identifier for several dropouts in 1990. We retain the observation if the individual resided in the same state observed in 1988 and 1992 and assume that this was their state of residence in 1990. To be consistent with this assumption, we do not consider the behavior of *any* child who moves during the 1988-1992 period.

[18] Because the response "smoke less than 1 cigarette a day" is available only in 1990, we group this outcome with "smoke 1 to 5 cigarettes." Due to the small number of responses in the 40+ category, our top category is defined as "smoke more than half a pack."

[19] Because very few children younger than age 14 smoke, because most individuals are age 14 in 8th grade, and because our data do not indicate first age smoking, we assume that our sample has experienced no smoking prior to 8th grade.

also tend to migrate to higher levels of smoking over time. For example, one-third of previous heavy smokers continue this behavior in 1990 while two-thirds of them continue to smoke heavily in 1992.

The rich set of variables used to explain variations in individual smoking behavior are summarized in Table 3. These include both stationary and time-varying variables describing characteristics of the student, his family, and his school. Unfortunately the data do not provide any measures of health. We considered using levels of activity (e.g., after school sports participation), which might be compromised by the negative health effects of smoking, as explanatory variables. For parsimony, we do not model these endogenous and simultaneously determined variables, nor do we include them as exogenous regressors.

In order to estimate price effects separate from state effects, there must be variation in youth smoking rates and cigarette prices across states and within states over time. Table 4 shows smoking participation rates and real cigarette prices by state for each wave of the NELS:88 data. There is indeed variation across states and within states in both of these measures. In 1988, smoking participation levels range from 0% in Delaware, Maine, South Dakota, and Wyoming to 10.2% in Nebraska. By 1992, smoking participation rates had increased in every state but at very different rates. Oregon had the lowest smoking participation rate (12.4%) while Idaho had the highest (29.5%). Real cigarette prices are as high as \$1.87 per pack in Alaska in 1992 and as low as \$0.98 in Kentucky in 1988.[20]

4 Empirical Model

We take a linear approximation of the value functions in (1) to approximate the latent value of smoking alternative j in period t, conditional on one's smoking behavior in the previous period (k). We decompose the error component (u_t) into a permanent individual component (μ) and an idiosyncratic, i.i.d. component (ϵ_t). That is,

$$V_{jkt} = \mathbf{z}_t \alpha_{1jk} + \mathbf{X}_t \alpha_{2jk} + \alpha_{3jk} q_{st} + \rho_{1jk}\mu + \epsilon_{jkt} \qquad (2)$$

where the ρ's are estimated factor loadings on the unobserved heterogeneity components.[21]

[20] The variation in real cigarette prices across states over time is composed of variation in producer prices and variation in state cigarette taxes. Although twenty states did not change their excise tax on cigarettes between 1988 and 1992, the remaining states did. Between 1988 and 1992, increases in state excise taxes on cigarettes ranged from one cent in Arkansas and Oregon to 25 cents in California (33 cents in Washington, DC). During this same period, cigarette tax levels range from 2 cents in North Carolina to 48 cents in Hawaii.

[21] The contribution of permanent unobservables, $\rho_{1jk}\mu$, could be modeled as an individual fixed effect ν_n. As discussed in the next section, we treat the individual unobservables as random effects having a discrete

Our main concern in this paper is accurately measuring price sensitivity in order to evaluate cigarette taxes as a policy tool. The price faced by a consumer is the sum of the manufacturer's price of cigarettes and state cigarette taxes.[22] If state cigarette taxes were random across states, then our dynamic empirical model of smoking behavior would be complete. However, if observed or unobserved social norms within a state influence state tax-setting behavior and these same factors also influence youth smoking propensities but are omitted from the specification, then the coefficient on price is likely to be biased. Taxes might be high in one state because of underlying concern for health or they might be low because of underlying support for smoking or tobacco production. These same sentiments may impact individual smoking behavior. More specifically, the state cigarette tax is correlated with part of the error in (2). Some detailed evidence suggesting that cigarette taxes are not random is presented in the Appendix. We can eliminate much of the bias in the estimated coefficients on price by allowing unobserved state heterogeneity to influence smoking decisions. Thus, (2) is rewritten as

$$V_{jkt} = \mathbf{z}_t\alpha_{1jk} + \mathbf{X}_t\alpha_{2jk} + \alpha_{3jk}q_{st} + \rho_{1jk}\mu + \sigma_s + \epsilon_{jkt} \tag{3}$$

where σ_s is a state fixed effect.[23]

The model is dynamic because of the (testable) assumption that the probability of smoking today depends on the smoking state occupied in the previous period, and because $\mathbf{z}$ contains other lagged variables. Notice that future values of $\mathbf{X}$ do not influence current smoking decisions in (2) and (3). In contrast, rational addiction theory proposes that future cigarette prices affect current smoking behavior. While our theoretical model suggests that the current value of smoking today includes the expected discounted value of all smoking alternatives in the future (which involves integration over the expected price distribution), the approximation would contain future prices only if future prices were

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distribution with estimated mass points μ and estimated weights. Estimation of the random effects in this manner imposes no distributional assumptions on the unobservables and should improve efficiency over a model of individual fixed effects which would introduce 10,232 additional parameters to be estimated. Additionally, the use of fixed effects in discrete dependent variable models is compromised without imposing strong assumptions (Hsiao, 1986).

[22] We assume that the manufacturer's price (which includes federal taxes in this analysis) varies randomly across states. Variation in federal taxes are subsumed by year dummies in our estimates.

[23] It is possible that the unobserved state heterogeneity (the social norm) is not permanent but varies over time. Because prices (and taxes) are assumed to be constant within a state each year, it is not possible to account for the variation in state unobservables over time with state-specific time dummies and still measure price effects. The random effects procedure that we use to model individual heterogeneity could be modified to allow for time-varying state unobservables and still produce unbiased estimates of the price effects. However, this requires modeling tax-setting behavior within a state. Jointly estimating a set of equations that includes smoking behavior, state tax-setting behavior, and the correlation between unobservables influencing both individual behavior and state taxes is reserved for future work.

observed with perfect foresight. Although knowledge of future cigarette prices is unlikely for long leads, it is not unreasonable to assume that near future tax rates are announced prior to the change (Gruber and Köszegi, 2000). We do not consider the effect of such anticipated price changes because it would be difficult to accurately account for the timing of these announcements relative to the date of the reported smoking behavior in our data. Rather, we assume in the theory that individuals use current and lagged prices and taxes to forecast future consumer cigarette prices. Additionally, while empirical tests of the rational addiction model consider the influence of future prices, most authors admit that high multicollinearity between contemporaneous price and leads of price (as well as lags of price) compromise their inclusion (Chaploupka, 1991). Having learned about the difficulty of interpretation from our own preliminary work and the work of other authors, we only include contemporaneous price. Results that consider the effects of lags and leads of price are available from the authors.

The approximation to the value functions is used to form a set of jointly estimated equations that summarize individual smoking behavior. Current smoking behavior is modeled in two parts: the probability of smoking and the quantity of cigarettes smoked conditional on smoking. Undoubtedly there is correlation between the error terms in these two equations. For example, individuals who heavily discount the future may be more likely to smoke and, conditional on smoking, to smoke more. We allow such permanent individual heterogeneity to influence both equations. Rather than treating dropout behavior as exogenous, we include an equation explaining the probability of leaving school between observed waves in the data ($\ell_t = 1$). We model the unobserved heterogeneity that influences the decision to drop out of school as well as smoking behavior. We also include in the smoking equation a dummy variable indicating that an individual is no longer in school and interact this indicator with the price variable.

Assuming that the idiosyncratic components of the error terms (ϵ_t) are independently Extreme value distributed, the equations are:

$$\mathrm{p}(d_t^0 = 1|\mu) = \frac{\exp(\mathbf{z}_t\alpha_{10} + \mathbf{X}_{1t}\alpha_{20} + \alpha_{30}q_{st} + \rho_{11}\mu + \sigma_{1s})}{\sum_{j'=0}^{1}\exp(\mathbf{z}_t\alpha_{1j'} + \mathbf{X}_{1t}\alpha_{2j'} + \alpha_{3j'}p_t + \rho_{1j'}\mu + \sigma_{1s})} \tag{4}$$

$$\mathrm{p}(d_t^j = 1|d_t^0 \neq 1, \mu) = \frac{\exp(\mathbf{z}_t\alpha_{1j} + \mathbf{X}_{2t}\alpha_{2j} + \alpha_{3j}q_{st} + \rho_{21}\mu + \sigma_{2s})}{\sum_{j'=1}^{J}\exp(\mathbf{z}_t\alpha_{1j'} + \mathbf{X}_{2t}\alpha_{2j'} + \alpha_{3j'}q_{st} + \rho_{2j'}\mu + \sigma_{2s})}, \quad j = 1, \ldots, J \tag{5}$$

$$\mathrm{p}(\ell_t = 1|\ell_{t-1} = 0, \mu) = \frac{\exp(\mathbf{X}_{3t}\gamma + \rho_3\mu)}{1 + \exp(\mathbf{X}_{3t}\gamma + \rho_0\mu)} \tag{6}$$

The three equations of our empirical model are estimated jointly and are linked by dependence on the common individual unobservables.[24] We follow Heckman and Singer (1984) and Mroz (1999) and treat the unobservables as random effects which are integrated out of the model. That is, we assume a discrete distribution of μ and estimate the points of support of the distribution, the probability weights on each point of support, and the factor loadings in each equation. This procedure addresses the joint endogeneity of outcomes arising from common unobserved factors, but imposes no distributional assumption (such as joint normality) on the unobserved factors. Mroz shows there are strong econometric advantages to using this approach rather than parametric random effects techniques. The estimated likelihood function for a sample of N individuals is

$$\begin{aligned} \mathcal{L}(\mathbf{\Theta}, \theta) \quad = \quad & \prod_{n=1}^{N} \left\{ \sum_{m=1}^{M} \theta_m \prod_{t=1}^{T} \prod_{\ell=0}^{1} \mathrm{p}(\ell_{nt}= \ell | \ell_{nt-1}= 0, \mu_m)^{\ell_{nt}} \mathrm{p}(d_{nt}^0= 1 \,|\, \mu_m)^{d_{nt}^0} \right. \\ & \left. \cdot \left[(1 - \mathrm{p}(d_{nt}^0= 1 \,|\, \mu_m)) \prod_{j=1}^{J} \mathrm{p}(d_{nt}^j= 1 \,|\, d_t^0 \neq 1, \mu_m)^{d_{nt}^j} \right]^{(1-d_{nt}^0)} \right\} \end{aligned} \tag{7}$$

where $\mathbf{\Theta}$ denotes the estimated parameters of the model, including the points of support (μ_m) and their factor loadings (ρ), and the θ's are the probability weights on the M points of support of the discrete heterogeneity distribution. The parameters in this set of equations are identified by functional form, covariance matrix restrictions, and exclusion restrictions. The dropout equation includes variables indicating whether the youth has a sibling who dropped out of school and the percent of students who drop out of one's school which are omitted from the smoking equations. We also eliminate the contemporaneous school characteristics in the smoking decisions of dropouts.

[24]The dependence of the probabilities on vectors of explanatory variables is omitted for convenience. We have chosen to specify a multinomial logit model given the categorical data we have on smoking intensity (discussed in Section 3) but linear regression techniques can be used if smoking consumption is continuous. The multinomial logit specification is preferred over an ordered logit specification because it allows for different sensitivities to prices (and other variables) by outcome. More formally, we can reject the ordered logit assumption of common coefficients across outcomes using a likelihood ratio test. Also, we do not report results from estimating separate multinomial logit models conditional on smoking history (i.e., previous non-smoker or smoker), and hence, we have dropped the k subscript on the estimated coefficients. We do, however, interact these indicators with key variables such as cigarette price to allow for different price sensitivities. See Subsection 5.1 for further discussion of alternative model specifications.

5 Estimation Results

5.1 Comparative Results

Before discussing the results from our preferred model that explicitly captures the dynamic influences of one's smoking history, we discuss results obtained from a typical specification found in the older literature. We then make several additions to the simple model (some of which have been included in the relevant literature) which help motivate our full model. We use the estimates from each specification to generate behavioral responses to price changes. These results are summarized in Table 5 which presents the estimated behavioral change when cigarette prices are increased from 100 to 200 cents in all years of the sample.[25] The left panel displays the percentage point change in smoking behavior under the two pricing policies, while the right panel lists the associated (arc) price elasticity.[26]

The top rows of Table 5 display results from a typical model estimated in the literature that includes few covariates, no observations on dropouts, and no state fixed effects (which we refer to as Model 1). The first column of each panel shows there are large reductions in smoking participation from the price increase with an overall price elasticity of -1.01. The remaining three columns of each panel show that, conditional on smoking, the price increase noticeably increases light smoking and reduces moderate smoking intensity. Also, the participation reduction from the price increase falls over time. The reduced price sensitivity of NELS:88 youth as they grow older could stem from behavioral differences related to the aging process or from some national trend in smoking behavior. In general, these results are comparable to the behavioral responses for young adults typically found in the older literature.

To reflect some advantages of the NELS:88 data over other datasets used in the smoking literature, we modify Model 1 by adding additional individual, parental, and school characteristics and including dropouts in the sample (Model 2). At this point, however, we do not include variables measuring one's smoking history. These additions slightly reduce the participation response (the elasticity is -0.85) and the conditional reduction in moderate and heavy smoking intensity. These results indicate that better control for observable variables that are correlated with smoking behavior provide better

[25] Real prices in the data range from 98 to 188 cents. As a robustness check, three other price changes were considered: adding 1, 25, or 100 cents to the actual price in each year. The elasticities are similar to those in Table 5 under these alternative price changes.

[26] The arc elasticity is calculated as $\eta = \left[\frac{p(outcome|q_{st2})-p(outcome|q_{st1})}{(p(outcome|q_{st2})+p(outcome|q_{st1}))/2}\right] / \left[\frac{q_{st2}-q_{st1}}{(q_{st2}+q_{st1})/2}\right]$.

estimates of the price effect by purging it of some omitted variable bias. This issue is a particularly important problem for the majority of smoking results based on sparse sets of covariates or aggregated individual observations.

Adding state fixed effects to the specification dramatically changes the results (Model 3). We see that there is no longer any significant effect of prices on smoking participation (the elasticity is -0.04) while there is a larger conditional reduction in heavy smoking. This suggests that there are state-specific factors which influence both individual smoking behavior and cigarette price variation. This is consistent with anti-smoking sentiment, for example, boosting prices (by increasing state cigarette taxes) and independently reducing smoking rates. Failure to model such state specific differences incorrectly attributes the negative effect of anti-smoking sentiment to prices. The more negative price elasticity in Model 2 relative to Model 3 is evidence of such a spurious negative correlation between prices and smoking propensity.

Finally, we investigate the role of previous smoking behavior by including exogenous indicators of previous use, previous intensity, and smoking duration (Model 4).[27] (Parameter estimates and standard errors from this model are displayed in Appendix Table A1.) While Table 5 reveals that the overall behavioral change remains roughly the same (as Model 3), Model 4 can be used to show that various subgroups behave differently. While a price increase has virtually no influence on previous non-smokers' participation, it *increases* previous smokers' participation. There are also differences based on the duration and intensity of previous smoking behavior which are not displayed. It must be emphasized, however, that we cannot yet attribute differences in the behavior of previous smokers and non-smokers to addiction. Without modeling the endogeneity of past use it is not clear whether there is an addictive effect of smoking or if unobserved individual differences explain persistent behavior. We also include a dropout indicator and interact it with price. The results reveal that dropouts are much less likely to smoke in response to a price increase and have a larger conditional reduction in smoking intensity than do non-dropouts. Again, we cannot yet conclude that dropping out directly influences smoking since unobserved individual characteristics may influence both leaving school and smoking behavior causing the dropout effect in the smoking equations to be biased. This possibility motivates our modeling of dropout behavior in our preferred model discussed below.

[27] In order to investigate price sensitivity variation over time we include interactions of price with several dynamic variables including previous behavior and year indicators. In unreported specifications, we also interact price with the continuous age variable and found similar price sensitivities suggesting that elasticities differ by year but not by age within a particular year or grade.

Our preliminary results are roughly consistent with previous studies of teen smoking behavior.[28] DeCicca et al. (1999), who also use NELS:88 data, find that prices and taxes have a non-significant (and sometimes positive) effect on smoking initiation during high school. They also find that the price elasticity of smoking participation becomes less negative as the cohort ages. In contrast, Gruber (2000) finds prices have a significant negative effect on smoking participation and that this effect is more marked for older teens. In addition to obvious differences in our datasets (i.e., different time periods (1988-1992 vs. 1991-1997) and four years of data from a single cohort vs. cross-sections from several cohorts), our different price sensitivity age profiles may result from sample selection. While our dataset contains a nationally representative sample of all youth including dropouts, Gruber (2000) mainly relies on datasets (Monitoring the Future (MTF) and the Youth Risk Behavior Risk Survey (YRBS)) which omit certain states and dropouts.[29] We estimated a smoking participation logit similar to Gruber (our Model 1 with state fixed effects) and compared the results with and without these omissions. In all cases, restrictions on the NELS:88 sample produced price elasticities which are more positive for younger teens and more negative for older teens than those obtained using the full sample of states.[30] This suggests that much of the difference between our results regarding smoking participation elasticities over time (or as youth age) can be explained by the composition of states or individuals used in each sample. While limited to one cohort, the NELS:88 data have the unique

[28] Overall, these estimates give a price elasticity of *total consumption* of -0.532. The predicted total number of cigarettes consumed for any set of prices is $[p(smoke) \sum_i p(i|smoke) \times (number\ of\ cigarettes\ in\ i)]$ where i is a conditional smoking intensity category. We assigned the following number of cigarettes smoked to these categories (which are reported as a range in the data): 3 for category 1 (1-5 cigarettes), 8 for category 2 (6-10 cigarettes), and 15 for category 3 (11+ cigarettes). Because this numerical assignment is ad hoc, we do not report total consumption elasticities in the remainder of the paper.

[29] The MTF sample of states (roughly 35 per year on average) was generously provided to us by MTF personnel while the YRBS sample of states (roughly 31 per year on average) is listed in the Centers for Disease Control (2000a and various years) and Kolbe et al. (1993).

[30] For example, when we include all states the price elasticities for 8th, 10th and 12th grade are (-2.050, 0.911, and 1.202). However, when we only include individuals from states in the 1991 MTF (the first year of Gruber's sample), the price elasticities by grade are (-1.074, -1.987, and -0.790). We find similar differences when dropouts are included, when the YRBS sample of states is used, or when various permutations of these omissions are used. Because the MTF and YRBS samples of states differ over time and our NELS:88 data cover a different period than Gruber's, we considered three subsets of states from each dataset: states present in the first year of Gruber's sample, states present in all years of Gruber's sample, and states present in any year of Gruber's sample. The patterns discussed in the text appear clearly in the first two state subsets and to a lesser degree in the last state subset. Because the MTF sample differs by grade in certain years, we formed separate grade-specific subsets and estimated the equations separately by grade for our MTF sample and its full sample comparison. In all cases we limited the non-price covariates to gender, race, age, and state fixed effects (year dummies are included in the YRBS sample).

feature of providing a representative sample of youth from all 50 states which appears to generate significantly different measures of price sensitivity.

We also performed several robustness checks on our specifications (and these results are available upon request). First, we used state taxes in place of cigarette prices to control for the simultaneity of prices and aggregate demand for cigarettes. The simulated behavioral changes are virtually identical for smoking participation and conditional smoking intensity (there is a slightly greater reduction in heavy smoking under taxes than prices).[31] Second, we checked whether the results are sensitive to the date of prices and taxes since NELS:88 individuals are surveyed on different dates. We considered several monthly dates for taxes (which are available on a day-by-day basis) and several interpolated monthly dates and averages for prices (which are surveyed once a year). Shifting these dates did not alter the results significantly. Third, we estimated the smoking participation and intensity equations separately by year and by previous smoking status. The price sensitivities were similar and thus we report results from the model with fewer estimated parameters.

5.2 Results from the Preferred Model

Having motivated the importance of including both observed and unobserved individual heterogeneity, allowing for unobserved state differences, and modeling previous behavior, we now turn to the results from our preferred model that incorporates these concerns (Model 5). We begin by discussing the effect of previous behavior on smoking decisions when permanent individual unobserved heterogeneity is modeled. We then discuss differences in the immediate and long-run effects of previous smoking behavior. Because subgroups have different price sensitivities we continue to interact price with the smoking history variables and year indicators.

If the smoking history variables reflect part of the permanent unobservable differences among youth, then the estimated coefficients on the (assumed exogenous) behavioral variables and their interactions are biased in Model 4. Model 5 controls for these unobserved differences and the parameter estimates for all variables are listed in Table 6.[32] Comparing the estimates in this table with those

[31] The simulations are based on a 25 cent increase in either prices or taxes. This value was selected to avoid using out of sample values for taxes.

[32] Results are reported from a model with three points of support in the heterogeneity distribution; four points of supports did not provide significant improvement in the likelihood function. Individuals with unobserved characteristics at the right of the distribution are more likely to smoke and more likely to drop out of school. The estimated mass point values are 0.00, 0.72, and 1.00 with estimated weights of 0.24, 0.58, and 0.18.

in Appendix Table A1 (Model 4) we see that, together, the new parameter estimates (on smoking history variables and their interactions with the price variable) do move in the expected direction.[33] For example, these estimates imply that the arguments of the logit smoking probability increase by 1.74 if an individual smoked 6-10 cigarettes in the previous period (relative to not smoking) at a price of 100 cents; the analogous increase using Model 4 is 2.28. This translates to 20 percentage point (3.43 times) increase in the predicted smoking propensity using Model 5 and to a 37 percentage point (4.59 times) increase in the predicted probability of smoking using Model 4. These substantial differences can be attributed to upwardly biased estimates in Model 4. While unobserved differences may drive certain individuals to smoke or not smoke in every period, Model 4 incorrectly incorporates this effect in the coefficient on previous behavior. When this endogeneity of previous smoking behavior is modeled, smoking history continues to have a significant (but smaller) effect on current behavior. We believe this to be among the first direct evidence of smoking addiction (as opposed to simple persistence which might be explained by both addiction and unobserved heterogeneity).

In addition to reducing the effect of previous smoking behavior, modeling unobserved individual preferences for smoking changes the estimated price sensitivities. Here, we suspect that ignoring unobserved heterogeneity makes both previous smokers and non-smokers appear less price sensitive since it incorrectly attributes their unobserved differences to the highly collinear previous smoking behavior. The bias in the price interaction coefficients is evident by comparing the reported price elasticities in the top panel of Table 7 with those from Model 4 in Table 5. We see that the overall participation price elasticities generated from a model without unobserved individual heterogeneity are biased upwards. Those from the preferred model have an overall price elasticity of -0.24 compared to -0.03 from Model 4. Elasticities by year also fall with a more negative sensitivity in 1988 and a sign change in 1990. The sensitivity in 1992 continues to be positive, but is closer to zero. The conditional smoking intensity price elasticities also change, with noticeably more negative values for heavy smoking.

The differences in participation price sensitivities between previous smokers and previous non-smokers becomes more apparent when unobserved heterogeneity is modeled. Non-smokers exhibit a price elasticity of -0.29 (vs. -0.07 in Model 4) although smokers' elasticity remains unchanged (0.46 vs. 0.47). Similarly, because leaving school is modeled, the parameters on the dropout indicator and

[33] The price interactions in Table 6 are jointly significant at the 5% level.

its interaction with price are now consistent. Relative to Model 4, the reduction in bias is reflected by the changes in calculated price sensitivities of dropouts (-0.60 vs. -0.41) and non-dropouts (0.20 vs. 0.45).

Having modeled the unobserved individual heterogeneity and obtained unbiased estimates of the parameters we can now predict the behavior of individuals over time. Previous predictions of behavior involved using the *observed* history of individuals in the sample. Calculations in this manner provide an estimate of the immediate response to price changes (as in Table 5 and the top panel of Table 7). However, the appropriate calculation requires *simulating* behavior of the sample in 1988 (where all individuals were previously non-smokers) and *updating* their smoking histories using the simulated behavior. Subsequently, behavior in 1990 is simulated using simulated 1988 behavior and histories are updated. Finally, we simulate behavior for 1992 using the updated histories.[34] This updating procedure leads to different predictions because previous behavior influences current decisions through channels like addiction.

The bottom panel of Table 7 describes the changes in behavior and elasticities when we use the updating procedure. These changes now reflect long-run responses as opposed to immediate responses to price changes. Relative to not updating (the top panel), the overall elasticity is more negative (-0.29 vs. -0.24) as is the price elasticity in 1990 and 1992.[35] The greatest changes are among previous smokers who now have a much smaller, but still positive, price sensitivity (0.08 vs. 0.46). Although not reported in the table, moderate and heavy previous smokers are now predicted to reduce smoking participation in response to higher prices. We also observe larger price sensitivities in the conditional level of smoking. In particular, using the updating procedure we observe more movement from moderate to light smoking levels when prices increase. The price sensitivity of dropouts is further enhanced. These simulations demonstrate that price changes modify behavior and influence subsequent smoking decisions of youth. Prices have a dynamic effect as they prevent smoking today which in turn makes teens more price sensitive and less likely to smoke in future periods.

[34]Additional details on the updating procedure are available from the authors.

[35]By construction, updating has no effect on behavior in 1988, the first year of the sample.

5.3 Policy Simulations

It is important to see whether our refined estimates imply economically meaningful different responses to policy changes. Although it is unlikely that cigarette taxes (or prices) would increase temporarily and return to their previous level, we simulated this policy experiment in order to demonstrate the effect of a one-time tax increase on future behavior. Obviously any change in smoking behavior in future years is the result of modified behavior in the year of the tax increase.[36] We simulated a 100 cent increase in real prices in 1988, with prices held at their original 1990 and 1992 real levels. Relative to behavior at original prices, there is a 2.30 percentage point drop in smoking participation rates in 1988. This decrease in smoking in 1988 results in a 1.05 percentage point decrease in smoking rates in 1990 and a 0.69 percentage point decrease in 1992. Movement away from moderate and heavy levels of smoking continues after the 1988 tax increase but the magnitude is much smaller. Also, there is a decrease in the smoking participation rates among both non-smokers and smokers. Despite low smoking rates among 8th graders (and hence, few individuals for whom the price increase will deter smoking), the participation changes are large relative to their baseline levels. These results suggest that price changes have important dynamic implications.

We can also show the importance of modeling unobserved individual heterogeneity and accounting for the behavior modification associated with previous price changes by comparing the aggregate smoking participation predictions of Models 3, 4, and 5 when various permanent increases in prices occur. Table 8 displays the proportion of individuals who are predicted to smoke at the unchanged original prices in the data and under various price scenarios. As seen in the left panel, the overall smoking participation rates are larger in Models 3 and 4 than in Model 5 for each price change simulation. Separated by year, we see that the probability of smoking is overestimated in Models 3 and 4 by as much as four percentage points.[37] These results highlight the importance of modeling previous behavior and allowing for behavioral modification through updating of the smoking history.

These calculations also demonstrate that the role of updating is more important for larger price changes than for smaller price changes. The substantial differences between Model 5 and the other

[36]Predictions of these future responses are not feasible without modeling behavior over time. Similarly, it is necessary to update behavior in response to a price change because predictions based on actual behavior would indicate no change in long-run behavior under this temporary increase.

[37]The increased smoking response to higher prices in 1992 (in Model 5) and in 1990 and 1992 (in Models 3 and 4) is due to a positive year$*$price interaction coefficient. This estimated effect might be an artifact of national trends towards greater smoking permissiveness and not attributable simply to age or grade effects.

specifications as price changes increase are due to the discrete nature of smoking participation. A large price increase (but not a small one) induces individuals to not smoke; and because non-smokers are more price sensitive, there is a cumulative dynamic effect. These results suggest that price (or tax) increases have a very non-linear effect in long-run behavior: high prices are much more powerful detterents than low prices.

The right panel of Table 8 demonstrates the degree of inaccuracy in the predictions of population subgroups when previous behavior is not modeled. The most marked differences are between previous smokers and non-smokers. Model 3 simply relies on observed covariates other than previous behavior to explain differences between these groups. Model 4, on the other hand, overstates previous smokers' smoking propensities since the coefficient on previous behavior (assumed exogenous in this model) is strongly correlated with unobserved heterogeneity and is therefore biased. Similarly, the smoking participation of dropouts and non-dropouts is predicted with substantial error.

Our final experiment measures the pure effect of previous behavior on smoking decisions. As we have argued above, the parameters on the smoking history variables in Model 5 more precisely reflect behavior modification (i.e., addiction) because there are controls for observed and unobserved heterogeneity that influence the smoking decisions. The estimates from Model 4 can only provide the combined effect of both addictive behavior and unobserved preferences. To measure these effects, we perform identical simulations and use the updating procedure (as opposed to observed previous behavior) on both Models 4 and 5. In the simulations (with results displayed in Table 9), we force all individuals in the sample to be non-smokers in 1988. We then update their history and simulate behavior in 1990 and 1992. This procedure is repeated forcing all individuals to be heavy smokers in 1988 and simulating their behavior in 1990 and 1992. From Model 5, the pure effect of smoking heavily in 1988 as opposed to not smoking in 1988 is to increase participation rates by 33.2 percentage points (47.15 - 13.95) in 1990 and by 20.6 percentage points in 1992 (42.33 - 21.74). That is, individuals who smoke in 1988 are 3.4 times more likely to smoke in 1990 and twice as likely to smoke in 1992. The smaller difference in 1992 than 1990 reflects the fact that some individuals who were forced to smoke in 1988, who otherwise would not have, will choose not to smoke in 1990 decreasing their probability of smoking in 1992. Additionally, smoking in 1988 and 1990 increases the probability of smoking in 1992 by 46.8 percentage points.

In Model 4, the effect of previous behavior combines the pure effect with unobserved heterogeneity and thus the simulation differences are larger. Here we find that individuals who smoked in 1988 as opposed to not smoking in 1988 are 5.1 times more likely to smoke in 1990 and 3.0 times more likely to smoke in 1992. Smoking in 1988 and 1990 makes one 6.4 times more likely to smoke in 1992. These results from both models provide clear evidence that smoking behavior persists. More importantly, when we purge the estimated effects of unobserved heterogeneity, there is still a sizable effect of previous behavior. The Model 5 estimates allow us to measure the magnitude of smoking addiction exclusive of preferences.

6 Conclusion

This paper highlights the importance of explicitly taking endogenous smoking history and unobserved individual heterogeneity into consideration when measuring the price sensitivity of youth smoking decisions. By controlling for a wide range of observed and unobserved individual differences, we are able to show that behavior modification plays an important role in smoking persistence. Its role, however, is overstated when the endogeneity of previous behavior is not considered. The paper also demonstrates that price increases can influence future behavior by reducing the current number of smokers. We show that ignoring smoking dynamics can give misleading estimates of the aggregate effect of various cigarette tax increases. This bias is likely to be more severe over long time horizons as tax increases produce a population with a larger proportion of more price sensitive non-smokers. We also demonstrate that prices have a non-linear effect on smoking behavior, with large increases having a much stonger influence than small increases (at least for younger teens).

This dynamic framework can address questions of interest to policy-makers. For example, the model can forecast the immediate response of youth smoking to federal cigarette tax increases as well as predict how youth will be affected in the long run. We also show how tax changes can influence current smokers and non-smokers differently. The procedures we use can be extended to longer panels or an older population to obtain better estimates of long-run effects of tax increases and to determine the importance of dynamics among adults (i.e., are adult smokers less price sensitive than adult non-smokers?). With a more complete understanding of lifetime smoking dynamics, we will be able to forecast how overall population smoking rates will vary in the short and long run in response to various price changes. Investigating these extensions will help inform the current policy debate regarding the appropriate level of future cigarette taxes and other smoking policies.

References

Becker, G., M. Grossman, and K. Murphy (1994). An Empirical Analysis of Cigarette Addiction. *American Economic Review*, **84**: 396-418.

Centers for Disease Control (1994). Surveillance for Selected Tobacco-Use Behaviors – U.S., 1990-1994. *MMWR. Morbidity and Mortality Weekly Report.* U. S. Dept. of Health, Education, and Welfare, vol. 43 No. SS-3.

Centers for Disease Control (2000a). YRBS: Youth97. CD-ROM.

Centers for Disease Control (2000b). *Behavioral Risk Factor Surveillance System: Prevalence Data.* U. S. Dept. of Health, Education, and Welfare. `www.cdc.gov/nccdphp/brfss/`.

Centers for Disease Control (various years). *Morbidity and Mortality Weekly Report: CDC Surveillance Summaries.* U. S. Dept. of Health, Education and Welfare.

Chaloupka, F. (1991). Rational Addictive Behavior and Cigarette Smoking. *Journal of Political Economy*, **99**: 722-742.

Chaloupka, F. and M. Grossman (1996). Price, Tobacco Control Policies and Youth Smoking. National Bureau of Economic Research Working Paper No. 5740.

Chaloupka, F. and K. Warner (forthcoming). The Economics of Smoking. In *The Handbook of Health Economics*, J. Newhouse and A. Culyer, eds. North-Holland.

DeCicca, P., D. Kenkel, and A. Mathios (1999). Putting Out the Fires: Will Higher Taxes Reduce Youth Smoking? Mimeo, Cornell University.

Douglas, S. (1998). The Duration of the Smoking Habit. *Economic Inquiry*, **36**: 49-64.

Gruber, J. (2000). Youth Smoking in the U.S.: Prices and Policies. National Bureau of Economic Research Working Paper No. 7506.

Gruber, J. and B. Köszegi (2000). Is Addiction 'Rational'? Theory and Evidence. National Bureau of Economic Research Working Paper No. 7507.

Gruber, J. and J. Zinman (2000). Youth Smoking in the U.S.: Evidence and Implications. In *An Economic Analysis of Risky Behavior Among Youth*, J. Gruber, ed., NBER.

Heckman, J. and B. Singer (1984). A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica*, **52**: 271-320.

Hsiao, C. (1986) *Anlaysis of Panel Data.* Cambridge University Press: Cambridge.

Kolbe, L., L. Kann, and J. Collins (1993). Overview of the Youth Risk Behavior Surveillance System. *Public Health Reports*, **108** (Supplement 1): 2-10.

Mroz, T. (1999). Discrete Factor Approximations in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome. *Journal of Econometrics*, **92**: 233-274.

Tauras, J. and F. Chaloupka (1999a). Determinants of Smoking Cessation: An Analysis of Young Adult Men and Women. National Bureau of Economic Research Working Paper No. 7262.

Tauras, J. and F. Chaloupka (1999b). Price, Clean Indoor Air Laws, and Cigarette Smoking: Evidence from Longitudinal Data for Youth Adults. National Bureau of Economic Research Working Paper No. 6937.

Tobacco Institute (1997). *The Tax Burden on Tobacco: Historical Compilation.* vol. 32.

Appendix

Cigarette Taxes and Prices Across States

The following evidence suggests that cigarette taxes and prices in a state are not random. Figure 1 depicts real state tax rates (denominated in 1984 cents per pack), real cigarette prices (denominated in 1984 ten cents per pack), and smoking rates among individuals aged 18 or older. The upper left hand panel shows the means of these variables across all states and the District of Columbia over the period 1980 through 1997.[38] Both the real tax rate (the solid line) and the real price (the dashed line) follow the same general upward trend.[39] Mean adult smoking rates tend to trend downwards, the opposite pattern of tax rates and prices, though they are roughly level from 1992 through 1997. This pattern suggests that higher tax rates and prices tend to be associated with lower smoking rates among adults.

The story is more complicated at the state level. The remaining panels in Figure 1 plot real tax rates, real prices, and smoking rates for Washington, California, and North Carolina. First, notice that the ranking of states by tax rates is generally consistent: for all but a few years in the sample Washington's tax rate exceeds California's tax rate which in turn exceeds North Carolina's tax rate. This suggests that states have systematic differences in their tax setting policies. Second, states with higher tax rates also tend to have higher cigarette prices: Washington's cigarette price exceeds California's cigarette price (except in the few years where California's tax rate is higher) and both always exceed North Carolina's cigarette price. Third, the state plots also illustrate a key aspect of tax-setting policies: tax rates tend to be constant over long periods and are occasionally punctuated by sharp increases.[40] For example, California's tax rate was only significantly adjusted once during the sample period (the rate was tripled in 1989) while North Carolina's tax rate remains roughly constant. This suggests a strong degree of hysteresis in tax policies. Finally, there is no longer a clear negative relationship between adult smoking rates and cigarette prices or taxes. For example, during the 1990s Washington had large tax rate and price increases but its smoking rate actually increased slightly. Similarly, California's tax rate and price fell over the 1990s but its smoking rate declined.

[38] State smoking rates are only available starting in 1984 (Centers for Disease Control, 1994).

[39] The main divergence occurs in 1993 when prices fell while taxes continued to increase. The price drop resulted from a sharp one time reduction in manufacturer prices which was instituted as a means of preventing sales erosion to generic brands.

[40] Recall that the plots describe real tax rates which take into account inflation; when nominal tax rates remain constant, the real rates will decline.

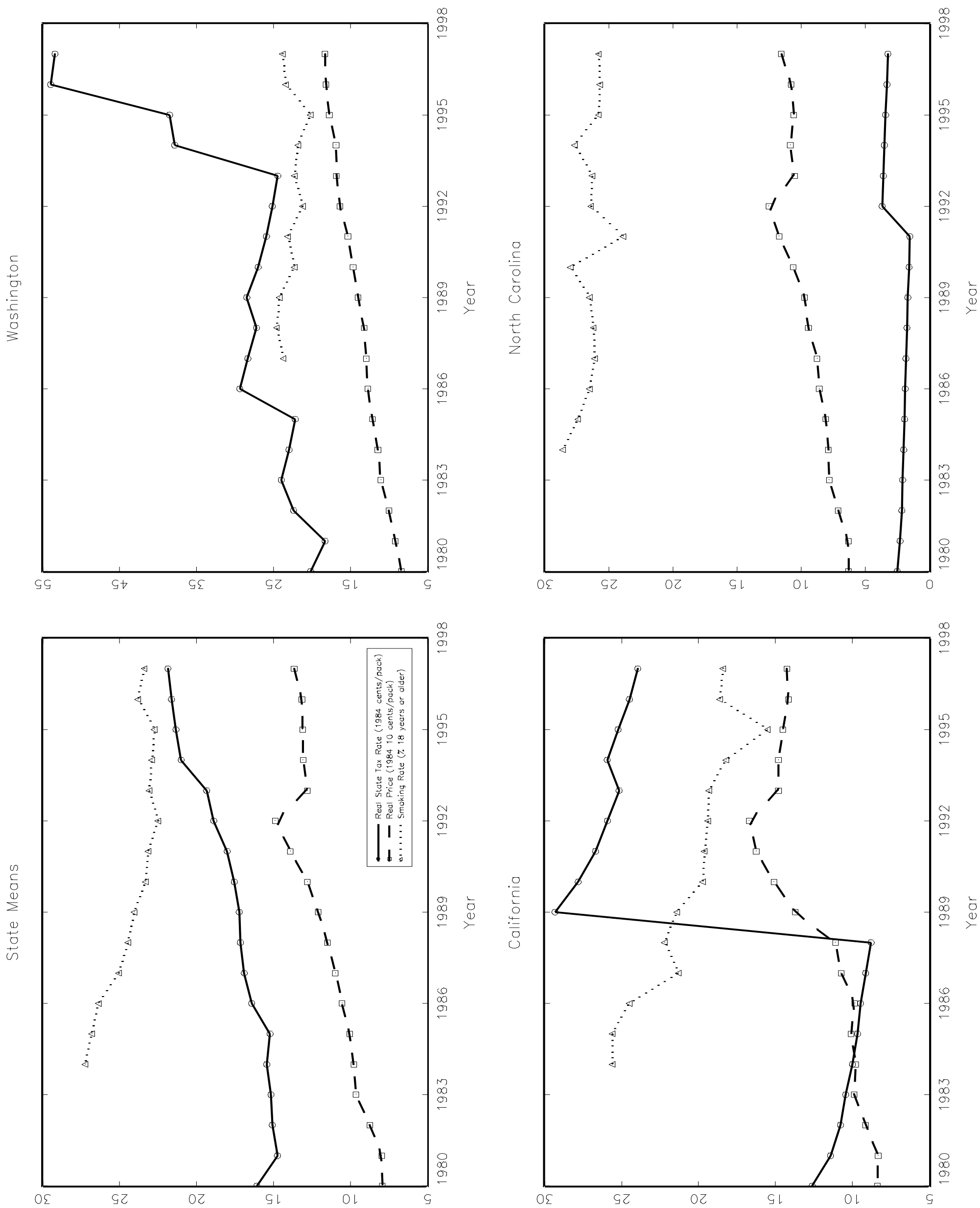

Figure 1: Smoking rates, Tax rates, and Cigarette prices
Sources: Centers for Disease Control (1994, 2000b) and Tobacco Institute (1997).

Table 1: Smoking Behavior of the Sample

Variable	1988 SS	1988 Prop	1990 SS	1990 Prop	1992 SS	1992 Prop
Full Sample						
Smoke any	10233	0.046	10233	0.160	10233	0.227
Smoke 1-5 cigs/day	471	0.665	1635	0.621	2322	0.478
Smoke 6-10 cigs/day	471	0.172	1635	0.206	2322	0.261
Smoke 11+ cigs/day	471	0.163	1635	0.173	2322	0.261
Leave School	10233	0.026	9964	0.052		
Non-dropouts						
Smoke any	10233	0.046	9964	0.150	9441	0.204
Smoke 1-5 cigs/day	471	0.665	1499	0.660	1930	0.534
Smoke 6-10 cigs/day	471	0.172	1499	0.191	1930	0.247
Smoke 11+ cigs/day	471	0.163	1499	0.149	1930	0.219
Dropouts						
Smoke any			269	0.506	792	0.495
Smoke 1-5 cigs/day			136	0.191	392	0.204
Smoke 6-10 cigs/day			136	0.368	392	0.327
Smoke 11+ cigs/day			136	0.441	392	0.469

Note: Prop measures proportion where the denominator is the full sample in the 'smoke any' calculation, the number of smokers in the consumption level calculations, and the number still in school in the 'leave school' calculation. These numbers are denoted SS.

Table 2: Dynamic Smoking Transitions

	Cigarette Use (per day) in t			
	0 cigs	1-5 cigs	6-10 cigs	11+ cigs
		$t = 1988$		
Cigarette Use in $t-2$				
0 cigs/day	95.40	3.06	0.79	0.75
		$t = 1990$		
Cigarette Use in $t-2$				
0 cigs/day	86.63	9.24	2.28	1.84
1-5 cigs/day	32.27	30.35	22.04	15.34
6-10 cigs/day	19.75	11.11	34.57	34.57
11+ cigs/day	31.17	12.99	20.78	35.06
Unconditional on prior use	84.02	9.93	3.28	2.77
		$t = 1992$		
Cigarette Use in $t-2$				
0 cigs/day	87.52	8.06	2.40	2.02
1-5 cigs/day	32.19	34.94	20.67	12.20
6-10 cigs/day	9.23	11.90	42.86	36.01
11+ cigs/day	9.89	7.77	15.90	66.43
Unconditional on prior use	77.31	10.85	5.91	5.93

Table 3: Descriptive Statistics of the Sample

Variable	1988 Mean	1988 Std Dev	1990 Mean	1990 Std Dev	1992 Mean	1992 Std Dev
<u>Student Characteristics</u>						
Non-time varying variables						
Female	0.535	0.499				
Black	0.087	0.281				
Hispanic	0.116	0.320				
Other/Non-white	0.082	0.275				
Baptist	0.067	0.250				
No religion	0.090	0.286				
Other/Non-Catholic	0.542	0.498				
Religion missing	0.019	0.137				
No. of older siblings	1.332	1.850				
Older siblings missing	0.112	0.315				
Sibling dropped out	0.004	0.301				
Sibling dropped out missing	0.033	0.179				
Time varying variables						
Previous smoker	0	0	0.046	0.210	0.160	0.366
Previous intensity = 6-10 cigs	0	0	0.008	0.088	0.033	0.178
Previous intensity = 11+ cigs	0	0	0.007	0.086	0.028	0.164
Duration smoking	0	0	0.046	0.210	0.206	0.477
Age as of January (in months)	166.557	6.594	190.557	6.594	214.557	6.594
Age missing	0.021	0.143	0.021	0.143	0.021	0.143
Standardized test score	50.649	13.251	50.053	13.762	42.438	22.093
Test score missing	0.030	0.170	0.038	0.190	0.187	0.390
Dropout indicator	0	0	0.026	0.160	0.077	0.267
% in school who drop out	0	0	6.072	9.457	3.000	4.805
% who drop out missing	0	0	0.099	0.298	0.156	0.363
<u>School Characteristics</u>						
Public school	0.816	0.387	0.837	0.369	0.792	0.406
Suburban school	0.433	0.496	0.395	0.489	0.377	0.485
Rural school	0.323	0.468	0.315	0.465	0.296	0.457
% on free lunch in school	0.213	0.217	0.159	0.195	0.165	0.196
% on free lunch missing	0.005	0.068	0.092	0.289	0.070	0.255
% with single parent in school	0.249	0.177	0.118	0.089	0.227	0.184
% with single parent missing	0.037	0.188	0.157	0.363	0.112	0.315
% Black in school	0.098	0.186	0.095	0.182	0.085	0.170
% Hispanic in school	0.088	0.197	0.084	0.182	0.078	0.178
Racial composition missing	0.005	0.070	0.050	0.217	0.064	0.244

Table 3: Descriptive Statistics of the Sample — continued

Variable	1988 Mean	1988 Std Dev	1990 Mean	1990 Std Dev	1992 Mean	1992 Std Dev
Household Characteristics						
Non-time varying variables						
Guardian born before 1940	0.096	0.295				
Guardian born 1940-1955	0.790	0.407				
Guardian's age missing	0.030	0.170				
Parent's education	14.122	2.698				
Parent's education missing	0.006	0.076				
Parent's work	0.964	0.187				
Parent's work missing	0.008	0.088				
Family socioeconomic status	-0.063	0.766				
Time varying variables						
Live with mom and dad	0.706	0.456	0.639	0.480	0.575	0.494
Live with mom only	0.143	0.350	0.125	0.331	0.139	0.346
Family composition missing	0.004	0.061	0.064	0.245	0.149	0.356
Income <10K	0.090	0.286	0.090	0.286	0.073	0.261
Income 10K-25K	0.230	0.421	0.230	0.421	0.190	0.392
Income 25K-50K	0.382	0.486	0.382	0.486	0.299	0.458
Income missing	0.087	0.283	0.087	0.283	0.153	0.360
Price Variables (adjusted for inflation)						
Cigarette Price$_t$ (cents/pack)	124.460	10.633	138.795	13.198	161.155	15.310
Sample size	10,233		10,233		10,233	

Table 4: Smoking Participation and Nominal Tax Rates by State

State	Percent who smoke 1988	Percent who smoke 1990	Percent who smoke 1992	Real Cigarette Price 1988	Real Cigarette Price 1990	Real Cigarette Price 1992	State	Percent who smoke 1988	Percent who smoke 1990	Percent who smoke 1992	Real Cigarette Price 1988	Real Cigarette Price 1990	Real Cigarette Price 1992
AL	4.6	15.4	25.1	119.1	132.7	157.9	MT	2.6	15.8	21.1	120.1	133.9	153.5
AK	0.0	8.3	29.2	130.6	162.4	187.8	NE	10.2	22.7	21.6	128.4	136.8	157.8
AZ	8.7	19.4	35.0	118.2	124.2	155.6	NV	4.6	18.5	21.5	135.0	165.7	172.1
AR	2.2	16.9	27.0	124.9	134.7	159.6	NH	3.4	20.7	31.0	118.2	129.7	152.4
CA	2.6	9.1	14.3	122.3	156.3	185.1	NJ	3.3	11.2	18.8	137.3	142.4	174.8
CO	3.6	13.1	17.9	120.8	142.4	148.0	NM	6.1	21.4	27.5	118.4	127.5	153.5
CT	1.1	8.7	25.0	135.1	163.3	178.5	NY	3.6	14.8	22.3	131.1	159.7	181.4
DE	0.0	13.0	34.8	124.2	133.6	166.7	NC	7.5	17.5	23.0	100.0	111.0	133.7
FL	4.3	10.0	14.3	135.9	143.2	172.7	ND	1.2	12.0	20.5	128.4	137.7	159.6
GA	1.2	13.6	17.9	113.7	126.2	144.0	OH	5.7	17.1	24.4	112.9	129.2	149.0
HI	5.7	14.3	14.3	139.3	157.9	186.4	OK	5.5	14.4	26.7	127.7	139.4	157.6
ID	8.1	24.4	39.5	126.9	134.8	149.0	OR	2.1	6.2	12.4	136.2	149.7	163.1
IL	2.7	16.6	27.9	129.2	140.5	166.0	PA	5.1	21.2	26.0	116.9	127.6	161.8
IN	4.1	17.0	23.2	113.8	124.8	144.3	RI	2.7	18.9	13.5	126.5	144.0	173.4
IA	7.2	20.3	22.9	129.3	142.7	165.1	SC	5.4	19.1	19.5	104.0	119.4	137.0
KS	2.6	15.8	20.2	129.0	139.1	158.9	SD	0.0	33.3	33.3	129.9	132.5	152.1
KY	6.5	16.8	28.1	98.3	110.3	125.7	TN	5.2	15.5	19.8	116.7	128.8	143.9
LA	9.0	19.4	23.7	125.4	136.8	162.9	TX	3.1	12.9	19.1	133.3	139.0	163.2
ME	0.0	9.1	21.2	134.3	152.7	175.2	UT	2.5	8.9	15.2	128.0	144.9	145.2
MD	3.7	13.9	24.1	113.7	125.5	146.3	VT	3.6	21.4	28.6	128.8	137.1	148.1
MA	5.0	18.3	24.8	137.0	145.4	162.5	VA	7.3	17.6	22.7	106.3	122.7	138.2
MI	7.5	22.0	28.6	127.3	137.3	161.9	WA	7.8	16.1	25.0	147.3	159.8	174.7
MN	4.1	18.9	29.7	147.6	154.8	184.2	WV	9.1	22.7	27.3	127.3	136.3	139.2
MS	2.3	14.8	15.9	127.7	133.5	147.4	WI	5.0	22.9	30.0	133.9	144.2	154.9
MO	5.6	18.0	26.3	119.3	123.2	143.8	WY	0.0	15.9	20.5	117.6	123.5	136.1

Note: The percent of observations who smoke in each year (1988, 1990, 1992) is measured using our selected sample from NELS:88 which follows the same individuals over time. Individuals are in 8th grade in 1988.
Real cigarette prices (in cents) are composed of producer prices and tax rates in November of the previous year.

Table 5: Measures of Behavioral Change from Preliminary Models

	Percentage Point Difference				*(Arc) Elasticity*			
		Conditional on Smoking				Conditional on Smoking		
Price = 200 vs. Price = 100	Smoke any	Smoke 1-5 cigs	Smoke 6-10 cigs	Smoke 11+ cigs	Smoke any	Smoke 1-5 cigs	Smoke 6-10 cigs	Smoke 11+ cigs
<u>Model 1</u>								
Overall	-6.6	17.2	-14.9	-2.3	-1.01	0.44	-1.11	-0.29
By Year: 1988	-4.0	31.4	-23.6	-7.8	-1.52	0.68	-2.45	-0.92
1990	-10.1	16.8	-12.0	-4.8	-1.06	0.38	-1.01	-0.53
1992	-5.8	14.1	-15.1	1.0	-0.42	0.42	-0.85	0.05
<u>Model 2</u>								
Overall	-6.0	17.3	-13.4	-3.9	-0.85	0.63	-1.03	-0.21
By Year: 1988	-3.5	25.4	-21.7	-3.7	-1.32	0.59	-2.32	-0.40
1990	-8.8	19.1	-14.1	-5.0	-0.87	0.57	-1.17	-0.35
1992	-5.7	14.3	-11.1	-3.2	-0.35	0.67	-0.66	-0.07
<u>Model 3</u>								
Overall	1.7	24.1	-10.0	-14.0	-0.04	0.85	-0.86	-0.98
By Year: 1988	-2.1	26.0	-18.1	-7.9	-0.76	0.60	-2.02	-0.86
1990	1.3	25.7	-12.2	-13.6	0.15	0.74	-1.08	-1.23
1992	6.0	22.5	-6.9	-15.6	0.49	0.98	-0.48	-0.83
<u>Model 4</u>								
Overall	2.3	25.3	-9.4	-16.0	-0.03	0.83	-0.94	-1.26
By Year: 1988	-2.4	31.6	-18.7	-12.9	-0.89	0.70	-2.10	-1.48
1990	1.2	29.3	-12.3	-17.1	0.10	0.82	-1.22	-1.63
1992	8.0	21.2	-5.4	-15.8	0.70	0.86	-0.50	-0.96
Non-Smokers	0.9	27.0	-13.8	-13.2	-0.07	0.69	-1.35	-1.32
Smokers	20.8	22.4	-1.4	-20.9	0.47	1.07	-0.18	-1.17
Non-Dropouts	5.2	22.6	-10.7	-11.9	0.45	0.60	-0.96	-1.15
Dropouts	-2.3	33.9	-1.1	-32.7	-0.41	1.76	-0.35	-1.58

Note: Model 1 contains a sparse set of covariates and dropouts are omitted from the sample.
Model 2 is identical to Model 1 but additional covariates are added and dropouts are included.
Model 3 is identical to Model 2 but includes state fixed effects.
Model 4 is identical to Model 3 but includes (exogenous) controls for previous behavior and interacts them with price.
Non-smoker and smoker refer to previous behavior. Non-dropouts and dropouts are in 1990 & 1992.

Table 6: Parameter Estimates from Model 5

	Smoke Any			Smoke 6-10 Cigs			Smoke >10 Cigs			Leave School		
Cig price$_t$	-0.007	(0.008)		-0.028	(0.013)	**	-0.028	(0.015)	*	-	-	
Cig price$_t$ × Year 1990	0.007	(0.006)		0.008	(0.010)		0.000	(0.012)		-	-	
Cig price$_t$ × Year 1992	0.012	(0.006)	**	0.014	(0.010)		0.010	(0.013)		-	-	
Cig price$_t$ × Previous smoker	0.011	(0.007)	*	0.006	(0.014)		-0.002	(0.015)		-	-	
Cig price$_t$ × Previous intensity = 6-10 cigs	0.020	(0.008)	**	0.026	(0.011)	**	0.024	(0.012)	**	-	-	
Cig price$_t$ × Previous intensity = 11+ cigs	0.013	(0.009)		0.015	(0.014)		0.022	(0.014)		-	-	
Cig Price$_t$ × Years smoking	-0.006	(0.006)		-0.010	(0.013)		-0.009	(0.013)		-	-	
Cig price$_t$ × Dropout	-0.012	(0.006)	**	-0.016	(0.007)	**	-0.032	(0.008)	**	-	-	
Cig price$_t$ × Female	-0.001	(0.003)		0.003	(0.006)		0.008	(0.006)		-	-	
Previous smoker	-0.048	(1.019)		0.077	(2.189)		0.604	(2.381)		-	-	
Previous intensity = 6-10 cigs	-2.058	(1.171)	*	-2.682	(1.636)		-2.165	(1.829)		-	-	
Previous intensity = 11+ cigs	-1.690	(1.381)		-1.906	(2.178)		-1.603	(2.114)		-	-	
Duration smoking	1.390	(0.966)		1.398	(2.003)		1.693	(2.148)		-	-	
Dropout indicator	1.520	(0.924)	*	3.408	(1.136)	**	5.432	(1.173)	**	-	-	
Female	0.135	(0.489)		-0.840	(0.938)		-1.837	(0.970)	*	0.237	(0.121)	*
Black	-1.690	(0.139)	**	-1.711	(0.557)	**	-1.903	(0.700)	**	-1.618	(0.318)	**
Hispanic	-0.353	(0.094)	**	-1.398	(0.306)	**	-1.464	(0.362)	**	0.157	(0.245)	
Other/Non-white	-0.584	(0.108)	**	-0.268	(0.277)		-0.651	(0.391)	*	-0.815	(0.363)	**
Age as of January (in months)	0.009	(0.004)	**	0.002	(0.005)		0.007	(0.007)		0.101	(0.009)	**
Age missing	1.672	(0.768)	**	0.667	(1.153)		0.706	(1.383)		19.089	(1.640)	**
Standardized test score	0.011	(0.030)		-0.086	(0.044)	**	-0.022	(0.049)		-0.163	(0.075)	**
Test score^2	-0.001	(0.000)	*	0.000	(0.001)		0.000	(0.001)		0.001	(0.001)	
Test score missing	-0.690	(0.750)		-2.332	(1.056)	**	-0.651	(1.181)		-5.928	(1.822)	**
Baptist	-0.019	(0.105)		-0.154	(0.326)		-0.061	(0.453)		-0.206	(0.602)	
No religion	0.387	(0.090)	**	0.288	(0.228)		0.649	(0.294)	**	1.015	(0.311)	**
Other/Non-Catholic	0.065	(0.059)		0.067	(0.167)		0.406	(0.216)	*	0.414	(0.251)	*
Religion missing	0.021	(0.183)		0.561	(0.625)		0.877	(0.713)		0.599	(0.783)	
No. of older siblings	0.065	(0.014)	**	0.051	(0.027)	*	0.037	(0.032)		-0.065	(0.038)	*
Older siblings missing	0.125	(0.075)	*	-0.052	(0.155)		0.118	(0.179)		0.207	(0.184)	
Live with mom and dad	-0.381	(0.064)	**	-0.392	(0.139)	**	-0.374	(0.171)	**	-0.787	(0.218)	**
Live with mom only	-0.096	(0.082)		-0.139	(0.190)		-0.265	(0.227)		-0.288	(0.255)	
Family composition missing	-0.298	(0.099)	**	-0.123	(0.271)		-0.083	(0.324)		0.267	(0.494)	

Table 6: Parameter Estimates from Model 5 — continued

	Smoke Any			Smoke 6-10 Cigs			Smoke >10 Cigs			Leave School		
Family socioeconomic status	0.099	(0.087)		-0.300	(0.166)	*	-0.010	(0.208)		-0.239	(0.193)	
Parent's education	-0.023	(0.026)		0.008	(0.042)		-0.089	(0.049)	*	-0.101	(0.050)	**
Parent's education missing	-0.374	(0.800)		-0.204	(0.988)		-1.754	(1.043)	*	-0.653	(0.950)	
Income <10K	0.057	(0.118)		0.021	(0.366)		-0.016	(0.477)		1.304	(0.398)	**
Income 10K-25K	-0.011	(0.082)		-0.083	(0.255)		0.052	(0.332)		1.093	(0.333)	**
Income 25K-50K	0.002	(0.064)		0.101	(0.192)		0.130	(0.244)		0.740	(0.308)	**
Income missing	-0.040	(0.095)		0.135	(0.300)		0.294	(0.356)		1.004	(0.398)	**
Parent's work	-0.213	(0.205)		-0.305	(0.334)		-0.285	(0.424)		-1.183	(0.313)	**
Parent's work missing	-0.273	(0.726)		0.143	(0.854)		0.135	(0.931)		-2.269	(0.856)	**
Guardian born before 1940	-0.208	(0.123)	*	0.386	(0.331)		0.110	(0.380)		-0.354	(0.389)	
Guardian born 1940-1955	-0.124	(0.089)		0.208	(0.224)		0.174	(0.246)		-0.371	(0.240)	
Guardian's age missing	-0.143	(0.166)		0.101	(0.439)		0.211	(0.517)		0.142	(0.472)	
Public school	-0.155	(0.090)	*	0.153	(0.261)		0.054	(0.357)		1.556	(0.471)	**
Suburban school	-0.004	(0.080)		0.095	(0.209)		-0.185	(0.298)		-0.092	(0.184)	
Rural school	-0.175	(0.092)	*	-0.025	(0.229)		-0.053	(0.322)		-0.221	(0.189)	
% on free lunch in school	0.017	(0.215)		0.338	(0.543)		-0.306	(0.702)		-0.772	(0.426)	*
% on free lunch missing	-0.076	(0.122)		0.185	(0.370)		0.234	(0.451)		-0.440	(0.323)	
% Hispanic in school	-0.567	(0.304)	*	0.159	(0.619)		-0.946	(0.867)		0.358	(0.458)	
% Black in school	-0.173	(0.319)		-0.576	(0.773)		0.142	(0.865)		1.633	(0.479)	**
Racial composition missing	-0.002	(0.146)		0.256	(0.466)		0.220	(0.608)		0.531	(0.482)	
% with single parent in school	0.097	(0.184)		0.265	(0.647)		0.026	(0.726)		-0.392	(0.601)	
% with single parent missing	-0.028	(0.088)		0.109	(0.234)		-0.200	(0.294)		0.063	(0.210)	
Year 1990	0.334	(0.771)		-0.547	(1.302)		0.117	(1.570)		-0.353	(0.254)	
Year 1992	-0.640	(0.794)		-1.023	(1.331)		-0.878	(1.613)		-	-	
Sibling dropped out	-	-		-	-		-	-		0.537	(0.195)	**
Sibling dropped out missing	-	-		-	-		-	-		4.815	(0.416)	**
% in school who drop out	-	-		-	-		-	-		0.011	(0.007)	
% who drop out missing	-	-		-	-		-	-		-0.119	(0.467)	
Constant	-4.974	(1.497)	**	1.659	(2.135)		-2.862	(3.239)		-24.308	(3.613)	**
ρ (factor loading)	4.210	(0.823)	**	3.151	(1.155)	**	6.569	(1.803)	**	10.619	(2.940)	**

Note: Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level. State fixed effects are also estimated.

Table 7: Measures of Behavioral Change from Model 5

Price = 200 vs. Price = 100	*Percentage Point Difference* Smoke any	Conditional on Smoking: Smoke 1-5 cigs	Smoke 6-10 cigs	Smoke 11+ cigs	*(Arc) Elasticity* Smoke any	Conditional on Smoking: Smoke 1-5 cigs	Smoke 6-10 cigs	Smoke 11+ cigs
Calculations using observed previous behavior → immediate response								
Overall	0.8	25.2	-10.9	-14.4	-0.24	0.64	-1.28	-1.68
By Year: 1988	-2.7	25.7	-15.8	-9.9	-1.02	0.50	-2.37	-2.05
1990	-0.7	27.3	-13.3	-14.0	-0.13	0.62	-1.62	-2.08
1990	5.9	23.7	-8.2	-15.5	0.44	0.69	-0.82	-1.33
Non-Smokers	-0.3	25.0	-13.7	-11.4	-0.29	0.55	-1.68	-1.78
Smokers	16.5	25.6	-5.9	-19.7	0.46	0.83	-0.56	-1.50
Non-Dropouts	3.1	22.0	-11.0	-11.0	0.20	0.50	-1.23	-1.54
Dropouts	-3.3	38.4	-9.3	-29.1	-0.60	1.28	-1.03	-2.06
Calculations using updated behavior from dynamic simulations → long-run response								
Overall	-0.2	27.3	-12.6	-14.6	-0.29	0.65	-1.42	-1.76
By Year: 1988	-2.7	25.7	-15.8	-9.9	-1.02	0.50	-2.37	-2.05
1990	-2.1	28.3	-14.6	-13.8	-0.19	0.61	-1.75	-2.13
1990	4.2	26.8	-10.6	-16.2	0.34	0.71	-1.00	-1.44
Non-Smokers	-0.3	25.9	-13.1	-12.9	-0.32	0.58	-1.61	-1.84
Smokers	1.2	29.6	-11.9	-17.8	0.08	0.79	-1.10	-1.61
Non-Dropouts	1.9	22.9	-11.6	-11.3	0.13	0.51	-1.33	-1.59
Dropouts	-7.4	45.2	-15.7	-29.5	-0.75	1.26	-1.39	-2.27

Note: Our preferred model includes individual unobserved heterogeneity, endogenous controls for smoking history, and state fixed effects. Non-smoker and smoker refer to previous behavior. Non-dropouts and dropouts are in 1990 & 1992.

Table 8: Smoking Participation Predictions under Alternative Price Increases

	Smoking Participation Rates				Smoking Participation Rates		
Price	Model 3	Model 4	Model 5	Price	Model 3	Model 4	Model 5
Overall				Previous Non-Smokers			
Original price	14.42	14.42	14.50	Original price	13.26	9.96	9.87
Price + 1 cent	14.44	14.45	14.50	Price + 1 cent	13.27	9.97	9.87
Price + 25 cents	14.88	14.98	14.36	Price + 25 cents	13.65	10.23	9.78
Price + 100 cent	16.58	16.82	14.14	Price + 100 cent	15.18	11.54	9.85
Year 1988 (8th graders)				Previous Smokers			
Original price	4.60	4.60	4.58	Original price	30.26	74.98	37.56
Price + 1 cent	4.58	4.58	4.55	Price + 1 cent	30.31	75.18	37.64
Price + 25 cents	4.05	3.96	3.86	Price + 25 cents	31.53	79.51	39.01
Price + 100 cent	2.76	2.52	2.28	Price + 100 cent	35.69	88.46	42.35
Year 1990 (10th graders & dropouts)				Non-Dropouts (1990 & 1992)			
Original price	15.98	15.98	15.93	Original price	17.67	17.67	18.94
Price + 1 cent	15.99	15.99	15.92	Price + 1 cent	17.71	17.72	18.95
Price + 25 cents	16.29	16.28	15.37	Price + 25 cents	18.73	18.95	19.27
Price + 100 cent	17.31	17.11	13.76	Price + 100 cent	22.24	22.81	20.25
Year 1992 (12th graders & dropouts)				Dropouts (1990 & 1992)			
Original price	22.69	22.69	23.00	Original price	49.76	49.76	29.16
Price + 1 cent	22.75	22.77	23.03	Price + 1 cent	49.73	49.72	29.01
Price + 25 cents	24.29	24.69	23.84	Price + 25 cents	48.90	48.60	25.76
Price + 100 cent	29.67	30.83	26.38	Price + 100 cent	46.32	45.14	16.80

Note: Model 3 includes state fixed effects and no controls for previous behavior.
Model 4 is identical to Model 3 but includes (exogenous) controls for previous behavior.
Model 5 includes individual unobserved heterogeneity, endogenous controls for smoking history, and state fixed effects and these predictions are based on updating behavior.

Table 9: Effect of Previous Behavior on Predicted Smoking Participation Rates

	1990	1992
Effect of forced previous behavior using Model 5		
Forced to not smoke in 1988	13.95	21.74
Forced to smoke heavily in 1988	47.15	42.33
Forced to not smoke in 1988 and 1990		14.94
Forced to smoke heavily in 1988 and 1990		61.73
Effect of forced previous behavior using Model 4		
Forced to not smoke in 1988	13.58	21.37
Forced to smoke heavily in 1988	69.90	64.26
Forced to not smoke in 1988 and 1990		13.31
Forced to smoke heavily in 1988 and 1990		85.51

Table A1: Parameter Estimates from Model 4

	Smoke Any			Smoke 6-10 Cigs			Smoke >10 Cigs		
Cig price$_t$	-0.006	(0.007)		-0.024	(0.016)		-0.020	(0.015)	
Cig price$_t$ × Year 1990	0.007	(0.007)		0.007	(0.012)		-0.001	(0.010)	
Cig price$_t$ × Year 1992	0.013	(0.007)	*	0.013	(0.012)		0.008	(0.010)	
Cig price$_t$ × Previous smoker	0.010	(0.006)		0.005	(0.014)		-0.003	(0.014)	
Cig price$_t$ × Previous intensity = 6-10 cigs	0.018	(0.008)	**	0.023	(0.011)	**	0.022	(0.012)	*
Cig price$_t$ × Previous intensity = 11+ cigs	0.012	(0.010)		0.014	(0.015)		0.019	(0.014)	
Cig Price$_t$ × Years smoking	-0.005	(0.006)		-0.008	(0.013)		-0.007	(0.013)	
Cig price$_t$ × Dropout	-0.010	(0.006)	*	-0.013	(0.007)	*	-0.027	(0.007)	**
Cig price$_t$ × Female	-0.001	(0.003)		0.003	(0.006)		0.008	(0.007)	
Previous smoker	0.288	(0.973)		0.203	(2.193)		0.813	(2.230)	
Previous intensity = 6-10 cigs	-1.715	(1.253)		-2.315	(1.684)		-1.741	(1.782)	
Previous intensity = 11+ cigs	-1.216	(1.483)		-1.506	(2.258)		-0.822	(2.084)	
Duration smoking	1.404	(0.971)		1.244	(2.011)		1.439	(2.004)	
Dropout indicator	2.021	(0.887)	**	3.273	(1.069)	**	5.348	(1.069)	**
Female	0.063	(0.442)		-0.817	(0.955)		-1.877	(0.977)	*
Black	-1.473	(0.127)	**	-1.493	(0.809)	*	-1.470	(0.798)	*
Hispanic	-0.305	(0.086)	**	-1.340	(0.392)	**	-1.315	(0.442)	**
Other/Non-white	-0.488	(0.100)	**	-0.182	(0.342)		-0.478	(0.525)	
Age as of January (in months)	0.005	(0.003)		-0.001	(0.006)		-0.002	(0.006)	
Age missing	0.771	(0.688)		-0.098	(1.166)		-1.217	(1.251)	
Standardized test score	-0.050	(0.054)		0.025	(0.024)		-0.072	(0.047)	
Test score^2	0.000	(0.001)		-0.001	(0.000)	**	0.000	(0.001)	
Test score missing	-2.910	(1.277)	**	-0.206	(0.612)		-1.891	(1.141)	*
Baptist	-0.006	(0.092)		-0.163	(0.373)		-0.060	(0.471)	
No religion	0.303	(0.075)	**	0.199	(0.251)		0.441	(0.269)	*
Other/Non-Catholic	0.048	(0.051)		0.032	(0.184)		0.329	(0.200)	*
Religion missing	0.021	(0.146)		0.454	(0.612)		0.661	(0.628)	
No. of older siblings	0.052	(0.012)	**	0.040	(0.030)		0.008	(0.033)	
Older siblings missing	0.102	(0.063)		-0.070	(0.165)		0.070	(0.170)	
Live with mom and dad	-0.322	(0.054)	**	-0.340	(0.200)	*	-0.276	(0.229)	
Live with mom only	-0.092	(0.072)		-0.124	(0.249)		-0.246	(0.282)	
Family composition missing	-0.263	(0.088)	**	-0.101	(0.446)		-0.044	(0.500)	

Table A1: Parameter Estimates from Model 4 — continued

	Smoke Any			Smoke 6-10 Cigs		Smoke >10 Cigs		
Parent's education	-0.020	(0.022)		0.017	(0.047)	-0.072	(0.050)	
Parent's education missing	-0.384	(0.706)		-0.073	(0.956)	-1.639	(0.985)	*
Income <10K	0.058	(0.107)		0.017	(0.532)	-0.050	(0.584)	
Income 10K-25K	0.005	(0.073)		-0.084	(0.367)	0.053	(0.380)	
Income 25K-50K	0.001	(0.057)		0.095	(0.275)	0.129	(0.278)	
Income missing	-0.048	(0.086)		0.107	(0.421)	0.242	(0.425)	
Parent's work	-0.103	(0.213)		-0.236	(0.401)	-0.142	(0.468)	
Parent's work missing	-0.143	(0.937)		0.252	(0.823)	0.388	(0.907)	
Guardian born before 1940	-0.170	(0.098)	*	0.391	(0.481)	0.168	(0.555)	
Guardian born 1940-1955	-0.087	(0.072)		0.215	(0.319)	0.211	(0.343)	
Guardian's age missing	-0.144	(0.139)		0.079	(0.729)	0.220	(0.709)	
Public school	-0.141	(0.077)	*	0.176	(0.303)	0.102	(0.343)	
Suburban school	0.001	(0.078)		0.096	(0.223)	-0.163	(0.274)	
Rural school	-0.143	(0.084)	*	-0.013	(0.234)	-0.022	(0.298)	
% on free lunch in school	0.012	(0.243)		0.325	(0.643)	-0.322	(0.654)	
% on free lunch missing	-0.071	(0.125)		0.185	(0.525)	0.247	(0.562)	
% Hispanic in school	-0.573	(0.419)		0.218	(0.750)	-0.799	(0.821)	
% Black in school	-0.144	(0.350)		-0.621	(0.781)	0.067	(0.796)	
Racial composition missing	0.007	(0.152)		0.248	(0.639)	0.197	(0.693)	
% with single parent in school	0.070	(0.180)		0.274	(0.818)	0.010	(0.799)	
% with single parent missing	-0.029	(0.082)		0.112	(0.336)	-0.199	(0.426)	
Year 1990	0.169	(0.923)		-0.594	(1.436)	0.081	(1.216)	
Year 1992	-0.889	(0.937)		-1.041	(1.429)	-0.807	(1.186)	
Constant	-1.819	(1.131)		3.776	(2.499)	2.388	(2.831)	

Note: Huber standard errors with clustering on individuals are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
State fixed effects are also estimated.