An Empirical Analysis of Biases in Cigarette Addiction

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Abstract

I embed rational choice along with two types of psychological biases into a model describing the consumption of an addictive good, and empirically investigate the extent to which these biases help explain observed smoking patterns. Rational agents correctly maximize their lifetime utility, whereas “present-biased” agents have a taste for immediate gratification, and “projection-biased” agents underestimate how much their future tastes are affected by current behavior. Consumers may have any degree, including zero, of both biases. I use MSA-level variation in cigarette price shocks over a 26-year span to examine individual smoking responses to current and predicted future prices, and to price volatility. I find that while both young smokers and mature smokers respond to the current price (with a 1% price increase lowering the probability of smoking by between 1% and 2%), only mature smokers respond to the future price. This youthful myopia is consistent with either type of biased consumers but not with fully rational ones. The ratio of the future-price response to current-price response among mature response yields an estimate of the net discount rate. Decomposing prices into a permanent and a transitory component, I use mature smokers’ responses to separate out a short-run discount factor $\beta \in [0.70, 0.83]$ and long-run discount factor $\delta \approx 0.9$. Because projection-biased agents do not fully appreciate the effect of current consumption on future behavior, they under-appreciate the “option value” of remaining unaddicted in an uncertain price environment. With an additional assumption on the utility function, I use the under-response to price volatility to estimate a degree of projection bias $\alpha \in [0.41, 0.49]$, meaning that people underestimate changes in tastes from smoking behavior by 40%. Overall, I find that a combination of present bias and projection bias explains significant deviations from rational cigarette consumption. Manipulating the price path to take full advantage of these biases could increase the cost in present value that a consumer pays for a lifetime smoking habit by a factor of 3. I find that relatively large taxes—between $8 and $11—would correct for the overconsumption caused by the two psychological biases.

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1 Introduction

Many studies have looked at the response of cigarette consumption to changes in prices and taxes. In general, these studies find substantial price and tax elasticities of cigarette consumption across different income levels, different ages, and different countries. There is also a growing collection of theoretical models describing how agents treat addictive goods, which differ in both their behavioral and their welfare implications. However, there is little work attempting to link the two literatures and empirically identify which, if any, model applies to cigarette addiction. This paper derives testable implications from a unified model of addiction that allows the extent of two biases to freely vary, and then estimates the degree of each bias.

I present a simple model of addiction based on O’Donoghue and Rabin (2000)’s adaptation of Becker and Murphy (1988), where infinitely-lived agents choose in every period consumption of a numeraire and an addictive good. Addiction is captured by two key features: a negative effect of current consumption on the utility of future selves, and a “reinforcement” effect whereby current consumption increases the temptation to consume in future periods. I then allow for consumers to have varying degrees of two biases, with fully rational consumers—who maximize their true lifetime utility function—embedded as a special case. This case corresponds to the “rational addiction” described in Becker and Murphy (1988), where addicts correctly assess their maximization problem and consume only when addiction is utility-maximizing.

A growing literature—summarized in DellaVigna (2009)—finds that many people display a taste for immediate gratification. I allow agents to exhibit this “present bias” according to the quasi-hyperbolic discounting \( \beta - \delta \) model of Laibson (1997) and O’Donoghue and Rabin (1999a). The degree of present bias is indexed by the parameter \( \beta \), which is an additional discount factor applied to any future utility in addition to the usual exponential discount factor \( \delta \). Setting \( \beta = 1 \) therefore reduces to exponential discounting. Consumers with \( \beta < 1 \) will be more impatient in choices involving both present and future utility—only future utility receives extra discounting—while not overly impatient in choices involving only future utility tradeoffs. I focus on “naive” present-biased agents, who are unaware of their self-control problem. Their

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3Gruber and Köszegi (2000) discuss optimal taxes for present-biased consumers; Gruber and Mullainathan (2005) find that taxes can improve happiness among those otherwise likely to have been smokers.
4The exception is Gruber and Köszegi (2001), which proposes a test of present bias but does not implement it. Becker, Grossman and Murphy (1994) test forward-looking behavior against the extreme of pure myopia, but this does not distinguish between the three types presented in this paper.
5By embedding the rational case within the model, I am not presupposing the existence of non-rational consumers.
6Later rational-addiction models, such as Orphanides and Zervos (1995), allow initial uncertainty to produce both ex post inefficient addictions and ex post inefficient abstentions. Once addicted, however, steady-state behavior will mimic that in Becker and Murphy (1988).
7In contrast, “sophisticated” present-biased agents are aware of their self-control problem and will seek out commitment
taste for immediate gratification causes them to under-weigh the negative effect that consuming the addictive good will have on their future selves, while their naivete causes them to underestimate the extent to which their future selves will be tempted to consume the addictive good. These two forces can lead to costly overconsumption, as well as mistaken beliefs about future consumption paths. In particular, it can lead to procrastination in which an addict always hits today and always plans to start refraining tomorrow. Being patient in the long-run, such an addict will want to quit smoking. Her short-run impatience, however, causes her to prefer quitting tomorrow over quitting today, even in a stationary environment. Because she does not realize that she will also want to delay when tomorrow arrives, she will procrastinate forever on quitting.

Finally, consumers may under-appreciate the extent to which changes to their “state”—in this context, addicted or unaddicted—will affect their utility. The “simple projection bias” of Loewenstein, O’Donoghue and Rabin (2003) allows consumers to maximize a weighted average of their utility conditional on their true future state, and their utility conditional on their state remaining constant. The extent of consumers’ projection bias is indexed by the parameter $\alpha \in [0, 1]$, with $\alpha = 0$ embedded as the fully rational case.\(^8\) Because they do not currently crave the addictive good, unaddicted consumers underestimate how much current consumption will make their future selves crave it. Currently addicted consumers, conversely, fail to appreciate the extent to which refraining will decrease their future cravings. This can lead both addicts and non-addicts to overconsume the addictive good. It can also cause unexpected revisions to the consumption plan if a person intends to consume only for a short duration but, finding herself unexpectedly addicted and her marginal utility unexpectedly high, then continues to consume in all periods.

In order to yield testable predictions, I place three restrictions on the instantaneous utility function. First, it is quasi-linear in consumption of a numeraire and an addictive good. Second, utility from the addictive good can be further separated into two components: one that depends on the agent’s level of addiction, and one that depends on the period. Finally, I assume that consumers’ lives can be divided into their “youth” and their “maturity”. The period-dependent component of utility is constant within each phase, and normalized to be zero during smokers’ adulthood.\(^9\) The non-stationarity introduced by this last restriction is intended to help the rational model explain actual smoking patterns. Setting the value during maturity to the youth value reduces to the stationary model often used elsewhere. These assumptions narrow the range of plans that consumers may form, enabling the estimation of behavioral parameters from devices to restrain their future selves. Although I include them in the model in Section 2, I later rule them out generically using the restriction that sophisticates, like fully rational consumers, must have rational expectations.\(^8\)

\(8\)That is, if a consumer’s current state is $s_c$ but her actual future state will be given by $s_f$, she believes her future utility will be $\tilde{U}(x) = (1 - \alpha)U(x|s_f) + \alpha U(x|s_c)$.\(^9\)

\(9\)I assume that teenagers are still in their youth, while smokers over 30 or 35 are in their adulthood. The distribution of maturity dates is investigated in Section 5.2.3. This assumption is a simplified version of the “youthful preferences” in O’Donoghue and Rabin (2000), which allow for a more gradual decay over time in the instantaneous incentive to consume the addictive good.
responses to different types of price shocks.

Section 2 develops the model and tests that distinguish between biased and unbiased agents based on their consumption responses to anticipated changes in cigarette prices. In doing so, I am assuming that smokers hold rational expectations of the future cigarette price but do not have perfect foresight: the realized future price will be higher than an individual’s expectation about as often as it is lower. To avoid strong assumptions on smokers’ ability to predict prices, Gruber and Kőszegi (2000) use high-frequency smoking data from the National Vitality Statistics Natality Data in order to identify tax changes that have been legislated but not yet implemented, and still find a future-price effect. In order to use the more representative data from the NHIS, however, I can only look at tax and price changes at an annual frequency. I instead use current-period information—taxes and state budget tightness—as instruments for future prices in order to address consumers’ imperfect foresight and avoid attenuation bias from their noisy predictions. To avoid strong assumptions on smokers’ ability to predict prices, Gruber and Kőszegi (2000) use high-frequency smoking data from the National Vitality Statistics Natality Data in order to identify tax changes that have been legislated but not yet implemented, and still find a future-price effect. In order to use the more representative data from the NHIS, however, I can only look at tax and price changes at an annual frequency. I instead use current-period information—taxes and state budget tightness—as instruments for future prices in order to address consumers’ imperfect foresight and avoid attenuation bias from their noisy predictions. While I assume that consumers make use of the available information, this approach does not require the seeming clairvoyance assumed by some previous research, such as Becker, Grossman and Murphy (1994), that have included future prices directly into the regressions. Because current consumption affects the marginal utility from smoking in the future, consumers who expect to smoke in the next period will react immediately to an anticipated future price change. Alternatively, if an unaddicted consumer knows a price increase will cause her future self to not smoke, she may choose not to start smoking so as to avoid withdrawal in the future. Because present-biased agents heavily discount the costs to future selves, they will under-respond to anticipated future price changes. The ratio of the response to a change in the expected next-period price to the response to a change in the current price will be exactly the net discount factor \( \beta \delta \). A different function of \( \beta \) and \( \delta \) can be estimated by comparing reactions to transitory and permanent price changes. Because the response to a permanent shock is the discounted response to a series of transitory shocks, the ratio of the responses will yield \( 1 + \beta \delta/(1 - \delta) \). These estimates can be combined to separate out each discount factor.

Next, I consider the effect of changes in the variance of the cigarette price distribution on smokers with different degrees of biases. Rational smokers will react to volatility because remaining unaddicted can be viewed as a “real option”. While an addict will be stuck hitting for high realized prices, a non-addict can always start hitting if prices are low. For example, if there is uncertainty about whether a large excise

\footnote{The use of budget tightness as an instrument is similar in spirit to the enacted-but-not-implemented taxes used by Gruber and Kőszegi (2000), as budget tightness proves to be a predictor of the enactment of new taxes.}

\footnote{In Section 5.3, I explore a departure from rational expectations that, while it can explain some features of the data, cannot account for the full set of results explained by the model of psychological biases.}

\footnote{This is also a feature explored in Becker, Grossman and Murphy (1994). In that more restrictive model, however, this ratio yields the single discount factor \( \delta \) rather than the net discount factor \( \beta \delta \). The authors note that “the estimates are not fully consistent with rational addiction, because the point estimates of the discount factor ... are implausibly low.” This paper will also estimate a low value for this ratio, but is able to interpret this as \( \beta < 1 \) rather than implausible long-run impatience.}
tax will be applied in the next period, there is value in remaining un-addicted until the uncertainty is
resolved. Because projection-biased agents do not appreciate how much current consumption affects their
future cravings, they will tend to underestimate the option value. As a result, they will under-respond to
changes in volatility relative to a rational or purely present-biased agent.

The data are presented in Section 3. To estimate consumers’ responses, I use repeated cross-sectional
data on self-reported smoking status and number of cigarettes from the National Health Interview Survey
for a large sample over a 26-year span. The individual-level data in the NHIS provides better identification
than the state aggregate sales data used in Becker, Grossman and Murphy (1994), and is more representative
than the National Vital Statistics Natality Data used in Gruber and K˝ oszegi (2001). It also allows me to
estimate responses separately for youth smokers and for mature smokers, as well as control for demographic
characteristics.

To estimate the prices facing smokers, I form metropolitan statistical area (MSA)-level price indexes.
These reflect an average of national, state, and local taxes faced within the MSA. In order to deal with the po-
tential endogeneity of both prices and future taxes with respect to current smoking rates, I use current taxes
and states’ budgetary tightness as an instrument for prices. Because most states have a balanced-budget
requirement, budget shortfalls necessitate revenue increases. “Sin taxes” may be a politically expedient way
to close a budget gap.¹³ Budget tightness proves to be a predictor of tobacco tax increases, and therefore
of price, in the following year. I also decompose prices into permanent components and transitory shocks
using taxes and agricultural variation in Kentucky burley tobacco—an important constituent of domestic
cigarettes.¹⁴ MSA fixed effects and a time trend are included in the decomposition.

I then test the above predictions empirically in Section 4. I find that smokers differ from the rational
model in ways that suggest both present bias and projection bias. Young smokers react to the current price
of cigarettes but have almost no response to future price changes. This contrasts with the finding for mature
smokers, who respond both to current and anticipated future prices. A 1% increase in the current price of
cigarettes lowers the probability of smoking between 1% and 2%, with the effect monotonically decreasing in
age. Examining the responses to permanent versus temporary price changes for mature smokers, I estimate
\[ \beta = 0.7 \] and \[ \delta = 0.89 \], suggesting that present bias is a significant factor in smoking behaviors. Finally,
there is strong evidence that price volatility per se increases the likelihood of smoking. A 1% increase in the
standard deviation of price increases the probability of smoking by 0.02 percentage points—approximately
one-tenth the effect of a direct 1% decrease in the current price level. One would expect a negative, or at least

¹³Gul and Pesendorfer (2007), for example, discuss a $0.61 increase in the Connecticut cigarette tax, which was “expected to
be used primarily to reduce the budget deficit.”

¹⁴Poor growing conditions in a given year will increase the price temporarily in a way that is uncorrelated either with demand
characteristics or with future prices.
much smaller, response from agents without projection bias. Further restrictions are needed, however, to estimate the $\alpha$ this implies. In Section 5, I linearize the addictive component of utility and make additional distributional assumptions about prices. With these additional assumptions, I estimate a degree of projection bias $\alpha \in [0.41, 0.49]$, meaning that people underestimate the changes in tastes caused by smoking behavior by approximately 40%.

I conclude in Section 6 by considering the welfare effects of the estimated degrees of bias. Whereas fully rational agents without credit constraints should care only about the lifetime costs of smoking, I find that manipulating the price path can “trick” a consumer into accepting an expensive lifelong addiction. Because of her impatience in early periods, a consumer will be tempted to smoke if prices start low and then increase sharply later—much in the way Shui and Ausubel (2004) find that consumers are drawn to credit cards with low “teaser rates”. Moreover, projection bias in later periods causes mature smokers to underappreciate the possibility of quitting. I estimate that a person with the estimated degrees of bias could be a lifetime smoker at a cost 2–3 times as great in present value as another price path that she would refuse. I also estimate that a corrective tax of between $8 and $11 would be needed for mature smokers to consume optimally. This tax does not include the effects of secondhand smoke or the effect of premature deaths on the government’s budget constraint, but focuses only on the intervention necessary to correct the over-consumption due to the psychological biases.

2 Model

2.1 General Setup

Following O’Donoghue and Rabin (2000)’s simplification of Becker and Murphy (1988), consider a setting with infinitely-lived agents who consume two goods in every period: an addictive good $a \in \{0, 1\}$ and a numeraire $y \in \mathbb{R}^+$. Consuming $a = 1$ is considered “hitting”, while consuming $a = 0$ is “refraining” from the addictive good. The utility derived from hitting or refraining depends on the accumulated “stock of addiction” $k \in \mathbb{R}^+$, with the initial taste for the addictive good drawn from some distribution $\kappa(\cdot)$.

I let the addictive stock evolve according to:

$$k_{t+1} = \begin{cases} \gamma k_t + 1, & \text{if } a_t = 1 \\ \gamma k_t, & \text{if } a_t = 0 \end{cases}$$  \hspace{1cm} (1)$$

15 Although smokers can indeed choose their nicotine consumption from a continuum of possible levels, formulating the problem as a binary choice captures the intuition that many smokers choose between smoking at a set level (e.g. a pack a day, half a pack a day, etc.) and quitting. Gruber and K˝ oszegi (2001) derive a model for present-biased agents that can choose a continuous quantity of the addictive good, and obtain qualitatively similar results.
The parameter $\gamma \in [0,1]$ thus captures how quickly the addictive stock evolves. For example, $\gamma = 0$ implies that a consumer is either completely addicted or completely unaddicted as a result of her behavior in the previous period. That is, consuming just once puts her in a fully addicted state, but she can become unaddicted again by refraining for just one period. Larger values of $\gamma$ capture a slower addiction process, where it takes time both to become addicted and to go through withdrawal.\footnote{Using just one parameter $\gamma$ to describe the process embeds a degree of symmetry in the processes of becoming addicted and becoming unaddicted. This assumption is not important for the results in this paper, and can be relaxed by assigning separate parameters to the cases where $a=1$ and where $a=0$. The assumption that the addictive stock decays geometrically, however, is standard in the literature.} The value of $\gamma$ will influence the magnitudes of how consumers react any particular shock to the price of the addictive good, but it will not affect the ratio of how they react to different shocks. It will also determine the maximum steady-state level of addiction: $k^{max} = \frac{1}{1-\gamma}$. For generality, I do not assume a specific value of $\gamma$.

The key features of the evolution of the addictive stock are that past consumption smoothly increases the current addiction level, past abstention decreases it, and that the effect is stronger for more recent past consumption. Alternative formulations that preserve these features will not substantively alter the model. Conversely, functional forms like $k_t = \max\{a_\tau|\tau < t\}$ that eliminate the possibility of becoming un-addicted would change many of the predictions of the model. Although one could think of many alternative forms, a geometric process has been used in the economics literature since Becker and Murphy (1988) and is used here for simplicity.\footnote{Becker and Murphy (1988) assume the stock of addictive capital, $S(t)$, evolves according to $\dot{S}(t) = c(t) - \delta S(t) - h[D(t)]$, where $c(t)$ is consumption and $D(t)$ is expenditures on endogenous depreciation. The model in this paper is identical if $h(\cdot) = 0$ and $(1-\delta) = \gamma$.}

To abstract away from the wealth effects from choosing to consume the addictive good, consumers’ instantaneous utility function is quasilinear in their consumption of the the numeraire $y_t$ and the addictive good $a_t$:

$$u_t(a_t, y_t|k_t) = \begin{cases} y_t + f_t(k_t), & \text{if } a_t = 1 \\ y_t + g_t(k_t), & \text{if } a_t = 0 \end{cases}$$

(2)

The functions $f_t(\cdot)$ and $g_t(\cdot)$ are continuously differentiable and, because this is a harmful good, I assume:\footnote{A negative first derivative stands in contrast to what can be considered positive addictive goods, such as exercise. Such goods would be underconsumed by the biased types in this model, rather than over-consumed. The set of consumption plans allowed under positive addictive goods, however, is inconsistent with the patterns observed in the data. More directly, the medical consensus is that the delayed health consequences of smoking are indeed negative (DHHS, 1982).}

$$f_t'(k) < 0 \ \forall \ t$$

$$g_t'(k) < 0 \ \forall \ t$$

(3)

The negative effect of past consumption thus comes indirectly through its effect on the current addictive
stock. Increased past consumption raises $k_t$, and therefore lowers current utility regardless of whether one hits or refrains today.

The second effect of past consumption on present utility comes through reinforcement—the more one has consumed in the past, the more tempting it is to hit today. Let the instantaneous temptation to hit be given by $h_t(k) = f_t(k) - g_t(k)$. Reinforcement requires that:

\[ h_t'(k) = f_t'(k) - g_t'(k) > 0 \quad \forall t \tag{4} \]

The exact functional form of $f_t(\cdot)$ and $g_t(\cdot)$ will, along with $\gamma$, determine the magnitude of consumer responses to price shocks. For now, I assume that $f(\cdot)$ and $g(\cdot)$ are each weakly convex.\(^\text{19}\) In Section 5, following O’Donoghue and Rabin (2000), I linearize these addiction functions.

Finally, assume that the price of the addictive good in period $t$ is $p_t$ and let the consumer’s disposable income in period $t$ be $Y_t$.\(^\text{20}\) Instantaneous utility can then be re-written only as a function of the addictive stock and the decision of whether to hit or refrain:\(^\text{21}\)

\[
    u_t(a_t | k_t) = \begin{cases} 
    [Y_t - p_t] + f_t(k_t), & \text{if } a_t = 1 \\
    Y_t + g_t(k_t), & \text{if } a_t = 0 
    \end{cases} \tag{5}
\]

The model assumes that all agents have perfect information about the health risks of smoking. It is possible that if there is significant heterogeneity in beliefs about the costs of smoking, differences in beliefs may lead to sorting: those with relatively positive beliefs about cigarettes choose to smoke and those with relatively negative beliefs refrain. It is unclear to what extent information drives smoking behaviors within the United States: while Cutler and Glaeser (2008) attribute almost half the difference in smoking rates between the US and Europe to differences in beliefs about the health effects of smoking, Khwaja et al. (2008) find that mature smokers in the US are either correct or too pessimistic about their health risks. While heterogeneity in beliefs may change the mean smoking rate and the absolute magnitude of price responses, it will not affect the ratios used for identification in this paper. A time trend is included in all regressions to control for any changes in information about smoking over time (or other secular changes in the attractiveness of smoking).

The preferences described above are general preferences over an addictive good, and say nothing about

\(^\text{19}\)This will understate the harm from smoking if $f(\cdot)$ and $g(\cdot)$ are concave, and will bias the results towards the rational case.

\(^\text{20}\)Assuming that spending on the numeraire is large relative to spending on the addictive good, one may interpret $Y_t$ as the portion of permanent income allocated to period $t$.

\(^\text{21}\)I assume that all agents know the functions $f_t(\cdot)$ and $g_t(\cdot)$. That is, smokers are aware of the health and welfare consequences of smoking. Previous studies suggest that this may be a reasonable approximation for most people (Viscusi 1990, Schoenbaum 1997, Khwaja, Silverman, Sloan and Wang 2008).
a consumer’s degree of rationality. The psychological biases introduced in the following section do not change the underlying instantaneous utility function, but rather represent systematic departures in how consumers maximize this utility. While the list is not exhaustive in the set of explanations it considers, I focus on projection bias and present bias as important examples. For example, I omit among others the “cue-triggered decision processes” of Berheim and Rangel (2004) and the preferences over choice sets of Gul and Pesendorfer (2007).

2.1.1 Rational Consumers

As Becker and Murphy (1988) show, there is no reason why a fully rational agent could never consume an addictive good. If the benefits are large enough, or the future costs sufficiently small, it may be utility-maximizing to hit. In this model, they will tend to do so whenever \( h_t(\cdot) \) is large or their initial addictive stock \( k_0 \) is large. Let the discount rate be given by \( \delta \). Formally, the fully rational consumer forms a period-\( t \) consumption plan

\[
\mathbf{a}_t = (a_t, a_{t+1}, a_{t+2}, \ldots)
\]

in order to:

\[
\max_{\mathbf{a}_t} U_t(k_t) = \sum_{\tau=t}^{\infty} \delta^{\tau-t} u_t(a_\tau | k_\tau)
\]

s.t. \( k_{\tau+1} = \gamma k_\tau + a_\tau \)

\[
Y_{\tau} - p_{\tau} a_{\tau} \geq 0
\]

That is, fully rational consumers form a consumption plan that maximizes their true utility subject to their budget constraint and the actual addictive process. Because fully rational consumers with perfect information about the addiction functions only consume the addictive good when the upfront benefits outweigh the future costs, they will be responsive to any anticipated future price shocks that affect the cost of future consumption.

2.1.2 Projection-Biased Consumers

Projection-biased consumers do not appreciate the degree to which their “state” in the future will differ from their current “state”. For example, Read and Van Leeuwen (1998) show that people who are currently hungry act as though their future selves will also be relatively hungry, and people who are currently sated

\[22\] While present bias and projection bias make firm predictions about how consumers react to different types of price shocks, other models are more ambiguous. Cue-triggered addiction or utility over choice sets do make predictions about other facets of behavior, but they will not be well-identified using the approach of this paper.

\[23\] This forward-looking behavior has been used to test the rational model against the alternative model of complete myopia (Becker and Murphy (1988), Becker, Grossman and Murphy (1991)). However, both types of biased consumers presented herein will also display forward-looking behavior in many circumstances. The tests in Section 4 are designed to distinguish between these alternative models.
behave as though their future selves will also be relatively sated. Similar effects have been shown for the “endowment effect” (Loewenstein and Adler 1995), sexual arousal (Ariely and Loewenstein 2005), weather and catalog orders (Conlin, O’Donoghue and Vogelsang 2007), adaptation to changing life circumstances (Gilbert, Pinel, Wilson, Blumberg and Wheatley 1998, Loewenstein and Frederick 1997), and, indeed, drug addiction (Giordano et al. 2002).

Projection bias may be very important in the consumption of additive goods if people do not appreciate the degree to which they will become addicted, or conversely if addicts do not appreciate that they can become un-addicted. In either case, the effect of projection bias will be to increase consumption relative to the perfectly rational case. It may also introduce some time-inconsistencies between her plans and her behavior, if future selves find themselves experiencing an unexpectedly strong addiction.

Following Loewenstein, O’Donoghue and Rabin (2003), a projection-biased agent believes her future utility will be a weighted sum of her actual future utility and her utility if she remained in her current state. The weight she places on the incorrect term, \( \alpha \), indexes the degree of the bias. She then forms a period-\( t \) consumption plan \( \tilde{a}_t \) in order to maximize her (incorrect) assessment of her lifetime utility:

\[
\max_{\tilde{a}_t} \tilde{U}_t(k_t) = u(\tilde{a}_t|k_t) + \sum_{\tau=t+1}^{\infty} \delta^{\tau-t} \left[ (1 - \alpha)u(\tilde{a}_\tau|\tilde{k}_\tau) + \alpha u(\tilde{a}_\tau|k_t) \right]
\]

\[
s.t. \quad \tilde{k}_{\tau+1} = \gamma \tilde{k}_\tau + \tilde{a}_\tau \\
Y_\tau - p_\tau \tilde{a}_\tau \geq 0
\]

The projection-biased consumer then consumes the first component of her plan in the current period. In the next period, however, she re-optimizes according to (7) and may form a very different plan.

This formulation of projection bias is different from other forms of ignorance about the addictive process. A projection-biased person has the correct model of \( f(k) \) and \( g(k) \), just as a sated person knows what it feels like to be hungry or an unaroused person knows what it feels like to be sexually aroused. The mistake is strictly about the evolution of their state \( k \)—they believe it will not differ as much from their current state as it truly will. One key difference between this model of projection bias and simply overestimating \( f'(k) \), for example, is that projection bias leads both addicts and non-addicts to over-consume. An addict who hit due to an early mistake about \( f'(k) \), but who did not suffer projection bias, would not make mistakes in her consumption going forward.

\[24 \text{ Alternatively, one could imagine projection-biased people making a mistake directly about } \tilde{k}_\tau \text{ of the form } \tilde{k}_\tau = (1 - \alpha)\tilde{k}_\tau + \alpha k_t, \text{ and then believing their future utility to be } u(\tilde{a}_\tau|\tilde{k}_\tau). \text{ If } f(\cdot) \text{ and } g(\cdot) \text{ are linear, this approach is identical to the one used in this paper.} \]
2.1.3 Present-Biased Consumers

Consumers with present bias are impatient—they value consumption in the present at a premium to any delayed consumption. This taste for immediate gratification has been identified in a range of contexts, from long-term savings behaviors by Angeletos, Laibson, Repetto, Tobacman and Weinberg (2001) to caloric intake by Shapiro (2005). An overview of the literature is provided in DellaVigna (2009). Following the formulation of Laibson (1997), the degree of present bias is captured by an extra discount factor $\beta < 1$ applied uniformly to all future periods. As a consequence of this short-run impatience, present bias generates time-inconsistency. For example, because she is patient about long-run decisions, a consumer in period 1 may prefer having her period-2 self refrain from smoking. When period 2 arrives, however, she is now trading off long-run costs against instantaneous benefits and may be tempted to hit. O’Donoghue and Rabin (2000) and Gruber and Kőszegi (2001) show that present bias can lead biased consumers to greatly overconsume the addictive good, at a substantial welfare loss. Present-biased consumers can be divided into two categories based on whether they are aware that their future selves will also be present-biased: naifs are unaware of this fact, while sophisticates are aware of it.

A naive present-biased agent has $\beta < 1$, but does not recognize that her future selves will also be impatient—following O’Donoghue and Rabin (1999a), she believes that $\beta = 1$ for all future selves. The problem for a naive present-biased agent is then to form a consumption plan $\hat{a}_t$ in order to maximize her current self’s lifetime discounted utility, since she does not realize her time-inconsistency. That is, because she believes her future selves will not feel impatient in the way she does, she believes they will behave in a manner consistent with the plans she forms today. She therefore performs the simple optimization given here, and forms the plan $\hat{a}_t$. Her maximization problem is:

$$\max_{\hat{a}_t} \hat{U}_t(k_t) = u_t(\hat{a}_t|k_t) + \beta \sum_{\tau=t+1}^{\infty} \delta^{\tau-t} u(\hat{a}_\tau|\hat{k}_\tau) \quad (8)$$

$$s.t. \quad \hat{k}_{\tau+1} = \gamma \hat{k}_\tau + \hat{a}_\tau$$

$$Y_\tau - p_\tau \hat{a}_\tau \geq 0$$

Having formed $\hat{a}_t$, the naive present-biased consumer does consume the first component, $a_t$, in the current period. In the next period, however, she forms a new plan according to (8) which may differ from her plan at time $t$. For example, she may expect to hit today when she is impatient but refrain in all future periods when she thinks she will be patient. In the next period, however, she finds that $\beta < 1$, and hits again. This naivete about present bias may therefore lead a consumer always to think she is going to quit, but procrastinate forever in doing so.
Sophisticates are aware of their taste for immediate gratification—and that future selves will also have such a taste—and therefore must play a subgame-perfect Nash equilibrium with their future selves. Their maximization problem is therefore the same as that of a naive present-biased consumer, but with the additional constraint that future consumption in each period $\tau$ must be optimal from self $\tau$’s point of view. The sophisticate forms a plan $\hat{a}_t = (\hat{a}_t, \hat{a}_{t+1}, \ldots)$ and chooses $\hat{a}_t$ in order to maximize:

$$
\max_{\hat{a}_t} \hat{U}_t(\hat{a}_t|k_t) = u_t(\hat{a}_t|k_t) + \beta \sum_{\tau=t+1}^{\infty} \delta^{\tau-t} u(\hat{a}_\tau|k_\tau)
$$

subject to:

$$
\hat{k}_{\tau+1} = \gamma \hat{k}_\tau + \hat{a}_\tau
$$

$$
Y_\tau - p_\tau \hat{a}_\tau \geq 0
$$

$$
\hat{a}_\tau = 1 \iff h_\tau(\hat{k}_\tau) \geq \beta \delta \left[ \hat{U}_{\tau+1}(\hat{a}_{\tau+1}|\gamma \hat{k}_{\tau}) - \hat{U}_{\tau+1}(\hat{a}_{\tau+1}|\gamma \hat{k}_{\tau+1} + 1) \right] \quad \forall \tau > t
$$

where $\hat{a}_\tau = (\hat{a}_\tau, \hat{a}_{\tau+1}, \ldots) \forall \tau \geq t$.

The solution to this problem is sensitive to the parameters of the model. On the one hand, if sophisticates realize that their future selves will eventually start consuming regardless of their current behavior (as they would with any finite horizon), this sense of “inevitability” makes them more likely to begin their habit today. On the other hand, if they believe that they can overcome their future selves’ impatience by refraining today, there is a strong “incentive effect” to do so. In general, one cannot state which effect will dominate. The apparent myopia of young smokers, combined with the requirement that sophisticates have rational expectations, will ultimately rule out sophisticates except for the knife-edge case where this incentive effect exactly counterbalances the direct effect of a price increase on average.

One can form some comparative statics for sophisticates—for example, O’Donoghue and Rabin (2000) show that the addition of “youthful preferences” of the sort in Section 2.2 can cause a sophisticate to switch from always refraining to always hitting only when it would also cause a naif to make the same switch. Unfortunately, this highlights the fact that sophisticates in this model will not be separately identified from fully-rational and naive present-biased agents. In some instances (e.g. when they believe they are consuming only for a short duration), they will behave like fully rational consumers. In others (e.g. when they believe they will consume always), they will behave like their naive counterparts. Because without additional parametric assumptions it is impossible to predict when they will behave like each type, I focus only on rational consumers, or naive consumers experiencing projection- and present-bias.\footnote{The difficulties in making firm predictions for sophisticated present-biased agents are two-fold. First, there may be multiple equilibria in the infinite-period model described here. In general, the substantive predictions will be similar across the multiple equilibria. For example, in models of procrastination such as those in O’Donoghue and Rabin (1999a), sophisticated agents may delay doing a task for a brief number of periods but never for very long. Moreover, the equilibria of this game will be generically unique if one moves from an infinite horizon to a finite time horizon.}
2.2 Consumption Plans Under “Youthful Preferences”

Without further structure on $u_t(a_t | k_t)$, the model does not yield a closed-form solution for consumers’ plans. Moreover, any observed behavior could be reconciled with any type of consumer. In order to derive testable predictions, then, we make two assumptions:

**Assumption 1 (Separability)** $\exists x = \{x_1, x_2, \ldots\}, f(k), g(k)$ s.t.

\[
\begin{align*}
    f_t(k) &= x_t + f(k) \quad \forall t \\
    g_t(k) &= g(k) \quad \forall t
\end{align*}
\]

This assumption implies that a consumer’s utility is determined partly by a time-independent component which depends only on her addictive state, and partly by a purely instantaneous incentive to hit. The non-addictive component is normalized to zero for the case where she refrains. The time-independent component is meant to largely capture the biological and psychological process of addiction. $x_t$ captures any external incentives to hit (e.g. peer pressure) as well as any other changes in the enjoyment of the addictive good across ages.

This assumption implies that the instantaneous incentive to hit at age $t$ can be re-written as $h_t(k) = x_t + h(k)$ or alternatively that $\frac{\partial^2 h_t}{\partial k \partial t} = 0$. That is, while consumers at different points in the life-cycle may certainly find hitting more or less tempting, the degree to which this temptation grows for more addicted consumers does not depend on age.

**Assumption 2 (Nondecaying Youthful Preferences)** $\exists m, x$ s.t.

\[
x_1 = x_2 = \ldots = x_m = x \geq 0; \quad x_{m+1} = x_{m+2} = \ldots = 0
\]

The second difficulty for sophisticated agents is that their comparative statics are much harder to predict. In general, they will be “well-behaved” in the manner described later for other types of agents. However, they may sometimes behave in counterintuitive ways. Consider, for example, the following example. Agents live for 3 periods, and may “hit” or “refrain” in periods 1 and 2, and hits if indifferent. Everyone refrains in period 3. Utility is defined as above, such that $f_t(k) = x_t - \rho k$ and $g_t(k) = -\sigma k$. Let $p_1 = p_2 = 0$, $x_1 = 1.2$, $x_2 = 0$, $x_3 = 0$, $\gamma = 0$, $\delta = 1$, $\beta = \frac{1}{2}$, $\rho = 1$, $\sigma = 2$ and consider the effects of applying a tax $\tau = 1$ in period 2. A naive consumer will hit in the first period with or without the tax—she does not expect to smoke in period 2 in either case. Without the tax, the sophisticate believes she will smoke in period 2 only if she smokes in period 1. She therefore refrains without the tax in order to give her future self an incentive to refrain as well. With the tax, however, she realizes that her period-2 self will refrain no matter what, and therefore chooses to smoke in period 1. Increasing the future price can therefore actually raise smoking for sophisticates, if it acts as a control device for their future selves.

Consider any plan $a$. It can be rationalized easily by setting $h_t(\cdot) = +\infty$ in any period in which $a_t = 1$ and $h_t(\cdot) = -\infty$ in any period in which the consumer abstains. Less extreme changes in $h_t(\cdot)$ could also generate the same pattern, while keeping consumers’ price sensitivity intact.


Although there is some evidence that the effects of nicotine withdrawal may differ over time, there is no conclusive evidence for how these changes occur or the magnitudes of the effects. For example, Wilmouth and Spear (1998) find that adolescent rats suffer more from cognitive disruption effects during withdrawal and adult rats suffer more from anxiety-like symptoms. It is unclear how this could be translated into utility measures.
The youthful-preferences assumption is meant to capture the social pressures, physiological differences, and other reasons why it may be quite tempting for a teen to experiment with a first cigarette, but that an unaddicted 40-year-old would have no desire to do so.\textsuperscript{29} This version of the youthful preferences assumption is the simplest way to capture that the addictive good is initially very tempting due to external influences, but is not tempting later.\textsuperscript{30}

If one alternatively found that $x < 0$, one would have a good that is not very tempting initially but that older consumers enjoy (e.g. scotch). If this were the case, however, one would expect to see very few consumers starting a consumption habit when young, and then initiating once reaching maturity. Neither an intuitive assessment of cigarettes nor the empirical hazard rates of initiation (shown in Figure 3) correspond to this story. Consumers may of course still differ on their values for $m$ and $x$. Indeed it is this heterogeneity, along with differences in the initial addictive state $k_0$, that allows the model to account for differences in starting and quitting behavior across individuals.

The general maximization problem for a consumer with discount rate $\delta$, degree of present bias $\beta$, degree of projection bias $\alpha$, and period-$t$ addiction level $k_t$ is then:

$$\max_{\tilde{a}_t} \tilde{U}_t(k_t) = u(\tilde{a}_t|k_t) + \beta \sum_{\tau=t+1}^{\infty} \delta^{\tau-t} \left[ (1 - \alpha)u(\tilde{a}_\tau|\bar{k}_\tau) + \alpha u(\tilde{a}_\tau|k_t) \right]$$

$s.t. \quad \bar{k}_{t+1} = \gamma \bar{k}_t + \tilde{a}_t$

$$Y_\tau - p_\tau \tilde{a}_\tau \geq 0$$

Lemma 1 establishes that in the current period, all three types of consumers follow a cutoff strategy. That is, given the price path, they will consume if and only if their current addictive state is above a certain threshold.

**Lemma 1** Given $x$, $m$, and $p$, and let a strategy $a(k, t)$ denote consumption in any period $t$ as a function of the addiction level $k$:

1. There is a unique strategy $A(k, t)$ that is optimal from self-$t$’s perspective
2. The optimal strategy follows a cutoff rule: $A(k, t) = 1$ if and only if $k > \bar{k}_t$
3. $\bar{k}_1 \leq \bar{k}_2 \leq \ldots \leq \bar{k}_m = \bar{k}_{m+1} = \ldots$, and $x > 0 \Rightarrow \bar{k}_m < \bar{k}_{m+1}$.

\textsuperscript{29}Alternatively, one could interpret $x_t$ as representing “divorce, unemployment, death of a loved one, and other stressful events” that Becker and Murphy (1988) believe “stimulate the demand for addictive goods”.

\textsuperscript{30}The “youthful preferences” discussed in O’Donoghue and Rabin (2000) simply require $x_t \geq x_{t+1}$ if $t < m$, and $x_t = x_{t+1}$ if $t \geq m$. Some structure on $\{x_t\}_{t=1}^{\infty}$ is necessary for identification. A more relaxed assumption than Assumption 2 is to restrict the magnitude of $|x_t - x_{t+1}|$, $t \leq m - 1$. Using this in place of nondecaying youthful preferences will not change the overall pattern of predictions, but will expand the number of cases in Lemma 2, as consumers may heterogeneously plan to consume until some intermediate date $s \leq m$. 

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Because of the pattern the addiction threshold follows, rational or projection-biased consumer may only expect to consume never, to consume always, or to consume only until maturity. With the addition of present-bias, people may form any of these plans or may plan only on yielding to temptation today and refraining in the future. Consider a consumer after date m, when the problem becomes stationary. Whereas rational consumers realize that consuming today will increase their temptation to consume tomorrow and projection-biased consumers believe that tomorrow’s problem will be identical to today’s (and therefore must believe that if they find it optimal to hit today, they will also find it optimal to hit tomorrow), a naive present-biased consumer may believe that the slight increase in her temptation to hit will be undone by the disappearance of $\beta$ starting tomorrow. She may thus believe that today is the last time she will hit, and that she will virtuously refrain starting tomorrow.

For all of these plans, a positive shock to the price of the addictive good in a period in which the consumer expects to hit will lower the utility of consumption, and hence the consumer will only consume at higher levels of addiction. The magnitude of this change in the cutoff level of addiction depends on the specific functional form of the utility function. However, the ratios of the responses to price changes at different times depend only on the discount rate. Lemma 2 establishes the relationships between the reactions of consumers to different sorts of potential price shocks.

**Lemma 2** Suppose $p_t = \bar{p}$ for all $t$, $m > 1$, and $\bar{k} \in (0, k^{\text{max}})$.

1. If a consumer plans to consume today and in all future periods, then:

$$\frac{d\bar{k}_1}{dp_\tau} = \beta \delta^{\tau-1} \quad \text{and} \quad \frac{d\bar{k}_1}{dp_1} = \frac{1 - (1 - \beta)\delta}{1 - \delta}$$

2. If a consumer plans to consume today and until date $m$ but refrain thereafter, then:

$$\frac{d\bar{k}_1}{dp_\tau} = \begin{cases} 
0 & \tau > m \\
\beta \delta^{\tau-1} & \tau \leq m
\end{cases} \quad \text{and} \quad \frac{d\bar{k}_1}{dp_1} = 1 + \frac{\beta \delta (1 - \delta^{m-1})}{1 - \delta}$$

3. If a consumer plans to consume today and refrain thereafter, then:

$$\frac{d\bar{k}_1}{dp_\tau} = 0 \quad \text{and} \quad \frac{d\bar{k}_1}{dp_1} = 1$$

Consider a marginal smoker with $\beta = 1$, so if she believes she will hit in all periods she will discount a shock to the price in period $t+1$ relative to a shock in period $t$ by a factor of $\delta$. Because a permanent price shock is equivalent to a temporary price shock in all periods, her response is just the sum of the responses
to a series of instantaneous shocks: \(1/(1 - \delta)\). If she believes she will only hit until maturity, then she will respond in exactly the same way to shocks in periods in which she expects to be hitting, and ignore shocks in periods in which she does not expect to be hitting.

A naive present-biased agent reacts very similarly to the rational agent in most cases, except that her response to all shocks in the future is discounted by an additional factor of \(\beta\). Part (3) of Lemma 2 further allows that she may expect to hit only in the current period. In that case, she ignores all future price shocks and reacts equally to a temporary and to a permanent shock.

A projection-biased agent forms the same set of plans as the rational agent. The key difference, however, is that projection-biased people may not follow through on their plans later. That is, a projection-biased agent may believe she will only smoke until maturity and therefore ignore any price shocks after date \(m\), even though she may also then wind up continuing to smoke forever. Because a rational agent’s plans coincide with her actual consumption, she can only ignore those prices which truly will not affect her. Thus two consumers whose observed consumption history is identical may nonetheless differ in their response to price shocks.

Moreover, because consumption plans may depend on whether a consumer is mature—that is, whether \(t > m\)—Lemma 2 has different implications for youth smokers and adult smokers. It is therefore possible to distinguish between fully rational young smokers and biased ones using their future-price responses:

**Proposition 1** Let \(\pi(p|X)\) be the probability of being a smoker as a function of the price path and a vector of individual characteristics.

1. If young smokers are fully rational and expect to smoke in the next period, then \(\frac{\partial \pi}{\partial p_t} + \frac{\partial \pi}{\partial p_{t+1}} = \delta > 0\)

2. If young smokers are (naive) present-biased or projection-biased, then \(\frac{\partial \pi}{\partial p_t} \in \{0, \delta, \beta \delta\}\)

That is, forward-looking behavior is consistent with either rational or biased agents, while myopic behavior is only consistent with biased agents.\(^{31}\)

Using self reports not only of current smoking status but also of the age of smoking initiation and cessation, it is possible to estimate hazard rates of smoking. Although this data is not available in all years, Figure 3 plots the results from the 1987 NHIS. The overall quitting hazard rate is very low—below 2% through the first 20 years of a consumption spell. In order for young, fully-rational smokers to expect on average that they will only smoke during the current year, the quitting hazard in the first several years of a smoking spell would necessarily be much greater. Because rational agents must have correct beliefs on average, this is taken as evidence that rational teen smokers must expect to smoke in the future as well.

\(^{31}\)Provided that \(\delta > 0\). There is some evidence that teenagers do have a finite discount rate.
Older smokers, because they are past date $m$, are restricted in the consumption plans they can form. In particular, both fully rational and projection-biased smokers may only believe they will consume forever or consume never. Present-biased smokers may form either of these plans, or may additionally believe they will consume only in the current period.\footnote{Hammar and Carlsson (2005) find in a survey of mature smokers that only “5\% of the respondents stated that it is very likely that they will quit smoking.”}

Lemma 2 established how mature smokers will react to anticipated future price changes relative to current price changes, and to permanent changes relative to temporary changes. These two predictions allow for $\beta$ and $\delta$ to be separately identified:

**Proposition 2** Let $\pi(p|X)$ be the probability of being a smoker, and let the price be the sum of a permanent component and a transitory shock: $p_t = p_t^P + p_t^T$. Define $d = \frac{\partial \pi_t/\partial p_{t\mid t}}{\partial \pi_t/\partial p_t}$.

1. If mature smokers are not present biased, then $d = \delta$ and $\frac{\partial \pi_t/\partial p_t^P}{\partial \pi_t/\partial p_t} = \frac{1}{1-d}

2. If mature smokers are present biased, then $d = \beta \delta$, and $\frac{\partial \pi_t/\partial p_t^P}{\partial \pi_t/\partial p_t} = \frac{1-(1-\beta)\delta}{1-\delta} > \frac{1}{1-d}

Because present-biased consumers will somewhat over-react to temporary shocks relative to permanent ones, but greatly over-react to current shocks relative to delayed ones, Proposition 2 enables one to estimate the degree of present bias.

### 2.3 Effects of Price Volatility

The preceding analysis assumes that consumers have a single prediction for the price in the future. When consumers have a probability distribution over future prices, the main analysis is unchanged. Although the overall attractiveness of smoking may decrease, the ratios of elasticities calculated do not change. The following section analyzes how smokers will respond to different levels of volatility.

For the following analysis, consider only a two-period model. This is necessary for tractability, as agents can form consumption plans that are conditional not only on the current price, but on the entire history of prices that has occurred at time $t$. Unlike in the world with single expectations of prices, consumers explicitly considering uncertainty can rationally form plans other than “consume never” or “consume always” by setting period-specific conditional cutoffs. Reducing the number of periods to two clearly avoids complicated plans, and conveys the basic result.

Now let $p_t = \bar{p}_t + \nu_t$, with $\nu_t \sim i.i.d. N(0, s^2)$. That is, the current price in all periods varies independently about a known mean. The assumption of a normal error term is not important, except inasmuch as it
guarantees a nonzero support at all levels of addiction for the initiation decision.\footnote{We make the technical assumption that \( \bar{p} \) and \( s \) are such that \( \frac{d\Phi((x_k + h)(x_k))}{ds} < 0 \). If this assumption is not met, the predictions for projection-biased agents are unchanged. The predictions for rational agents, however, become ambiguous.} The following Lemma establishes the effect of changing the price volatility \( s^2 \) on different types of consumers.

**Lemma 3** Let \( p_t = \bar{p}_t + \nu_t \), with \( \nu_t \sim i.i.d. N(0, s^2) \) and \( t \in \{1, 2\} \). Let \( \pi(p|X, s^2) \) denote the probability the consumer hits in period 1. If the period-1 addiction level is fixed at \( k_1 \), then:

1. \( \exists d \) s.t. if \( \beta \delta > d \) and \( \alpha = 0 \), \( \frac{d\pi}{ds^2} < 0 \).
2. If the consumer is fully projection biased \( (\alpha = 1) \), \( \frac{d\pi}{ds^2} > 0 \).
3. If the consumer is partially projection biased \( (\alpha \in (0, 1)) \), \( \frac{d^2\pi}{ds^2d\alpha} > 0 \).

Lemma 3 states that for fully rational people, increasing the volatility of prices decreases the attractiveness of consuming the addictive good. They realize that their current choice will influence their future selves’ incentives to hit or refrain. If tomorrow’s realized price turns out to be exceptionally low, they can hit whether they are unaddicted or addicted. If the realized price turns out to be very high (and the addiction is strong enough), the consumer will hit only if they are in an addicted state. Because of this, refraining today in a volatile price environment has a real option value—the consumer can always choose to become addicted later on. Because the value of this option is increasing in the volatility of the price, rational consumers will lower their threshold price for smoking as the price volatility increases.

Present-biased people will also react by lowering their threshold price for consumption today, but to a lesser degree. In particular, their response will be \( \beta \) times the response of a fully-rational consumer. As long as \( \beta \) and \( \delta \) are sufficiently high, they value the option enough that they lower their threshold sufficiently to overcome the increased probability of extremely low prices being realized.\footnote{If instead an agent were extremely impatient and had \( \beta = 0 \), they would not lower their price threshold at all and would resemble the projection-biased agent.}

Fully projection-biased people do not realize the effect that today’s decision has on tomorrow’s incentives. As such, they do not adjust the cutoff price for hitting today. Increased price volatility increases the probability that today’s price realization falls beneath their threshold, and that they choose to hit. In this sense they are “fooled” into consuming—they believe they are just taking advantage of particularly low prices and do not realize the effect they are having on their future self. Partial projection bias may look like either type, with their reaction becoming monotonically more positive as \( \alpha \) increases to 1.
3 Data

3.1 Smoking Outcomes

All outcomes on smoking behavior are drawn from the National Health Interview Survey (NHIS) between 1965 and 1991. The NHIS is a large, national, repeated cross-sectional survey which in 15 years during this time included questions on smoking behaviors.\textsuperscript{35} The smoking questions were included either in the core set of questions or in various supplements. Specific questions include current cigarette consumption and past consumption, as well as broader questions such as “Have you ever smoked 100 cigarettes over your lifetime?” Despite the potential for some under-reporting, validation studies have found interview questions on smoking to be generally reliable (Patrick et al., 1994).

In addition to smoking outcomes, the NHIS provides an array of broad demographic, economic, and health-related data. Education and other socioeconomic factors are known to correlate with smoking behaviors, and are used as controls in all regressions.\textsuperscript{36} Respondents in the survey are classified into 31 large metropolitan statistical areas (as defined by the Bureau of the Census) or as other. Only the urban sample is used.

Table 1 presents summary statistics for the full urban sample, and separately by smoking status. Smoking status is defined by the current number of cigarettes consumed daily, with any positive number being considered a smoker. There is no difference in the average age of smokers and nonsmokers, although the higher standard deviation of nonsmokers’ age reflects some differences in composition of the groups: both young people and the elderly are more likely to be nonsmokers. Nonsmokers are slightly more likely to be female and slightly less likely to be black. Differences in education status also reflect the age compositions of the two groups. Regressions of smoking status on the demographic controls are presented in Appendix Table A-2, and confirm the pattern seen in the means: smoking correlates positively with age and non-white race groups, and correlates negatively with age\textsuperscript{2}, female, and high levels of education.

Among smokers in the sample, the average number of cigarettes smoked is 18.79—just under a pack a day. This figure may not be directly comparable to more recent data, as the mean number of cigarettes per smoker has fallen considerably in recent years. According to the CDC, the mean daily cigarettes per smoker was just under 20 prior to 1995, but had fallen to 13.9 by 2006.\textsuperscript{37}

\textsuperscript{36}For example, Townsend, Roderick and Cooper (1994) and Kenkel, Lillard and Mathios (2006) find that smoking behaviors and cigarette price elasticities vary by age, education, and income groups. Arnold et al. (2001), however, find that even though the perceived health risks of smoking are correlated with reading level among low-income women, actual smoking rates are not.
3.2 Price Measures

Price data on cigarettes are taken from the Tobacco Tax Council’s “The Tax Burden on Tobacco”, which contains annual state-average cigarette prices and taxes. The prices and taxes are collected in November of each year, and because the analysis in this paper relies on changes in prices rather than levels, no seasonal adjustment is performed. Taxes are a statewide average of federal, state, and local excise taxes. Prices and taxes are then translated into real terms using CPI data from the Bureau of Labor Statistics.

Figures 1 and 2 show real prices and nominal taxes over time, by Metropolitan Statistical Area. Changes in nominal taxes are lumpy in general and, although there is substantial variation in the timing between MSAs, tended not to occur during the 1970s. Because taxes are a large component of the retail price, this creates a U-shaped pattern in the real price. During the 1970s, high inflation and few tax increases actually caused the real price of cigarettes to fall. The real price during the 1980s and 1990s then rose largely due to a combination of lower inflation and more tax increases.

Ideally, one would want to know the exact price faced by every individual in the NHIS sample. Even knowing the average prices and taxes in the exact jurisdiction where an individual lives, however, would not be sufficient for calculating the effective price they face. Not only may they purchase their cigarettes in a nearby jurisdiction, the exact location at which they purchase (e.g. convenience store, gas station, etc.) and the quantities they buy at one time (i.e. by carton or by pack) will generate substantial heterogeneity in their effective price.\footnote{It is also possible that teen smokers rely on friends or parents for their cigarettes, and therefore do not face any price at all. Cummings, Sciandra, Pechacek, Orlandi and Lynn (1992), however, find that 88% of regular teen smokers usually purchase their own cigarettes.}

An individualized price is neither reported in the NHIS nor calculable from any potential data. Instead, I assign to each individual the average price and taxes for her MSA of residence. These averages are calculated as follows. The state average price and tax level is first assigned to each county in a MSA. The MSA price level is then the average (weighted by population) of all prices of its constituent counties. For a MSA located entirely within one state, this simply returns the state average. For MSAs comprising more than one state, it will be a mixture of these states. This reflects the fact that a smoker in Washington, DC may be affected not only by DC prices but by those in Maryland and Virginia. It also makes my price measure more robust to the short-distance smuggling discussed in Becker, Grossman and Murphy (1994) and Gruber and K˝oszegi (2000).

It will be useful to decompose the price level into a permanent component and a transitory shock—that is, to rewrite $p_t = p^T_t + p^P_t$. To do this, I observe that tobacco is an agricultural product and hence is dependent on the growing conditions of that particular year. Rainfall, the length of the growing season, and
other growing conditions affect the quality (as defined by the United States Department of Agriculture) of the tobacco crop, and are not correlated across years. Moreover, the amount of land eligible for tobacco farming is tightly regulated under two New Deal-era laws: the Agricultural Adjustment Act of 1933 and the Agricultural Adjustment Act of 1938.\footnote{Chaloupka and Warner (2000) provide an overview of the U.S. tobacco agriculture regulatory system.} As a summary statistic of a year’s growing conditions, I use the spot market price of Kentucky Burley tobacco, as reported by the United States Department of Agriculture Consumer and Marketing Service, Tobacco Division (1970–1990). Kentucky Burley tobacco proves to be a predictor of the current year’s price, but not future prices (see Appendix Table A-3.).

4 Results

4.1 Young Smokers

To test Proposition 1, I estimate the probability of young respondents being a current smoker. In order to control for potential differences across time and across metropolitan areas, the regressions include year dummies and MSA-specific time trends.\footnote{Because prices are measured at the year-by-MSA level, it is not possible to separately include year-by-MSA dummies.} A vector of individual controls is also included, comprising age, age$^2$, race, and education.\footnote{Much of the identification strategy of this paper relies on the fact that age is more than just a control. It is exactly the separation of smokers into “young” and “mature” categories that allows me to distinguish the various possible biases. However, after including dummies for this purpose, I leave in age as a control for other possible unobservables. Regressions that exclude age and age$^2$ as controls (available on request) yield virtually identical coefficients on regressors of interest.} The estimation equation is given by

$$\Pr(\text{smoker} = 1) = \theta_1 \cdot price_{jt} + \theta_2 \cdot price_{j(t+1)} + \theta_3 \cdot X_{it} + \lambda_j + \phi_j \cdot year_t + \eta_t + \epsilon_{ijt}$$  \hspace{1cm} (11)$$

where the left-hand side variable is the probability of being a smoker for an individual $i$, in metropolitan area $j$, in year $t$. Note that Proposition 1 implies a one-sided test, and does not allow for the future-price elasticity to exceed the current-price elasticity.

The prices in an MSA, however, may be endogenous. In particular, they may depend on smoking rates among youths. Although young smokers represent only a fraction of the entire market (and behave quite differently from the majority of their co-consumers), they represent a very important sub-market from the perspective of tobacco companies.\footnote{Because nicotine is addictive, it is in the interests of tobacco companies to get their customers “hooked” when they are young. According to the Department of Health and Human Services, 90% of all adult smokers began smoking when they were teens. (Department of Health and Human Services 1994)} Facing a drop-off of teen smoking, tobacco companies may lower prices temporarily in order to attract new customers. State legislatures may also raise taxes (an important
component of the variation in tobacco prices) in response to an increase in teen smoking, so future taxes may also be endogenous.

To alleviate this problem, I instrument for prices with current taxes and the tightness of state budgets as measured by the percentage gap between general fund expenditures and general fund revenues. According to the General accounting office, 48 states have balanced-budget requirements.\textsuperscript{43} Whereas midyear budget gaps are primarily closed through spending cuts and other “one-time actions”, gaps prior to the enactment of a budget are largely closed through revenue increases. A budget shortfall can thus predict increases in all taxes in the following year. Sin taxes in particular may be a politically expedient way of closing budget gaps. Although tobacco taxes may be raised for other reasons, this instrument relies only on the variation generated by budgetary necessity.\textsuperscript{44}

The results of this estimation are shown in Table 2.\textsuperscript{45} The main specification is in column (iv). This specification confines the analysis to smokers under the age of 20. Future price is instrumented using current taxes and the average percentage budget gap for the states comprising the MSA, with the results of this first-stage presented in Panel C. The impression given is one of near-complete myopia. The coefficient on $\ln(price_t)$ is highly significant, and highly negative at $-1.363$, suggesting that smokers in their later teens are highly price-sensitive. Even more importantly, the coefficient on the next year’s price, $\ln(price_{t+1})$, is both small and insignificant. That is to say that although very young smokers react to current price, they do not react to future prices. This is consistent with either the projection bias or present bias models, but not with the rational model.\textsuperscript{46}

Columns (iv) and (v) present something of a robustness check on this result by defining the cutoff for being a "young" smoker at 25 and 30, respectively. Several clear patterns emerge. First, the magnitude of current-price sensitivity is monotonically decreasing in the cutoff. More importantly, the coefficient on future price is increasing in magnitude, and strongly significant when both groups of older smokers are included. This suggests that the seeming myopia of teenage smokers is not permanent, and is consistent with smokers moving to a regime where they expect to smoke forever as the level of their addiction deepens. The ratio of the future-price response to the current-price response is therefore also increasing across the specifications. The null hypothesis that this ratio equals zero is equivalent to saying that teens do not react to future prices.

\textsuperscript{43}(General Accounting Office 1993). The exceptions are Vermont and Wyoming.

\textsuperscript{44}By instrumenting the future price with current-period observables, I also alleviate the problem caused by the fact that actual future price is a noisy measurement of expected future price. If expectations are on average correct, and the error in the first-stage is independent of the error in expectations and the second-stage error term, then this will solve the errors-in-variables problem.

\textsuperscript{45}Standard errors are robust and clustered by MSA. Appendix Table A-4 shows several alternative specifications, which the main results appear robust to.

\textsuperscript{46}While this is prima facie evidence of consumer biases, the range of parameters consistent with this result is not identified from this test alone. One therefore cannot yet suggest whether the necessary degree of projection bias or present bias is “plausible”.

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This ratio is not significantly different from zero for teenage smokers, but is significantly greater than zero for both older groups. While teen smokers’ myopia could be rational if the future price is fully unknown, columns (iv) and (v) suggest that older smokers are in fact capable of predicting future prices. Additionally, Table 4 confirms a non-zero future-price response among mature smokers.

Table 3 reports the results of a slightly different approach. Using the fact that smokers are not making the simple binary choice of smoking or not smoking, but rather choosing a level of consumption as well, I sort subjects into five categories: nonsmokers, up to $\frac{1}{2}$ pack/day, up to 1 pack/day, up to 2 packs/day, and over 2 packs/day. I then perform an ordered probit regression to assess the probability of being in each category. The key results are the coefficients on $\ln(price_{t+1})$ and the interaction of $\ln(price_{t+1})$ with a dummy for whether the subject is under 20 years old. Across all specifications, the coefficient on the former is large, and significantly negative. That is, anticipated future price increases will push smokers into lower categories. However, the interaction term is approximately the same magnitude and positive. That these two coefficients sum to zero is not rejected at a p-value of 0.8690. In other words, young smokers — unlike mature smokers—are not using information about future prices in their current consumption decisions.

At this point, there are multiple interpretations of this result. One could possibly conclude that the lack of a future-price response indicates that cigarettes are not addictive. However, the non-trivial future-price elasticity for mature smokers belies this interpretation. Within the model presented in Section 2, this result is consistent with either $\alpha > 0$ or $\beta < 1$, for appropriate parameters. That is, this test alone does not distinguish between the two types of bias. However, it is a strong rejection of the joint hypothesis that $\alpha = 0, \beta = 1$—that is, full rationality—for young smokers.

One could also conclude that consumers in their teen years are mistaken about the process by which prices evolve (e.g. they believe today’s price will be the price forever), but some time during their 20’s become able to predict prices. It would not be enough that teens have a noisier estimate of future prices that is still correct on average. Rather, it must be that even conditioning on the actual future price, teens believe it will too much resemble the current price. It is important to address this (admittedly ex-post) hypothesis, because it would have greatly different welfare implications. Unlike the cases of present bias or projection bias—where the losses come through $f(k)$ and $g(k)$—the welfare losses for an individual who makes price mistakes are limited to the present value of their financial error. However, this hypothesis is not supported by later results. In particular, if price misprediction were driving the results, then one would expect to see a similar pattern of learning in the results for price volatility. In Section 4.3, no such pattern

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47 Auld and Grootendorst (2004) warn that serial correlations in aggregate consumption data may spuriously return results in favor of addiction even when there is none, such as for milk demand. The individual responses used above lessen this concern. Moreover, the just-identified two-stage least squares specifications presented in Appendix Table A-4, which Auld and Grootendorst suggest “performs well”, are qualitatively similar to the main specifications.
is found. Both groups respond to price volatility (although, as will be discussed, not as much as they ought to), meaning that even youth smokers understand that prices are not immutable. Moreover, the response is not significantly different for young and mature smokers, indicating that no learning is taking place on this dimension. The pattern of learning and non-learning required for price misprediction to explain the results seems implausible, and I am unaware of other research that supports it. Section 5.3 formalizes this price extrapolation bias, and finds that while it can explain the myopia among teenagers, it is inconsistent with the rest of the results. Combined with the fact that this reaction to the second moment of the price distribution does not change as they mature, this story of teenage price misprediction is not consistent with the overall pattern of results.

4.2 Mature smokers and impatience

To get an estimate of the net discount factor $\beta \delta$, I estimate current-price and future-price responses on a sample restricted to respondents aged 30 and above—an identifying assumption is that whenever date $m$ occurs, it is before the age of 30. Current taxes and state budget gaps are used to instrument for prices in all specifications, which contain controls for age, age$^2$, sex, race, and education. As before, year dummies and MSA-specific time trends are also included. The estimation equation is given by:

$$Pr(smoker = 1)_{ijt} = \theta_1 * price_{jt} + \theta_2 * price_{j,(t+1)} + \theta_3 * X_{it} + \lambda_j + \phi_j * year_t + \eta_t + \epsilon_{ijt}$$

(12)

Table 4 presents the results of estimating (12). The dependent variable is an indicator for current smoker status, and all specifications control for age, age$^2$, race, and education, and include both year dummies and MSA-specific time trends.\(^{48}\) Where indicated, taxes and budget tightness are used to instrument for prices, as in Section 4.1.\(^{49}\)

Column (iii) is the preferred specification, using participants over age 30 as the sample. Similar results are obtained using 35 as the cutoff, suggesting that the “maturity” date does not fall within this window. The coefficient on current price is -0.725, so that a 1% increase in the price decreases the smoking rate by about 0.7%.\(^{50}\) That these are both smaller in magnitude than the current-price response for teenagers

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\(^{48}\) Appendix Table A-4 shows several alternative specifications, which the main results appear robust to.

\(^{49}\) As discussed earlier, this instrument will also alleviate the errors-in-variables problem arising from the fact that actual future price is a noisy measurement of expected future price. The increase in the magnitude of the coefficient on ln(price$_{t+1}$) in the instrumented specifications suggests that measurement error is indeed attenuating the coefficients from OLS.

\(^{50}\) The overall elasticity of smoking participation will be a mixture of the elasticity of initiation and the elasticity of cessation. DeCicca, Kenkel and Mathios (2008) use the National Education Longitudinal Survey to estimate a model that accounts for both explicitly, and find the cessation elasticity to be significantly greater than the initiation elasticity for 26-year-olds. Because the NHIS does not have panel data, I cannot distinguish initiation from cessation. However, virtually all of the response for
estimated in Table 2 is not surprising. The coefficients on future price are also significantly negative, at -0.531 and -0.496 for the two age cutoffs. While these estimates are not uniformly greater in magnitude than those for teens, such a comparison conflates the generally smaller price elasticity of older smokers with their relatively greater attention to future prices. The relevant comparison is the ratio of future-price response to current-price response, which ranges from 0.630 to 0.778 for mature smokers. For mature smokers, this ratio is interpreted as the net discount rate, $\beta \delta$. In all specifications, it is significantly different from zero. It is also significantly smaller than one in all but one specification.

I then estimate $\partial \pi_t / \partial p^P$ and $\partial \pi_t / \partial p^T$ by regressing consumption on the permanent and transitory components of price. As before, I include age, age$^2$, sex, race, and education as individual controls and include MSA dummies. Because annual variation determines $p^T_t$, I include either a trend or MSA-specific trends instead of year dummies and cluster standard errors at the year level. The estimation equation is:

$$Pr(smoker = 1)_{ijt} = \theta_1 * price^P_{jt} + \theta_2 * price^T_{jt} + \theta_3 * X_{it} + \lambda_j + \phi_j * year_t + \eta_t + \epsilon_{ijt}$$

(13)

where price is first decomposed into permanent and transitory components by estimating:

$$p_{jt} = \theta_4 * taxes_{jt} + \theta_5 * KYBurley_t + \theta_6 * year_t + \lambda_{2j}$$

(14)

The ratio of reactions to a permanent and to a transitory price shock is found by estimating (13). The decomposition of price into $p^P$ and $p^T$ is shown in Panel B of Table 5. All coefficients are highly significant, and $R^2$ values of 0.85 suggest that the greater part of price variation is accounted for. Taxes, MSA fixed effects, and a time trend are used to generate the permanent component of cigarette price, while the fluctuation in the tobacco price are used to generate the transitory portion. The burley tobacco price proves not to predict even the next year’s increase in price. Moreover, regressing the estimated $(p^T_{t+3} - p^T_t)$ on $(p^T_{t+1} - p^T_t)$ yields an insignificant coefficient (0.53 with a standard error of 0.44). The same regression for the “permanent” price yields a significantly positive coefficient (0.86 with a standard error of 0.19). This suggests that there is indeed little predictive power in the transitory component, but a lasting effect of the permanent component. I then include these estimates of $p^P$ and $p^T$ as regressors for an indicator of current

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51 A similar ratio is estimated in Becker, Grossman and Murphy (1994)—and is found to be comparably low— but is interpreted as the single discount factor corresponding to $\delta$.  
52 If the “permanent” shock is not truly permanent or the “temporary” shock not temporary, the estimates for $\delta$ will be biased downwards, and the estimates for $\beta$ biased upwards (i.e. too little present bias)
cigarette consumption, as in (13).

In general, the effect of the transitory component of price is significant and small. The effect of a permanent price shock is much greater—by almost an order of magnitude. Reassuringly, the sum of the coefficients is comparable to the earlier, non-decomposed price effects. The preferred specification is reported in column (iv) and includes MSA fixed effects and MSA-specific time trends, and is run on all respondents over 35 years old. A temporary price increase of 1% lowers the probability of smoking by 0.225%, while a 1% increase in the permanent price is associated with a 1.41% decrease in the smoking probability. The ratio of these effects will yield \((1 - (1 - \beta)\delta)/(1 - \delta)\), and is estimated at 6.267. That this is statistically different from 1 allows one to immediately reject the hypothesis that \(\beta = 1\) or \(\delta = 0\).

Column (v) presents the results of performing this analysis on teenage rather than mature smokers, and serves primarily as a robustness check on the model. Given the results in Table 2 and the restriction this puts on teen smokers' plans, one would expect teen smokers to react approximately equally to permanent and temporary price effects. This is precisely the pattern that emerges. With a coefficient of -0.33, teens are more responsive to temporary price shocks than mature smokers—consistent with their greater current-price sensitivity in Table 2—while their elasticity with respect to permanent price shocks, -0.822, is considerably lower than that of mature smokers. Although they do react more to permanent than to temporary shocks, the ratio of these responses is only 2.47 and is not statistically different from 1. That is, teen smokers continue to neglect future prices in their current smoking decisions.

Combining the estimates from Table 4 and Table 5, one can estimate both \(\beta\) and \(\delta\) individually for mature smokers. These estimates are shown in Table 7 for the instrumental variables specifications in Table 4 and Table 5. Using the preferred specifications from both, one obtains estimates for \(\beta\) of 0.701 and 0.828, and for \(\delta\) of 0.899 and 0.885. The estimates for \(\beta\) are significantly different from 1 (although the \(\delta\) estimates are less precise and not significantly different from 1).

4.3 *Price volatility and initiation*

The model presented in Section 2.3 predicts that price volatility has a differential impact on rational and projection-biased agents. Whereas volatility decreases the attractiveness of consumption to a fully-rational agent, projection-biased agents may be “fooled” into a lifelong habit when they try to take advantage of particularly low price realizations.

I use prices in the first half of the sample to estimate price volatility by metropolitan area. I then estimate the effect of this price volatility on smoking behaviors in the latter half of the sample. To control for any correlation between \(\sigma_{pj}^2\) and \(\bar{p}_j\), I include price directly as a control in all specifications. Demographic
controls again include age, age$^2$, sex, race, and education. The estimating equation is a regression of the form:

$$Pr(\text{smoker} = 1) = F(\theta_1 \cdot \text{price}_{jt} + \theta_2 \cdot \text{price}_{j(t+1)} + \theta_3 \cdot \text{std}_\text{price}_j + \theta_4 \cdot X_{it} + \phi_j \cdot \text{year}_t + \epsilon_{ijt}) \quad (15)$$

Where the left-hand side variable is one for current smokers and zero for current nonsmokers, prices are log real prices, and $\text{std}_\text{price}$ is estimated as above. $F(x) = \Phi(x)$ for specifications using the probit model and $F(x) = x$ for those using the linear probability model.$^{53}$

Table 6 shows the results of running the analysis described by (15). The first column shows the results of the analysis for all consumers. The sign on $P_t$ is highly significant and negative, as higher prices reduce the benefits of smoking for any type of consumer. The magnitude suggests that a 1% increase in the price lowers the probability of smoking rates by 0.36 percentage points, and is relatively stable across all specifications.

More interesting, however, is estimated the effect of price volatility per se on smoking rates. The regressor in the first row is the natural logarithm of the standard deviation of price (by MSA) between 1965 and 1977. In all specifications, the estimated coefficient is positive and approximately one-tenth the magnitude of the direct effect of price changes. For example, column (i) states that increasing the standard deviation of price realizations in an MSA by 10% increases the the probability of smoking by roughly 0.25 percentage points. This lends strong support to the conclusion that a mistake in predicting their future utility can lull consumers into a smoking habit. Columns (ii) and (iii) allow the volatility effect to vary between young and mature smokers. In neither case is the coefficient significantly different for the different age groups. This suggests that the effect is present for both mature and young smokers. However, without knowing a mature smoker’s MSA of residence during her adolescence, it is difficult to separate the enduring effect on initiation from a current effect on cessation.

One possible concern is whether the estimated coefficient is reasonable given any of the models presented in Section 2. Is it too high? One possible check is to perform a back-of-the envelope calculation of what one would expect this coefficient to be. Except for realizations extremely close to the mean, the assumption that $(P_t - \bar{P}) \sim \mathcal{N}(0, 0.087)$ fits the data well.$^{54}$ A quick estimate of $(P^* - \bar{P})$—the threshold price at which a person chooses to smoke—can be formed for teenagers by using the actual smoking rate of approximately 30% during this period.

Under these assumptions, a person who did not alter their price threshold would be 0.06 percentage points more likely to smoke in an environment where the prices were 1% more volatile. This purely mechanical

$^{53}$An alternative specification (available on request) instruments $\text{std}_\text{price}$ by the population of the MSA. The point estimates are approximately unchanged, but are imprecisely estimated.

$^{54}$Where $P_t$ is the real price and $\bar{P}$ is the best predictor using MSA fixed effects and a single time trend.
effect is considerably greater than the coefficients of between 0.02 and 0.03 estimated in Table 6. Any extent to which a consumer lowered their price threshold in more volatile environments would lower this estimate—meaning that this back-of-the-envelope calculation still leaves some room for consumers to alter their threshold in response to volatility. On an intuitive level, these estimates suggest that young smokers are not adjusting their thresholds “enough”. That is, they under-value the real option that derives from remaining unaddicted. Lemma 3 establishes that if $\alpha = 0$ and consumers are sufficiently patient, this elasticity must be negative. Unfortunately, the range of $\beta \delta$ for which this is true depends on the functions $f(\cdot)$ and $g(\cdot)$. Without further restrictions, one can reject the (somewhat extreme) joint hypothesis that $(\alpha = 0, \beta \delta = 1, h(\cdot) > 0)$, but cannot confirm if the $\beta$ found in Section 4.2 can explain this positive elasticity.

Rather than imposing the strength of addiction externally, the following section makes more parametric assumptions about the model in order to calibrate, among other things, how much projection bias these estimates imply.

5 Additional Parameter Estimates

The results from Section 4 require very few assumptions about the nature and strength of the addiction process. While this is sufficient for many ends—for example, estimating $\beta$ and $\delta$—other results are not identified. In particular, the degree of projection bias depends critically on how strong the addiction is.

In this section, I linearize $f(\cdot)$ and $g(\cdot)$ and make additional distributional assumptions about “maturity dates”, price volatility, and initial addiction states $k$.

5.1 Derivations

Rather than use the flexible addiction functions $f(\cdot)$ and $g(\cdot)$ with only (3) and (4) as restrictions, I follow O’Donoghue and Rabin (1999b) and assume $f(k_t) = x_t - \rho k_t$ and $g(k_t) = -\sigma k_t$. That is, smoking in the current period increases the next period’s incentive to smoke by $(\sigma - \rho)$.

**Proposition 3** Let the initial addictive state be distributed according to $\kappa(\cdot)$, and the “maturity date” $m$ be distributed according to $\mu(\cdot)$. If teen smokers expect to smoke only until maturity, response in the smoking rate of cohort $\tau$, $\pi_{\tau,t}$ to an anticipated shock to the price beginning in period $t+1$ is then:

$$\frac{d\pi_{\tau,t}}{dp_{t+1}} = -\kappa'(\bar{k}_t; \tau, t) \cdot \left( \frac{d\bar{k}}{dp_{t+1}} \right) \mu(t - \tau)$$
Where:
\[
\frac{d\bar{k}}{dp_{t+1}} = \left[ 1 + \beta \delta \left( (1 - \alpha) \gamma \frac{1 - (\delta \gamma)^{m-1}}{1 - \delta \gamma} + \alpha \frac{1 - \delta^{m-1}}{1 - \delta} \right) \right] \cdot (\sigma - \rho) \cdot 1\{m > t\}
\]

Suppose that all teens believe that they will smoke only until maturity and refrain thereafter, and that they believe maturity occurs in the current period. In this case, \(\frac{d\bar{k}}{dp_{t}}\) reduces to \(\frac{1}{\sigma - \rho}\). The change in the teen smoking rate given a change in the current price is then \(\frac{d\pi}{dp_{t}} = -\kappa'(\bar{k}) \cdot \frac{1}{\sigma - \rho}\). Let \(k \sim N(0, 1)\), so that consuming in the first period raises the addiction level by one standard deviation. Using the actual teen smoking rate of 30.52%, one can calculate \(\kappa'(\bar{k})\).

**Proposition 4** Let prices be distributed according to \(p_t \sim N(\hat{p}, s^2)\), where \(\hat{p}\) is the known MSA-specific mean price. For a consumer with discount rate \(\delta\), degree of present bias \(\beta\), and degree of projection bias \(\alpha\), the change in probability of smoking given a change in the standard deviation of the price distribution is given by:

\[
\frac{d\pi}{ds} = \frac{1}{\sqrt{2\pi s^2}} e^{-\left(\frac{s^2}{2s^2}\right)} \cdot \left( \frac{\hat{p}}{\sqrt{2\pi s^2}} e^{-\left(\frac{\hat{p}^2}{2s^2}\right)} \right) \cdot (\sigma - \rho) \beta \delta (1 - \alpha)
\]

\[-\frac{\hat{p}^*}{\sqrt{2\pi s^2}} e^{-\left(\frac{\hat{p}^*}{2s^2}\right)}\]

Proposition 4 states that, provided with an estimate of \((\sigma - \rho)\) and \(\beta \delta\), one can estimate the degree of projection bias implied by under-reactions to price volatility.

**5.2 Parameter Estimates**

**5.2.1 Addictiveness: \(\sigma - \rho\)**

Using Proposition 3 with the additional assumption that all teens expect to smoke only until maturity, one can re-interpret the estimates from Table 2 in order to recover \((\sigma - \rho)\). Using the under-20 sample from columns (i) and (iv) of Table 2, one estimates, respectively, 19.544 and 16.833. Because of the quasi-linearity of the utility function, these estimates can be interpreted as dollar amounts. That is, going from an unaddicted to an addicted state increases the willingness to pay by between $16 and $20.

One could repeat the analysis for the under-25 and under-30 samples. Because these groups are on average less price-sensitive, the estimates of \(\sigma - \rho\) will be greater than for the under-20 sample. However, this procedure requires that the young smokers expect to smoke only in the current period. Because these older samples include more consumers expecting a lifelong habit, the estimates of \(\sigma - \rho\) will be biased upwards. For this same reason, the estimates in Table 7 should be considered upper bounds of the addictiveness slope.
5.2.2 Projection Bias: $\alpha$

Given values for $\beta, \delta$, and $(\sigma - \rho)$, one can identify $\alpha$ from the response to price volatility. In the data, $(P_t - \hat{P}_t) \sim N(0, 0.087)$ (Kolmogorov-Smirnov p-value of 0.264). This implies that the mechanical effect of a 1% increase in the standard deviation of price is to increase smoking rates by 0.06 percentage points. To the extent that the estimated responses are smaller than this, consumers are reacting to volatility by changing their threshold price for smoking. However, the fact that they are not substantially smaller and, moreover, non-negative suggests that consumers are not reacting as much as they should in the fully-rational case.

Proposition 4 derives the net response to a change in the volatility of the price distribution. The second term is the purely mechanical response, and will be positive when consumers do not smoke on average. The first term is the behavioral response, and depends on the value of the real option that is generated by refraining. Using the estimated values of $\beta \delta$ and $(\rho - \sigma)$, it is possible to determine how big the behavioral response ought to be. The degree of under-reaction is attributed to $\alpha$.

The first column of Table 7 shows values for $\alpha$, using the estimate of $(\sigma - \rho) = 16.883$ and various estimates of the net discount rate.\footnote{Because this estimate depends on the net discount rate instead of $\beta$ and $\delta$ individually, the estimates do not vary across the columns of Table 7. Using higher estimates of $\sigma - \rho$ increases the values slightly, but never above 0.6.} The point estimates vary between 0.410 and 0.494, suggesting that consumers under-approve how their addictive state will change by 40%-50%. In the linear case, this is interpreted as consumers only expecting their instantaneous incentive to hit to increase by $\$8$ to $\$10$ instead of the full $\$16$, should they become addicted. Conversely, addicts under-appreciate their ability to become un-addicted by approximately the same amount. The estimate for projection bias compares favorably with the range of $\alpha \in [0.31, 0.50]$ found by Conlin et al. (2007). This lends support to the notion that projection bias is a general psychological phenomenon, rather than limited to specific domains such as smoking.

5.2.3 Maturity: $\mu(\cdot)$

Lastly, one can estimate the distribution of “maturity” from the changes in the ratio of future-price elasticity to current-price elasticity. In the model, maturity is simply defined at the age when the additional instantaneous incentive to hit, $x_t$, becomes zero. According to Proposition 3, one can estimate $\mu(t_1) - \mu(t_0)$ by the difference in \( \frac{d\pi}{dp_{t+1}} \) at ages $t_0$ and $t_1$ divided by the net discount rate. Using column (v) of Table 4 to estimate $\beta \cdot \delta$, Table 2 implies that between 27% and 39% of people cross this age between 20 and 25, and another 7% to 27% cross it between 25 and 30. This conclusion matches with the earlier result that very few people appear to be crossing the same threshold between the ages of 30 and 35.
5.3 Price-Extrapolation

I have interpreted the myopia towards future prices exhibited by teenagers as evidence that teens ignore predictable future price changes because they do not believe they will be smoking in the future. Similarly, I have interpreted mature smokers’ impatience as evidence of present bias. This requires no differential ability to predict future prices between young and mature smokers, and is consistent with the fact that teens are equally responsive to the second moment of the price distribution as mature smokers.\(^{56}\) It is possible, however, that consumers do not have rational expectations over prices.\(^{57}\) While there are any number of ways that expectations could differ from rationality, one theory that would seem to be a candidate for explaining teen myopia would be “price extrapolation”. Under this error, consumers believe too much that future prices will be similar to current prices, even conditional on all available information. This is a substantial departure from rational expectations and, while it is a post-hoc hypothesis, it initially seems to provide an alternative explanation for the results. One simple way to capture this would be to let a period-t consumer’s expectation of the period-\(\tau\) price, \(\hat{p}_{t,\tau}\), be given by:

\[
\hat{p}_{t,\tau} = (1 - \omega)E_t[p_\tau] + \omega \hat{p}_{t,\tau-1} + \epsilon_{t,\tau} \quad \text{for all } \tau > t
\]

\[\hat{p}_t = p_t\]

where \(E_t[p_\tau]\) is the correct expectation of the price in period \(\tau\) conditional on period-t information, \(p_t\) is the current price, and \(\epsilon_t\) is a normally-distributed error term. The degree of price-extrapolation error is indexed by the parameter \(\omega \in [0, 1]\), with \(\omega = 0\) reducing to the rational expectations assumed elsewhere in this paper. Under this form of error, coefficients from regressions of smoking status or cigarette consumption on current and future prices do not correspond to smokers’ responses to their price expectations. In particular, the coefficient on current price will load some of the future-price response because it is a component of the expectation of future price. An instrumental variables regression will solve the measurement error problem caused by \(\epsilon_{t+1}\), but will not correct for the extrapolation error.\(^{58}\)

Can such a mistake about prices explain the results found in Section 4 without the presence of present bias or projection bias? Suppose that all smokers have \(\beta = 1\), \(\alpha = 0\), that teens and mature smokers have \(\omega = \omega_t\) and \(\omega = \omega_m\), respectively, and that the addiction functions are linear. Then Lemma 3 implies \(\frac{d\pi/dp_t}{d\pi/dp_T} = \frac{1 - \omega\delta}{1 - \delta}\), and \(\frac{d\pi/dp_{t+1}}{d\pi/dp_t} = (1 - \omega)\delta\). One can then use the same regressions as in Section 4 to estimate \(\delta\)

\(^{56}\)It is also consistent with a theory that the error term for teens’ expectations is larger than that for mature smokers.

\(^{57}\)While consumers certainly do not have perfect foresight of future prices, the approach taken here has been to assume that they hold expectations that, while noisy, are correct on average. The actual future price is an estimate of consumers’ expectation of the future price measured with error, and can be overcome with an instrumental variables approach.

\(^{58}\)That is, if one estimates Equation (11) and \(\beta = 1\) and \(\alpha = 0\), then \(\frac{d\pi_t}{d\pi} = (1 - \omega)\delta < \delta\) if \(\omega > 0\).
and $\omega_m$. Using the baseline results from Column (iii) of Table 4 and Column (iv) of Table 5, one estimates $\delta = 0.90$, $\omega_m = 0.435$. For youth smokers, using Column (i) of Table 2 and Column (v) of Table 5, one estimates $\omega_T = 0.96$—that is, teens must be almost fully extrapolating the price.

However, the different values of $\omega$ required to explain the different future-price responses also make very different predictions about how consumers will respond to volatility. In particular, values close to 1 imply a zero response to price volatility that is contradicted by the teen response in Section 4.3. Moreover, this interpretation of the model also makes a strong prediction on the magnitudes of price responses. If one believes that the only thing changing over time is $\omega$, then one can ask what the price responses of one group imply about the $\omega$ of the other. Following Lemma 3, the magnitude of the current-price response will depend on an expression involving the discount rate, parameters of addiction, and degree of price-extrapolation error. If teens in fact expect to smoke in future periods, then the denominator in this expression will be the same as for mature smokers. The difference in price responses is attributed to different values of $\omega$. Given the estimates of $\omega_m$ and $\delta$ outlined above, one can therefore calculate the degree of price extrapolation consistent with the observed current-price elasticity for teen smokers. Far from the complete price extrapolation their myopia implies, this method finds that a value of $\omega_T = 0.68$ is allowed by the current-price response in Column (iv) of Table 2, and $\omega_T = 0.63$ for the response in Column (i). Intuitively, the change in the way teens and mature smokers react to current prices is not drastic enough to allow for a drastic change in the way they extrapolate prices. However, this lower value of $\omega_T$ implies a future-price response of -0.65, which is outside the 95% confidence interval of the actual estimate. Price-extrapolation error, while it may contribute along with the psychological biases estimated in this paper, therefore cannot on its own explain the pattern of price responses.

6 Conclusion

The overall conclusions to be drawn from this paper are three-fold. First, the patterns of cigarette consumption differ greatly from those predicted by the fully rational model. Second, the model of projection bias explains several different features of the data. Finally, evidence is found in favor of present bias as an additional contributing factor. I strongly reject the fully-rational case and, with additional assumptions, I estimate a degree of present bias $\beta$ between 0.7 and 0.8, and a degree of projection bias $\alpha$ between 0.4 and 0.5.

The parameter estimates obtained in this paper generally agree with those obtained elsewhere. The degree of impatience, $\beta \in [0.7, 0.8]$, matches estimates identified in very different contexts. For example, Laibson, Repetto and Tobacman (2007) estimate an annual $\beta = 0.7, \delta = 0.96$ in a structural model of
consumption and decisions. Using data on unemployment spells and accepted wages, Paserman (2008) finds some heterogeneity among income groups but still a comparable range of parameter estimates. A short-run discount factor $\beta \in \{0.40, 0.48\}$ is estimated for low-wage earners, while high-wage earners have $\beta = 0.89$. Both groups have an annual long-run discount factor $\delta = 0.99$. Using a large-scale experiment to measure consumer switching in credit cards, Shui and Ausubel (2004) estimate $\beta = 0.8$.59

Although there is a growing literature that identifies the presence of projection-bias, there has been less work attempting to estimate the parameter $\alpha$. In general, such estimates require structural assumptions on utility. Conlin, O’Donoghue and Vogelsang (2007) use catalog orders and returns of cold-weather clothing to test for projection bias with respect to the current weather. If consumers experience projection bias, they may over-order cold-weather clothing on cold days, because they expect their future selves will be cold as well. Returns are examined to control for potential confounds, such as attention. After making suitable structural assumptions, they estimate a degree of projection bias $\alpha \in [0.31, 0.50]$—strikingly similar to the range this paper estimates for projection bias with respect to cigarette addiction.

One could attempt to quantify the size of the mistake that consumers are making in several ways. For a rational consumer who is not credit-constrained, it is sufficient to know the present discounted cost of smoking to know if she will smoke. Biased consumers may be sensitive to the details of timing of prices. For example, Shui and Ausubel (2004) find that consumers are too sensitive to credit card “teaser rates” relative to the long-term interest rate—and in ways that end up being quite costly. For the analogue in cigarette prices, consider an unaddicted teenager with the degrees of bias and preferences estimated in this paper, who is deciding whether to smoke or not. By setting a very low price initially and raising the price in her adulthood—essentially a “teaser rate” for cigarettes—one can design a price path that will cause her to smoke forever at a very high present-value cost.60 Alternatively, by setting a high initial price and then lowering it considerably in her adulthood, one has a price path that will cause her to never smoke, even though the present-value cost of a lifelong habit is relatively low. Define the “overpayment ratio” as the ratio of the most expensive path that causes her to smoke to the least expensive path that causes her not to smoke. Using the consumer’s own discount rate to calculate present value, this ratio should be exactly one for rational consumers.61

---

59 If short-run impatience differs between smokers and non-smokers, these estimates of $\beta$ would not be directly comparable to the estimates in this paper obtained from smokers. That the results are similar suggests that this bias may be quite general. Indeed, using a specially-designed survey, Khwaja, Silverman and Sloan (2007) conclude that there is “no evidence that short-run and long-run rates of discount differ by smoking status.”

60 Although it is unrealistic to charge different age groups different prices for cigarettes, this thought experiment may be approximated by using brands that appeal differentially to teens and mature smokers.

61 The ratio is bounded below by 1 unless the attractiveness of smoking is increasing in the cigarette price. While this would never occur for standard preferences, it can sometimes occur for partially sophisticated present-biased agents for whom higher prices act as a failed commitment device on future selves.
Panel A of Figure 4 shows the overpayment ratio as a function of the parameter $\gamma$, which controls the evolution of the addictive stock. For a wide range of values, this teenager can be “tricked” into paying between 2 and 3.5 times as much for a smoking habit as she would have had to pay under a different price pattern that she would have turned down.\footnote{For comparison, the mean smoker in 2006 spent roughly $1080 annually on cigarettes (CDC, \url{http://www.cdc.gov/tobacco/data_statistics/}).} Panel B shows the ratio of the most expensive habit a biased smoker would accept to the most expensive habit a fully rational smoker would accept. Although the ratio is somewhat lower in Panel B, an agent with the biases estimated in this paper will still pay between 1.5 and 3 times too much. This suggests that most of the result is coming from people smoking when they rationally should not—teens impatiently starting, and mature smokers not quitting because they do not realize that withdrawal will be temporary. In addition to quantifying the consumer mistake, such a calculation is valuable to tobacco companies, which may design incentives to attract inexperienced smokers who unwittingly continue on to a lifelong habit.

Identifying present bias and projection bias as driving factors in addiction also suggests directions for effective policy interventions, including tax policy.\footnote{See, for example, Wertenbroch (1998) and O’Donoghue and Rabin (2003).} While there are many additional concerns that will affect the optimal cigarette tax, one can ask simply what lump-sum redistributed tax would maximize smokers’ own welfare.\footnote{In addition to the usual Ramsey rule for the overall tax, many studies include a Pigouvian component that reflects the negative externality of second-hand smoke and the positive externality that smokers’ early deaths impose on government health care and retirement programs. The calculations in this paper are separate from these concerns.} In the Becker and Murphy (1988) model, such a tax would clearly be zero, as any cigarette consumption is already chosen optimally.\footnote{Gul and Pesendorfer (2007) also find an optimal tax of zero in a model where smoking may not be desirable, because taxation does not remove smoking from the choice set. Their model does, however, predict that a ban on smoking may be welfare-enhancing.} When consumers are biased, however, there is substantial room for welfare-enhancing corrective taxes. Although such taxes will clearly not be Pareto efficient—some people may be smoking optimally—one can consider what tax would cause a biased consumer to hit only in circumstances when an unbiased consumer would have hit without such a tax. The derivation of this tax is presented in the Appendix, and because it depends on the addiction parameter $\gamma$, a range of values is presented in Appendix Table A-1. In general, a tax which corrects for both sources of bias will be quite large—on the order of $8-$11 per pack in current dollars. Using parameters of $\beta = 0.9$ and $\delta = 1$, Gruber and Kősze (2000) estimate that for a sophisticated present-biased agent, the optimal tax is between $1.50$ and $2.50$ per pack. Plugging in the same value of $\beta$ into the framework used by this paper yields a similar value for the optimal tax of between $1.10$ and $3.70$ per pack. Lowering $\beta$ rapidly increases the optimal tax, however. The estimate of $\beta = 0.8$, $\delta = 0.9$ yields significantly higher results: between $2.20$ and $5.30$ per pack. Including the effect of projection bias raises the corrective tax even further. Adding $\alpha = 0.4$, \n
\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
Parameter & Value \\
\hline
$\beta$ & 0.9 \\
$\delta$ & 1 \\
$\alpha$ & 0.4 \\
\hline
\end{tabular}
\caption{Optimal Tax Parameters}
\end{table}
the tax is between $8.60 and $11.40 per pack. By comparison, the highest current combined state-local tax on cigarettes is $4.25 in New York City.

Taken together, the results in this paper provide support for both present bias and projection bias as explanations for many smoking behaviors. When first starting a smoking habit, inexperienced smokers do not appreciate the degree to which they will become addicted to nicotine. Conversely, experienced smokers fail to fully appreciate how refraining from smoking will eventually make them un-addicted. Moreover, all smokers are too willing to sacrifice future well-being for the instantaneous benefits of smoking. Addiction offers a setting where projection bias and present bias interact to greatly alter consumer behavior. Further research may address whether this interaction of biases has a large effect in other contexts. Additionally, although consumer mistakes about prices cannot explain the pattern of results in this paper, it remains an open question how important such mistakes may be to both behavior and welfare.

References

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Tauras, John A and Frank J Chaloupka, “Impact of Tobacco Control Spending and Tobacco Control Policies on Adolescents’ Attitudes and Beliefs about Cigarette Smoking,” Evidence-Based Preventive Medicine, 2004, 1 (2), 11–120.


Proof of Lemma 1: Following O’Donoghue and Rabin (2000), let $A^t \equiv \{0, 1\}^\infty$, where $a^t \equiv (a_t, a_{t+1}, \ldots) \in A^t$ is a path of hitting and refraining starting in period $t$. Let $\tilde{V}_t(k_t, a^t)$ be the perceived long-run continuation utility from following $a^t$ conditional on period-$t$ addiction level $k_t$. Let $K_t(k_t, a^t) = [\gamma^{t-k_t} + \sum_{n=1}^{t-1} \gamma^{t-n-1} a_i]$ be the addiction level in period $\tau$ that results from following $a^t$. Then:

$$\tilde{V}_t(k_t, a^t) = \sum_{\tau=t}^\infty \delta^{\tau-t} \left[ a_\tau \left( Y_\tau - p_\tau + (1 - \alpha) f_\tau(K_t, a^t) \right) + \alpha f_\tau(k_t) \right] + (1 - a_\tau) \left( Y_\tau + (1 - \alpha) g_\tau(K_t, a^t) + \alpha g_\tau(k_t) \right)$$

Because $f_t(\cdot)$ and $g_t(\cdot)$ are weakly convex, $A^t$ is weakly convex in $k_t$. Now let $A(k, t)$ be an optimal strategy from self’s perspective—that is, is solves $\tilde{U}_t(k|A(k, t)) = \max_{a \in A_t} \tilde{V}_t(k, a)$.

To show uniqueness, suppose $A' \neq A$ is another optimal strategy. But from (10), $A(k, t) = 1 \iff h_t(k) \geq \beta \delta (1 - \alpha) \left[ U_{t+1}(\gamma k|A_t) - U_{t+1}(\gamma k + 1|A_t') \right]$ and $A'(k, t) = 1 \iff h_t(k) \geq \beta \delta (1 - \alpha) \left[ U_{t+1}(\gamma k|A') - U_{t+1}(\gamma k + 1|A') \right]$. Then $U_t(k|A) = U_t(k|A') \forall k$ and $t$, and so $A(k, t) = A'(k, t)$, so they are the same strategy.

Then because $\tilde{U}_t(k|A_t)$ is the upper envelope of $V_t$, it is also weakly convex in $k_t$. Therefore $\tilde{U}_{t+1}(\gamma k|A_t) - \tilde{U}_{t+1}(\gamma k + 1|A_t)$ is weakly decreasing in $k_t$. But for any type,

$$A(k, t) = 1 \iff h_t(k) \geq \beta \delta (1 - \alpha) \left[ U_{t+1}(\gamma k|A_t) - U_{t+1}(\gamma k + 1|A_t) \right]$$

Thus $\exists \tilde{k}_t \ s.t. \forall t, A(k, t) = 1 \iff k \geq \tilde{k}_t$.

If $t > m$, then $h_t(k)$ is independent of $t$ by Assumption 1. Then $A(k, t) = 1 \iff h(k) \geq \beta \delta (1 - \alpha) \left[ U_{t+1}(\gamma k|A_t) - U_{t+1}(\gamma k + 1|A_t) \right]$ is also independent of $t$, so $\exists \tilde{k} \ s.t. \forall t, A(k, t) = 1 \iff k \geq \tilde{k}$.

If $t < m$, then because future selves will be expected to follow a cutoff strategy and $x_t$ is weakly decreasing in $t$, $\tilde{U}_{t+1}(\gamma k|A_t) - \tilde{U}_{t+1}(\gamma k + 1|A_t)$ is weakly increasing in $t$. Thus for $t < m$, the cutoff $\tilde{k}_t$ is weakly increasing in $t$. Finally, because $h_m(k) \geq h_{m+1}(k)$, $\tilde{k}_m < \tilde{k}_{m+1}$.

Proof of Lemma 2: For any $p = (p_1, p_2, \ldots)$, define $k^*_1(p)$ to be the period-1 addiction level such that an agent with discount rate $\delta$, degree of present-bias $\beta$, and degree of projection-bias $\alpha$ is indifferent between hitting always and hitting never. That is,

$$Y_1 - p_1 + x_1 + f(k^*_1(p)) + \beta \sum_{t=2}^\infty \delta^{t-1} \left[ Y_t + p_t + x_t + (1 - \alpha) f \left( \gamma^{t-1} k^*_1(p) + \sum_{n=1}^{t-1} \gamma^{n-1} \right) + \alpha f \left( k^*_1(p) \right) \right]$$

which can be re-written as:

$$x_1 - p_1 + \beta \sum_{t=2}^\infty \delta^{t-1} (p_t) + \tilde{f}(k^*_1(p)) + \beta \sum_{t=2}^\infty \delta^{t-1} x_t = 0$$

where $\tilde{f}(k) = f(k^*_1(p)) - g(k^*_1(p)) + \beta \sum_{t=2}^\infty \delta^{t-1} \left[ (1 - \alpha) \left( f \left( \gamma^{t-1} k + \sum_{n=1}^{t-1} \gamma^{n-1} \right) - g \left( \gamma^{t-1} k \right) \right) + \alpha f(k) - g(k) \right]$. If $k^*(\bar{p}) \in \min\{k^*, \tilde{k}, \bar{k}\}$, then $\bar{k}_t = k^*_1(p) \forall t$. (i.e. behavior is governed by the threshold for hitting always relative to hitting never, and it is straightforward to show that this is true for sufficiently small changes to $\bar{p}$). Substituting $\bar{k}$
for $k_1^*$ into the above and differentiating with respect to $\bar{p}$ yields:

$$-1 + \frac{-\beta \delta}{1 - \delta} + \Phi'(k_1^*(p)) \cdot \frac{dk_1(p)}{dp} = 0$$

and similarly

$$\frac{dk_1(p)}{dp} = \frac{1 + \frac{\beta \delta}{1 - \delta}}{-\Phi'(k_1^*(p))}, \quad \frac{dk_1(p)}{dp_1} = \frac{1}{-\Phi'(k_1^*(p)), \quad \frac{dk_1(p)}{dp_2} = \frac{\beta \delta^{r-1}}{\Phi'(k_1^*(p))}$$

Now for any $p = (p_1, p_2, ...)$, define $k_1(p)$ to be the period-1 addiction level such that the is indifferent between hitting until maturity and hitting never. That is, $\bar{k}_1(p)$ is given by:

$$Y_1 - p_1 + f(k_1) + x_1 + \beta \sum_{t=2}^{m} \delta^{t-1} \left[ Y_t - p_t + x_t + (1 - \alpha) f \left( \gamma^{t-1} \bar{k}_1(p) + \sum_{n=1}^{t-1} \gamma^{n-1} \right) + \alpha f \left( \bar{k}_1(p) \right) \right] +$$

$$\beta \sum_{t=m+1}^{\infty} \delta^{t-1} \left[ Y_t + (1 - \alpha) g \left( \gamma^{t-1} \bar{k}_1(p) + \gamma^{t-m} \sum_{n=1}^{m} \gamma^{n-1} \right) + \alpha g \left( \bar{k}_1(p) \right) \right]$$

$$= Y_1 + g(k_1) + \beta \sum_{t=2}^{\infty} \delta^{t-1} \left[ Y_t + (1 - \alpha) g \left( \gamma^{t-1} \bar{k}_1(p) \right) + \alpha g \left( \bar{k}_1(p) \right) \right]$$

which can be re-written as:

$$x_1 - p_1 + \beta \sum_{t=2}^{m} \delta^{t-1}(-p_t) + \bar{\Psi}(\bar{k}_1(p), m) + \beta \sum_{t=2}^{m} \delta^{t-1}x_t = 0$$

where

$$\bar{\Psi}(k, m) = f(k_1) - g(k_1) + \beta \sum_{t=2}^{m} \delta^{t-1} \left[ (1 - \alpha) \left( f \left( \gamma^{t-1} k + \sum_{n=1}^{t-1} \gamma^{n-1} \right) - g \left( \gamma^{t-1} k \right) \right) + \alpha \left( f(k) - g(k) \right) \right] +$$

$$+ \beta \sum_{t=m+1}^{\infty} \delta^{t-1} \left[ (1 - \alpha) \left( g \left( \gamma^{t-1} k + \gamma^{t-m} \sum_{n=1}^{m} \gamma^{n-1} \right) - g \left( \gamma^{t-1} k \right) \right) \right]$$

For sufficiently small changes in $\bar{p}$, $\bar{k}_1^\alpha = \bar{k}(p) \forall t$. Thus differentiating with respect to $\bar{p}$ gives:

$$-1 + \beta \delta \frac{1 - \delta^{m-1}}{1 - \delta} \cdot (-1) + \bar{\Psi}_m(\bar{k}_1, m) \frac{dk_1}{dp}$$

Which can be re-arranged to yield:

$$\frac{dk_1}{dp} = \frac{1 + \beta \delta (1 - \delta^{m-1})/(1 - \delta)}{\bar{\Psi}_m(\bar{k}_1(p), m)}$$

And similarly differentiating with respect to $p_1$ and $p_2$, yield:

$$\frac{dk_1}{dp_1} = \frac{1}{\bar{\Psi}_m(\bar{k}_1(p), m)} \quad \text{and} \quad \frac{dk_1}{dp_2} = \left\{ \begin{array}{ll} \frac{\beta \delta^{r-1}}{\bar{\Psi}_s(\bar{k}_1(p), s)}, & \tau \leq s \\ 0, & \text{else} \end{array} \right.$$  

The case for a present-biased agent planning to hit only in the current period can be solved by setting $m = 1$.

**Proof of Proposition 1** Suppose the initial addictive state $k_0$ is distributed according to some function $\kappa(\cdot)$. For fully rational smokers who expect to continue smoking, $\bar{k}_1^\alpha = k^\alpha$. Then in period 1, $\pi(p|X) = 1 - \kappa(k^*(p))$. By Lemma 2, $\frac{\partial \pi}{\partial p_{t+1}} = \delta$.  

38
Present-biased and projection-biased consumers also only consume in period 1 when \( k_1 > \hat{k}_1 \) and \( k_1 > \hat{k}_1 \), respectively. Thus for present-biased consumers, \( \pi(p|\mathbf{X}) = 1 - \kappa(\hat{k}_1^\tau(p)) \) and for projection-biased consumers, \( \pi(p|\mathbf{X}) = 1 - \kappa(\hat{k}_1^\tau(p)) \). Lemma 2 then implies that if \( \hat{k}_n(\beta, p) = \min\{k_1^*, \hat{k}_n\} \) or \( \hat{k}_n = \min\{k_1^*, \hat{k}_n, \hat{k}_n\} \) and \( m = 1 \), then \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = 0 \). Otherwise if \( k^*(\beta, p) = \min\{k_1^*, \hat{k}_n, \hat{k}_n\} \) and \( \hat{k}_n = \min\{k_1^*, \hat{k}_n, \hat{k}_n\} \) and \( m > 1 \), then \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = \beta \delta \).

For projection-biased consumers, Lemma 2 implies that if \( \tilde{k}_j = \min\{k_1^*, \hat{k}_j\} \) and \( m = 1 \), then \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = 0 \). If \( \tilde{k}_j = \min\{k_1^*, \hat{k}_j\} \) and \( m > 1 \) or \( k^*_j = \min\{k_1^*, \hat{k}_j\} \), then \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = \delta \).

**Proof of Proposition 2** Let the addictive stock in period \( t \) among mature smokers be given by \( \kappa_{t}(\cdot) \). WLOG, let \( p_t = p_t^\tau \) \( \forall t \geq t \). The probability that a consumer of type \( i \) smokes is given by \( \pi(p|\mathbf{X}) = 1 - \kappa(\hat{k}_1^\tau(p)) \), and therefore \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = -\hat{k}_1^\tau(p) \). If consumers expect to continue smoking, Lemma 2 implies that \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = \beta \delta \).

For fully rational smokers, Lemma 2 further implies \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = \frac{1}{1-\beta} \). Projection-biased consumers follow identically, using \( k_1^\tau(p) \).

For present-biased consumers, either \( \hat{k}_n(\beta, \tilde{p}) < k_1^*(\beta) \) or \( \hat{k}_n(\beta, \tilde{p}) > k_1^*(\beta) \). In the first case, Lemma 2 implies \( d = 0 \) and \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = 1 = \frac{1}{1-\beta} \). If \( \hat{k}_n(\beta, \tilde{p}) > k_1^*(\beta) \), then \( \delta = \beta \delta \) and \( \frac{\partial \pi/\partial p_{n+1}}{\partial \pi/\partial p_n} = \frac{1-\beta \delta}{1-\delta} > \frac{1}{1-\beta} \).

**Proof of Lemma 3** (i) Rational and present-biased consumers:

In period 2, the consumer will smoke iff

\[
Y_2 + x_2 - p_2 + f(k_2) \geq Y_2 + g(k_2)
\]

\[
x_2 + f(k_2) - g(k_2) = x_2 + h(k_2) \geq p_2
\]

Let \( p_2^*(k_2) = x_2 + h(k_2) \) and let \( \psi(k_2) = \Phi(p_2^*(k_2)) \). Her ex-ante expected utility in period 2 is:

\[
V_2(k_2) = Y_2 + \psi(k_2) \cdot (x_2 - \hat{p}_2(k_2) + h(k_2)) + g(k_2)
\]

where \( \hat{p}_2 = E[p|p \leq p_2^*(k_2)] \)

She will choose to smoke in period 1 if:

\[
Y_1 + g(k_1) + V_2(\gamma k_1) \leq Y_1 - p_1 + x_1 + f(k_1) + V_2(\gamma k_1 + 1)
\]

\[
p_1 \leq p_1^* = x_1 + h(k_1) + \beta V_2(\gamma k_1 + 1) - \beta \delta V_2(\gamma k_1)
\]

\[
\approx x_1 + h(k_1) + \beta \delta V_2(\gamma k_1)
\]

Before proceeding, consider her expected price conditional on smoking in period 2, as a function of her period-2 addiction level:

\[
\hat{p}_2(k) = \frac{1}{\psi(k)} \cdot \int_{-\infty}^{x_2 + h(k)} p \cdot d\Phi(p)
\]

\[
\hat{p}_2^*(k) = \frac{1}{\psi(k)} \cdot \int_{-\infty}^{x_2 + h(k)} \frac{1}{\psi(k)} \cdot h(k) \cdot (x_2 + h(k)) \cdot \phi(x_2 + h(k))
\]

\[
= \frac{\psi(k)}{\psi(k)} \cdot p^*(k) = [p^*(k) - \hat{p}(k)] \cdot \frac{\psi(k)}{\psi(k)} > 0
\]

Because \( p^*(k) \) is necessarily greater than \( \hat{p}(k) \), the expression is positive. Intuitively, increasing one's addiction level increases the range of prices at which a purchase will be made, and hence the expected purchase price.
Now,
\[
V'_2(k) = \psi'(k) [p^*(k) - \tilde{p}_2(k)] + \psi(k) \cdot (-\tilde{p}'(k) + h'(k)) + g'(k)
\]
\[
= \psi'(k) [p^*(k) - \tilde{p}_2(k)] - \psi(k) \cdot \frac{\psi'(k)}{\psi(k)} [p^*(k) - \tilde{p}(k)] + h'(k)\psi(k) + g'(k)
\]
\[
= h'(k)\psi(k) + g'(k)
\]

Finally, then:
\[
p^*_1(k) \approx x_1 + h(k_1) + \beta \delta h'(\gamma k_1)\psi(\gamma k_1) + \beta \delta g'(\gamma k_1)
\]
\[
\frac{dp^*_1}{d\sigma^2} \approx \frac{d\psi(\gamma k_1)}{d\sigma^2} \cdot h'(\gamma k_1) \cdot \beta \delta
\]

The second term is, by assumption, positive for all values of \(k\). Thus the sign of effect on the threshold price is determined entirely by the first term, \(\frac{d\psi(\gamma k_1)}{d\sigma^2}\). The overall effect on the probability of initiation is then:
\[
\frac{dP(\text{smoke})}{d\sigma^2} = \Phi(\tilde{p}^*_1(k_1; \sigma^2), \tilde{p}; \sigma^2) + \Phi_p(p^*_1(k_1; \sigma^2), \tilde{p}; \sigma^2) \cdot \frac{dp^*_1}{d\sigma^2}
\]

(ii) Projection-Biased Consumers Because the fully projection-biased consumer believes her period-2 addiction level will be unchanged, her expected utility as a function of her period-1 consumption is simply:
\[
\hat{U}(a_1 = 0) = Y_1 + g(k_1) + \beta \delta [\Psi(k_1, \tilde{p}) \cdot (Y_2 - E[p_2|p_2 \leq \tilde{p}^*_1(k_1)]) + x_2 + f(k_1) + (1 - \Psi(k_1, \tilde{p})) \cdot (Y_2 + g(k_1))]
\]
\[
\hat{U}(a_1 = 1) = Y_1 - p_1 + x_1 + f(k_1) + \beta \delta [\Psi(k_1, \tilde{p}) \cdot (Y_2 - E[p_2|p_2 \leq \tilde{p}^*_1(k_1)]) + x_2 + f(k_1) + (1 - \Psi(k_1, \tilde{p})) \cdot (Y_2 + g(k_1))]
\]

Because the fully projection-biased consumer believes her current actions don’t influence her future incentives, she will smoke in period 1 exactly when the price is below the instantaneous temptation to hit:
\[
p_1 \leq x_1 + f(k_1) - g(k_1)
\]

Thus the threshold price of initiating smoking for a fully projection-biased consumer is unaffected by the variance of the price distribution. Assuming, however, that \(\tilde{p} > x_1 + f(k_1) - g(k_1)\), then the probability that \(p_1\) is less than the threshold is increasing in \(\sigma^2\).

(iii) Partial Projection Bias

Let \(\tilde{p}^*(k, k_1)\) be the threshold price at which a partially projection-biased consumer expects to purchase in period 2 if her current addiction level is \(p_t\) and her actual period-2 addiction level is \(k\). With simple projection bias, it follows that \(\tilde{p}^*(k, k_1) = x_2 + \alpha \cdot (f(k_1) - g(k_1)) + (1 - \alpha) \cdot (f(k) - g(k))\).

It then follows that a partially projection-biased agent’s perceived probability of smoking in the next period is \(\tilde{\Psi}(k, p|k_1) = \Phi(\tilde{p}^*(k, k_1) - p)\).

Her perceived expected utility, then, as a function of her period-1 choice is then:
\[
\hat{U}(a_1 = 0) = Y_1 + g(k_1) + \beta \delta [\tilde{\Psi}(\gamma k_1, p|k_1) \cdot (Y_2 - E[p_2|p_2 \leq \tilde{p}^*_2(\gamma k_1, k_1)]) + x_2 + \alpha f(k_1) + (1 - \alpha) f(\gamma k_1)] + (1 - \tilde{\Psi}(\gamma k_1, p|k_1)) \cdot [Y_2 + \alpha g(k_1) + (1 - \alpha) g(\gamma k_1)]
\]
\[
\hat{U}(a_1 = 1) = Y_1 - p_1 + x_1 + f(k_1) + \beta \delta [\tilde{\Psi}(\gamma k_1 + 1, p|k_1) \cdot (Y_2 - E[p_2|p_2 \leq \tilde{p}^*(\gamma k_1 + 1, k_1)]) + x_2 + \alpha f(k_1) + (1 - \alpha) f(\gamma k_1)] + (1 - \tilde{\Psi}(\gamma k_1 + 1, p|k_1)) \cdot [Y_2 + \alpha g(k_1) + (1 - \alpha) g(\gamma k_1 + 1)]
\]
Thus $a_1 = 1$ if:

\[
p_t \leq x_1 + f(k_1) - g(k_1) + \beta \delta \left[ \tilde{\Psi}(\gamma k_1 + 1, p|k_1) \cdot [(-E[p_2|p_2 \leq \tilde{p}_1^* (\gamma k_1 + 1, k_1)) + x_2 + \alpha f(k_1) + (1 - \alpha) f(\gamma k_1)]
\right.
\]

\[
- \tilde{\Psi}(\gamma k_1, p|k_1) \cdot [(-E[p_2|p_2 \leq \tilde{p}_1^* (\gamma k_1, k_1)) + x_2 + \alpha f(k_1) + (1 - \alpha) f(\gamma k_1)]
\]

\[
\left. + (1 - \tilde{\Psi}(\gamma k_1 + 1, p|k_1)) \cdot [\alpha g(k_1) + (1 - \alpha) g(\gamma k_1 + 1)]
\right]
\]

\[
- (1 - \tilde{\Psi}(\gamma k_1, p|k_1)) \cdot [\alpha g(k_1) + (1 - \alpha) g(\gamma k_1)]\]

In the limit as $\alpha$ approaches unity, this expression simplifies to exactly the full projection-bias case. Similarly, it simplifies to the fully rational case as $\alpha$ approaches zero. Thus the overall effect on the probability of smoking depends on the individual’s degree of projection bias. For large $\alpha$, the threshold will barely adjust as $\sigma^2$ increases, so as with a fully projection-biased agent, the probability of initiation increases. For small $\alpha$, the threshold drops enough that it dominates the increased probability of meeting any given threshold, so the probability of initiation decreases.

**Proof of Lemma 3:** Let $f(k_1) = x_1 - \rho k_1$ and $g(k_i) = -\sigma k_i$.

For any $p = (p_1, p_2, ...)$, define $k_1(\alpha, \beta, \delta)$ to be the period-1 addiction level such that a person with discount rate $\delta$, degree of present-bias $\beta$, and degree of projection-bias $\alpha$ is indifferent between hitting always and hitting never. That is,

\[
Y_1 - p_t + x_1 - \rho k_1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} (1 - \alpha)(x_1 - \rho k_1) + \alpha(-\rho)k_1 + Y_t - p_t + x_t
\]

\[
= Y_1 - \sigma k_1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} \left( (1 - \sigma)(x_1 - \rho k_1) + \alpha(\sigma)k_1 + Y_t \right)
\]

So that:

\[
(\sigma - \rho)k_1 + \beta \delta \left[ (1 - \alpha) \frac{1}{1 - \delta \gamma} + \alpha \frac{\sigma}{1 - \delta} \right] (\sigma - \rho)k_1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} x_1 - p_t - \beta \sum_{t=2}^{\infty} \delta^{t-1} p_t + \theta_1 = 0
\]

where $\theta_1 = \frac{1 - \alpha}{1 - \gamma} \beta \delta \left[ \frac{1}{1 - \delta \gamma} - \frac{1}{1 - \delta} \right] \rho$

If $k_1(\alpha, \beta, \delta) < k_1^*(\alpha, \beta, \delta)$, then $\tilde{k}_t = k_1(\alpha, \beta, \delta) \forall t$. (i.e. behavior is governed by the threshold for hitting always relative to hitting never, and it is straightforward to show that this is true for sufficiently small changes to $\tilde{p}$).

Substituting $\tilde{k}$ for $k_1$ into the above and differentiating with respect to $\tilde{p}$ yields:

\[
\left[ 1 + \beta \delta \left( (1 - \alpha) \frac{1}{1 - \delta \gamma} + \alpha \frac{1}{1 - \delta} \right) \right] (\sigma - \rho) d\tilde{k} = \left[ 1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} \right] \frac{d\tilde{p}}{(\sigma - \rho)}
\]

\[
\frac{d\tilde{k}}{d\tilde{p}} = \frac{\left[ 1 + \beta \delta \left( (1 - \alpha) \frac{1}{1 - \delta \gamma} + \alpha \frac{1}{1 - \delta} \right) \right]}{\left[ 1 + \beta \delta \left( (1 - \alpha) \frac{1}{1 - \delta \gamma} + \alpha \frac{1}{1 - \delta} \right) \right]} \cdot (\sigma - \rho)
\]
Proof of Lemma 4: A consumer with current addictive state $k_1$, discount rate $\delta$, degree of present-bias $\beta$, degree of projection-bias $\alpha$, and maturity date $m > 1$ is indifferent between hitting until maturity (and refraining thereafter), and hitting never. That is:

$$Y_1 - p_1 + x_1 - \rho k_1 + \beta \sum_{t=2}^{m} \delta^{t-1} \left[(1 - \alpha)(-\rho) \left(\gamma^{t-1} k_1 + \sum_{n=1}^{t-1} \gamma^{n-1}\right) - \alpha \rho k_1 - p_t + x_t\right]$$

$$+ \beta \sum_{t=m+1}^{\infty} \delta^{t-1} \left[(1 - \alpha)(-\sigma) \left(\gamma^{t-1} k_1 + \gamma^{t-m} \sum_{n=1}^{m} \gamma^{n-1}\right) - \alpha \sigma k_1\right]$$

$$= Y_1 - \sigma k_1 - \sigma \left((1 - \alpha) \beta \delta \gamma^{1 - (\delta \gamma)^{m-1}} - \alpha \beta \delta \frac{1}{1 - \delta}\right) k_1$$

where $\theta_2 = x_1 + \beta \sum_{t=2}^{m} \delta^{t-1} x_t - (1 - \alpha) \frac{\beta \delta}{1 - \delta} \left(1 - \delta\right) \frac{1 - (\delta \gamma)^m}{1 - \delta \gamma} \rho$.

If $k_0^\dagger(\alpha, \beta, \delta, m) < k_1(\alpha, \beta, \delta)$, then $\bar{k}_t = k_0^\dagger(\alpha, \beta, \delta) \forall t$. (i.e. behavior is governed by the threshold for hitting only until maturity and refraining thereafter over hitting never, and it is straightforward to show that this is true for sufficiently small changes to $\bar{p}$). Substituting $\bar{k}$ for $k_0^\dagger$ into the above and differentiating with respect to $\bar{p}$ yields:

$$\frac{dk}{d\bar{p}} = \frac{\left[1 + \beta \delta \left(1 - \alpha\right) \gamma^{1 - (\delta \gamma)^{m-1}} - \alpha \beta \delta \frac{1}{1 - \delta}\right]}{1 + \beta \delta \left(1 - \alpha\right) \gamma^{1 - (\delta \gamma)^{m-1}} - \alpha \beta \delta \frac{1}{1 - \delta}} \cdot (\sigma - \rho)$$

Similarly:

$$\frac{d\bar{k}}{d\bar{p}} = \frac{1}{1 + \beta \delta \left(1 - \alpha\right) \gamma^{1 - (\delta \gamma)^{m-1}} - \alpha \beta \delta \frac{1}{1 - \delta}} \cdot (\sigma - \rho)$$

$$\frac{dk}{d\bar{p}_{t+1}} = \beta \delta \left(1 - \alpha\right) \gamma^{1 - (\delta \gamma)^{m-1}} - \alpha \beta \delta \frac{1}{1 - \delta} \cdot (\sigma - \rho) \cdot 1\{m > t\}$$

Let the distribution of addictive states at time $t$ for the cohort born in $\tau$ be given by $\Pr(k \leq x) = \kappa(x; \tau, t)$. The probability of smoking, and the population smoking rate, is then $(1 - \kappa(k; \tau, t))$.

Finally, let the “maturity date” $m$ be distributed according to the probability distribution function $\mu(\cdot)$. The response in the smoking rate of cohort $\tau$, $\pi_{\tau,t}$ to an anticipated shock to the price beginning in period $t+1$ is then:

$$\frac{d\pi_{\tau,t}}{d\bar{p}_{t+1}} = -\kappa'(\bar{k}; \tau, t) \cdot \left(\frac{dk}{d\bar{p}_{t+1}}\right) (1 - \mu(t - \tau))$$

Proof of Lemma 4: A consumer with current addictive state $k_1$, discount rate $\delta$, degree of present-bias $\beta$, and degree
of projection-bias \( \alpha \) believes she will smoke in period 2 if the price and her period-2 addiction level are such that:

\[
Y_2 + x_2 - p_2 + (1 - \alpha)f(k_2) + \alpha f(k_1) \geq Y_2 + (1 - \alpha)g(k_2) + \alpha g(k_1)
\]

\[
p_2 \leq (1 - \alpha)h(k_2) + \alpha h(k_1)
\]

Let \( \hat{p}(k_2, k_1) = x_2 + (1 - \alpha)h(k_2) + \alpha h(k_1) \). If \( p \sim \Phi(\cdot) \), then her ex-ante expected utility in period is:

\[
\hat{V}(k_2, k_1) = EU(k_2, k_1) = Y_2 + \Phi(\hat{p})((1 - \alpha)f(k_2) + \alpha f(k_1) - E[p_2|p_2 \leq \hat{p}]) + (1 - \Phi(\hat{p})) ((1 - \alpha)g(k_2) + \alpha g(k_1))
\]

She will therefore smoke in period 1 if:

\[
p_1 \leq p_1^* = h(k_1) + \beta\delta\hat{V}(\gamma k_1 + 1; k_1) - \beta\delta\hat{V}(\gamma k_1; k_1)
\]

\[
\approx h(k_1) + \hat{V}_2(\gamma k_1; k_1) \cdot \beta\delta
\]

Let \( \hat{p}(k_2; k_1) = E[p_2|p_2 \leq \hat{p}(k_2; k_1)] \), and note that

\[
\hat{p}(k_2; k_1) = \frac{1}{\Phi(\hat{p})} \int_{-\infty}^{(1-\alpha)h(k_2) + \alpha h(k_1)} p \cdot d\Phi(p)
\]

So that

\[
\hat{p}'(k_2; k_1) = -\frac{\phi(\hat{p})h'(k_2)}{\Phi(\hat{p})^2} \int_{-\infty}^{(1-\alpha)h(k_2) + \alpha h(k_1)} p \cdot d\Phi(p) + \frac{1}{\Phi(\hat{p})} (1 - \alpha)h'(k_2)\hat{p}\phi(\hat{p})
\]

\[
= -\frac{\phi(\hat{p})h'(k_2)}{\Phi(\hat{p})} \hat{p} + \frac{1 - \alpha}{\Phi(\hat{p})} \phi(\hat{p})
\]

\[
= \frac{\phi(\hat{p})}{\Phi(\hat{p})} h'(k_2) [\hat{p} - \hat{p}]
\]

Thus

\[
V_2 = Y_2 + \Phi(\hat{p})(\hat{p} - \hat{p}) + (1 - \alpha)g(k_2) + \alpha g(k_1)
\]

\[
V_2'(k_2, k_1) = \phi(\hat{p})h'(k_2)(\hat{p} - \hat{p}) + \Phi(\hat{p})((1 - \alpha)h'(k_2) - \hat{p}') + (1 - \alpha)g'(k_2)
\]

\[
= \phi(\hat{p})h'(k_2)(\hat{p} - \hat{p}) + \Phi(\hat{p})\frac{\phi(\hat{p})}{\Phi(\hat{p})}h'(k_2)(\hat{p} - \hat{p}) + (1 - \alpha)h'(k_2)\Phi(\hat{p}) + (1 - \alpha)g'(k_2)
\]

\[
= (1 - \alpha) [h'(k_2)\Phi(\hat{p}(k_2, k_1) + g'(k_2)]
\]

And therefore

\[
p^* = h(k_1) + \beta\delta(1 - \alpha) [\Phi(\hat{p}) \cdot h'(\gamma k_1) + g'(\gamma k_1)]
\]

Let \( s \) be the standard deviation of \( \Phi(p) \).

\[
\frac{dp^*}{ds} = \frac{d\Phi(\hat{p})}{ds} \cdot h'(\gamma k_1) \cdot \beta\delta(1 - \alpha)
\]

\[
= \frac{d\Phi(\hat{p})}{ds} \cdot (\sigma - \rho) \cdot \beta\delta(1 - \alpha)
\]

If the agent changes their threshold in this manner, then the overall change in their probability of smoking in any period is:

\[
\frac{d\pi}{ds} = \phi(p^*) \cdot \frac{d\Phi(\hat{p})}{ds} \cdot (\sigma - \rho)\beta\delta(1 - \alpha) + \frac{d\Phi(\hat{p})}{ds}
\]

If one imposes normality on the price distribution such that \( (p_t - E[p_t]) \sim N(0, s^2) \), then this can be written in
closed form as:

\[
d\pi \over ds = \frac{1}{\sqrt{2\pi s}} e^{-\left(\frac{s^2}{2\pi s}\right)} \cdot \left(\frac{\bar{p}}{\sqrt{2\pi s^2}} e^{-\left(\frac{\bar{p}^2}{2\pi s^2}\right)}\right) \cdot (\sigma - \rho) \beta (1 - \alpha)
\]

\[-\frac{p^*}{\sqrt{2\pi s^2}} e^{-\left(\frac{p^*^2}{2\pi s^2}\right)} \cdot \left(\tilde{p} \sqrt{2\pi s^2} e^{-\left(\frac{\tilde{p}^2}{2\pi s^2}\right)}\right) \cdot (\sigma - \rho) \beta (1 - \alpha)
\]

**Derivation of Optimal Tax** Consider the current-period addiction for which an agent is indifferent between hitting always and hitting never, as given in the Proof of Lemma 3:

\[ (\sigma - \rho)k_1 + \beta \delta \left[ (1 - \alpha) \frac{\gamma}{1 - \delta \gamma} + \frac{\alpha}{1 - \delta} \right] k_1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} p_t - \beta \sum_{t=2}^{\infty} \delta^{t-1} p_t + \theta_1 = 0 \]

where \[ \theta_1 = \frac{1 - \alpha}{1 - \gamma} \beta \delta \left[ \frac{\gamma}{1 - \delta \gamma} - \frac{1}{1 - \delta} \right] \]

An agent with discount rate \( \delta \), degree of present-bias \( \beta \), and degree of projection-bias \( \alpha \) will therefore hit if:

\[ k_1 \geq \frac{p_1 + \beta \sum_{t=2}^{\infty} \delta^{t-1} p_t - \theta_1}{\theta_3 (\sigma - \rho)} \]

where \[ \theta_3 = 1 + \beta \delta \left( (1 - \alpha) \frac{\gamma}{1 - \delta \gamma} + \alpha \frac{1}{1 - \delta} \right) \]

Whereas a fully-rational agent (i.e. \( \alpha = 0, \beta = 1 \)) will hit if:

\[ k_1 \geq \frac{p_1 + \sum_{t=2}^{\infty} \delta^{t-1} p_t - \frac{1}{1 - \alpha} \frac{1}{\beta} \theta_1}{\theta_3^R (\sigma - \rho)} \]

where \[ \theta_3^R = 1 + \delta \left( \frac{\gamma}{1 - \delta \gamma} \right) \]

Consider applying a uniform excise tax \( \tau \) on consumption in every period. The level of tax that will cause a biased agent to consume only when the rational agent would have consumed is given by:

\[ \frac{p_1 + \tau + \beta \sum_{t=2}^{\infty} \delta^{t-1} (p_t + \tau) - \theta_1}{\theta_3 (\sigma - \rho)} = \frac{p_1 + \sum_{t=2}^{\infty} \delta^{t-1} p_t - \frac{1}{1 - \alpha} \frac{1}{\beta} \theta_1}{\theta_3^R (\sigma - \rho)} \]

\[ \tau \left( 1 + \frac{\beta \delta}{1 - \delta} \right) = \left[ \frac{1}{\theta_3^R} \frac{1}{\theta_3} \theta_3^R - (1 + \beta \delta) \frac{1}{1 - \delta} \right] \bar{p} - \left[ \frac{1}{\theta_3^R} \frac{1}{\theta_3} \theta_3^R \right] \theta_1 \]

where \( \bar{p} \) is the average future price.

<table>
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<tr>
<th>( \beta )</th>
<th>( \delta )</th>
<th>( \alpha )</th>
<th>( \gamma )</th>
<th>( \tau )</th>
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**Table A-1: Optimal Taxes**

**B Figures and Tables**
Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full NHIS Urban Sample</th>
<th>NHIS Smokers&lt;sup&gt;a&lt;/sup&gt;</th>
<th>NHIS Nonsmokers</th>
<th>1990 Census&lt;sup&gt;b&lt;/sup&gt;</th>
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<tbody>
<tr>
<td>Cigarettes/day</td>
<td></td>
<td>18.79</td>
<td>–</td>
<td>–</td>
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<tr>
<td></td>
<td></td>
<td>(13.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
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<td>42.59</td>
<td>41.63</td>
<td>43.05</td>
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<tr>
<td></td>
<td>(17.99)</td>
<td>(17.10)</td>
<td>(18.31)</td>
<td></td>
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<td>0.520</td>
<td>0.543</td>
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<td></td>
<td>(.499)</td>
<td>(.499)</td>
<td>(.498)</td>
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<td>0.461</td>
<td>0.626</td>
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<tr>
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<td>(.496)</td>
<td>(.482)</td>
<td>(.498)</td>
<td></td>
</tr>
<tr>
<td>College or More&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>0.633</td>
<td>0.539</td>
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<td>(.482)</td>
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<td>West</td>
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<td>0.238</td>
<td>0.237</td>
<td>0.21</td>
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<tr>
<td>N obs.</td>
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<td>33,637</td>
<td>91,574</td>
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</tbody>
</table>


Notes: Standard deviations are in parentheses. Cigarette consumption and demographic variables are self-reported in the NHIS. Regions correspond to census designations. Twenty cigarettes is approximately a pack a day. Census data are for combined urban and rural sample.

<sup>a</sup> Self-designated “Current Smoker”

<sup>b</sup> Estimates for total US population. Education outcomes are for persons 25 years old and over.

<sup>c</sup> Includes “Some College”
Figure 3: Hazard Rates of Cigarette Smoking Initiation and Cessation

Source: 1987 National Health Interview Survey.

Notes: Hazard rates are calculated from self-reported ages when started smoking and when last regularly smoked, and do not control for observable characteristics. Quitting hazard does not include exits from smoking habits due to death.
<table>
<thead>
<tr>
<th>Panel A – Dependent Variable: 1(Smoker = 1), Linear Probability Model</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
<th>(v)</th>
<th>(vi)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-1.853***</td>
<td>-1.256***</td>
<td>-1.019***</td>
<td>-1.363***</td>
<td>-0.994***</td>
<td>-0.744***</td>
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<tr>
<td></td>
<td>(0.226)</td>
<td>(0.135)</td>
<td>(0.104)</td>
<td>(0.525)</td>
<td>(0.334)</td>
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<tr>
<td>ln(price)$_{t+1}$</td>
<td>-0.118</td>
<td>-0.426***</td>
<td>-0.545***</td>
<td>-0.021</td>
<td>-0.389</td>
<td>-0.575**</td>
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<td></td>
<td>(0.161)</td>
<td>(0.096)</td>
<td>(0.075)</td>
<td>(0.471)</td>
<td>(0.289)</td>
<td>(0.251)</td>
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<tr>
<td>Ratio of coefficients$^a$</td>
<td>0.064</td>
<td>0.340**</td>
<td>0.534***</td>
<td>0.016</td>
<td>0.392**</td>
<td>0.773***</td>
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<tr>
<td></td>
<td>(0.093)</td>
<td>(0.110)</td>
<td>(0.124)</td>
<td>(0.339)</td>
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<th>Panel B – First-stage Estimates of Prices</th>
<th>ln(price)$_t$</th>
<th>ln(taxes)$_t$</th>
<th>Budget Gap$^b$</th>
<th>ln(price)$_{t+1}$</th>
<th>ln(taxes)$_t$</th>
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<td>Budget Gap$^b$</td>
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<td>ln(taxes)$_{t+1}$</td>
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<td>–</td>
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<tr>
<td>Budget Gap$^b$</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Notes: Standard errors (in parentheses) are robust and clustered at the MSA level. All specifications control for age, age$^2$, race, and education and include both MSA dummies and MSA-specific time trends. * denotes significance at the 10% level; ** at the 5% level; and *** at the 1% level. Coefficients in Panel A are average marginal effects from a probit regression.

$^a$ The ratio of the coefficients on ln(price)$_{t+1}$ and ln(price)$_t$ will equal the net discount factor $\beta\delta$ if consumers are fully rational, or may equal 0 if consumers are sufficiently present- or projection-biased. Standard errors are calculated by the delta method.

$^b$ Average percentage shortfall in state government budgets (general fund) within an MSA.
Table 3: Price Sensitivity – Ordered Probit

<table>
<thead>
<tr>
<th>Dependent Variable: Smoking Status</th>
<th>Less than Cutoff</th>
<th></th>
<th>Less than or Equal to Cutoff</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)</td>
<td>(ii)</td>
<td>(iv)</td>
<td>(v)</td>
</tr>
<tr>
<td>(\ln(price_t))</td>
<td>-1.019**</td>
<td>-0.816**</td>
<td>-1.277***</td>
<td>-1.063***</td>
</tr>
<tr>
<td></td>
<td>(0.414)</td>
<td>(0.385)</td>
<td>(0.412)</td>
<td>(0.382)</td>
</tr>
<tr>
<td>(\ln(price_t)) * under20</td>
<td>-2.233**</td>
<td></td>
<td>-2.380**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.966)</td>
<td></td>
<td>(0.948)</td>
<td></td>
</tr>
<tr>
<td>(\ln(price_{t+1}))</td>
<td>-1.627***</td>
<td>-1.821***</td>
<td>-1.575***</td>
<td>-1.768***</td>
</tr>
<tr>
<td></td>
<td>(0.332)</td>
<td>(0.305)</td>
<td>(0.331)</td>
<td>(0.303)</td>
</tr>
<tr>
<td>(\ln(price_{t+1})) * under20</td>
<td>1.946***</td>
<td></td>
<td>1.962***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.620)</td>
<td></td>
<td>(0.542)</td>
<td></td>
</tr>
<tr>
<td>under20</td>
<td>-0.021</td>
<td>-0.052</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.423)</td>
<td></td>
<td>(0.047)</td>
<td></td>
</tr>
<tr>
<td>Thresholds:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\mu_1) (nonsmoker)</td>
<td>218.6671</td>
<td>218.6596</td>
<td>212.8748</td>
<td>212.7885</td>
</tr>
<tr>
<td>(\mu_2) (1/2 pack)</td>
<td>219.155</td>
<td>219.1477</td>
<td>213.5996</td>
<td>213.5135</td>
</tr>
<tr>
<td>(\mu_3) (1 pack)</td>
<td>219.5799</td>
<td>219.5729</td>
<td>214.529</td>
<td>214.4437</td>
</tr>
<tr>
<td>(\mu_4) (2 packs)</td>
<td>220.7809</td>
<td>220.7751</td>
<td>215.6642</td>
<td>215.5800</td>
</tr>
<tr>
<td>p-value of (\beta_3 + \beta_4 = 0)</td>
<td>–</td>
<td>0.8690</td>
<td>–</td>
<td>0.7830</td>
</tr>
<tr>
<td>N obs.</td>
<td>43,537</td>
<td>43,537</td>
<td>43,537</td>
<td>43,537</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.167</td>
<td>0.167</td>
<td>0.173</td>
<td>0.174</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors (in parentheses) and are clustered at the MSA level. All specifications control for age, age^2, race, and education. * denotes significance at the 10% level; ** at the 5% level; and *** at the 1% level. Cutoffs for smoking status are: 0 = nonsmoker, 1 = 1/2 pack per day, 2 = 1 pack per day, 3 = 2 packs per day, 4 = 2+ packs per day.
Table 4: Price Sensitivity Among Mature Smokers

Panel A – Dependent Variable: 1(Smoker = 1), Linear Probability Model

<table>
<thead>
<tr>
<th></th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(price&lt;sub&gt;t&lt;/sub&gt;)</td>
<td>-0.824***</td>
<td>-0.879***</td>
<td>-0.725***</td>
<td>-0.787***</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.077)</td>
<td>(0.215)</td>
<td>(0.251)</td>
</tr>
<tr>
<td>ln(price&lt;sub&gt;t+1&lt;/sub&gt;)</td>
<td>-0.641***</td>
<td>-0.619***</td>
<td>-0.531***</td>
<td>-0.496**</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.057)</td>
<td>(0.183)</td>
<td>(0.213)</td>
</tr>
<tr>
<td>Ratio of Coefficients&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.778***</td>
<td>0.704***</td>
<td>0.734***</td>
<td>0.630***</td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.122)</td>
<td>(0.044)</td>
<td>(0.074)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSA-Specific Time Trends</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N. obs</td>
<td>40,436</td>
<td>34,775</td>
<td>40,436</td>
<td>34,775</td>
</tr>
</tbody>
</table>

Panel B – First-stage Estimates of Prices

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(price&lt;sub&gt;t&lt;/sub&gt;)</td>
<td></td>
<td></td>
<td>0.494***</td>
<td>0.498***</td>
</tr>
<tr>
<td>ln(taxes&lt;sub&gt;t&lt;/sub&gt;)</td>
<td>–</td>
<td>–</td>
<td>(0.035)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Budget Gap&lt;sup&gt;b&lt;/sup&gt;</td>
<td>–</td>
<td>–</td>
<td>0.146*</td>
<td>0.132*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.074)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>ln(price&lt;sub&gt;t+1&lt;/sub&gt;)</td>
<td></td>
<td></td>
<td>0.550***</td>
<td>0.559***</td>
</tr>
<tr>
<td>ln(taxes&lt;sub&gt;t&lt;/sub&gt;)</td>
<td>–</td>
<td>–</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Budget Gap&lt;sup&gt;b&lt;/sup&gt;</td>
<td>–</td>
<td>–</td>
<td>0.398***</td>
<td>0.384***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.138)</td>
<td>(0.136)</td>
</tr>
</tbody>
</table>

Notes: Standard errors (in parentheses) are robust and clustered at the MSA level. All specifications control for age, age<sup>2</sup>, race, and education and include both year dummies and MSA-specific time trends. * denotes significance at the 10% level; ** at the 5% level; and *** at the 1% level. Coefficients for in Panel A are average marginal effects from a probit regression.

<sup>a</sup> The ratio of the coefficients on ln(price<sub>t+1</sub>) and ln(price<sub>t</sub>) will equal the net discount factor βδ. Standard errors are calculated by the delta method.

<sup>b</sup> Average percentage shortfall in state government budgets (general fund) within an MSA.
Table 5: Permanent vs. Temporary Price Effects

### Panel A – Dependent Variable: \(1(\text{Smoker} = 1)\)

<table>
<thead>
<tr>
<th></th>
<th>Age &gt; 30</th>
<th>Age &gt; 35</th>
<th>Age &lt; 20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)</td>
<td>(ii)</td>
<td>(iii)</td>
</tr>
<tr>
<td>(\ln(p_P^t))</td>
<td>-1.111***</td>
<td>-1.380***</td>
<td>-1.113***</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.181)</td>
<td>(0.118)</td>
</tr>
<tr>
<td>(\ln(p_T^t))</td>
<td>-0.214***</td>
<td>-0.217***</td>
<td>-0.220***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.068)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Ratio of Coefficients(^a)</td>
<td>5.191***</td>
<td>6.359**</td>
<td>5.059***</td>
</tr>
<tr>
<td></td>
<td>(1.31)</td>
<td>(2.07)</td>
<td>(1.26)</td>
</tr>
<tr>
<td>MSA Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Trend</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Trends by MSA</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>N obs.</td>
<td>37,651</td>
<td>37,651</td>
<td>32,322</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.497</td>
<td>0.505</td>
<td>0.495</td>
</tr>
</tbody>
</table>

### Panel B – Decomposition (Dependent Variable = Real Price\(_t\))

<table>
<thead>
<tr>
<th></th>
<th>Age &gt; 30</th>
<th>Age &gt; 35</th>
<th>Age &lt; 20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)</td>
<td>(ii)</td>
<td>(iii)</td>
</tr>
<tr>
<td>Real Taxes</td>
<td>1.164***</td>
<td>1.160***</td>
<td>1.117***</td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
<td>(0.171)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Real KY Burley Price</td>
<td>0.109***</td>
<td>0.108***</td>
<td>0.101**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>MSA Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Trend</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Notes: Standard errors (in parentheses) in Panel A are approximate bootstrap standard errors to account for the generation of \(\ln(p_P^t)\) and \(\ln(p_T^t)\), clustered at the MSA level. Standard errors in Panel B are robust and clustered at the year level. Permanent price is predicted using MSA fixed effects and taxes. Temporary price is predicted using Kentucky burley tobacco auction price. All specifications include age, age\(^2\), sex, race, and education. All columns use a linear probability model. * denotes significance at the 10% level; ** at the 5% level; and *** at the 1% level.

\(^a\) The ratio of the coefficients on \(\ln(p_P^t)\) and \(\ln(p_T^t)\) will equal \((1 - (1 - \beta)\delta)/(1 - \delta)\). Standard errors are calculated by the delta method. Significance is calculated as difference from 1.
Table 6: Effect of Price Uncertainty on Smoking Rates

<table>
<thead>
<tr>
<th>Dependent Variable: ( I(Smoker = 1) )</th>
<th>Probit(^a)</th>
<th>Linear Probability Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(i)</td>
<td>(ii)</td>
</tr>
<tr>
<td>Std(Price)</td>
<td>0.0254*</td>
<td>0.0267**</td>
</tr>
<tr>
<td></td>
<td>(0.0135)</td>
<td>(0.0133)</td>
</tr>
<tr>
<td>Std(Price) X Under20</td>
<td>–</td>
<td>-0.0052</td>
</tr>
<tr>
<td></td>
<td>(0.0244)</td>
<td>(0.0170)</td>
</tr>
<tr>
<td>Under20</td>
<td>–</td>
<td>-0.0930***</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td>(0.0216)</td>
</tr>
<tr>
<td>Std(Price) X Under25</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(0.0118)</td>
<td>(0.0096)</td>
</tr>
<tr>
<td>Under25</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(0.0157)</td>
<td>(0.0138)</td>
</tr>
<tr>
<td>ln(price(_t))</td>
<td>-0.361***</td>
<td>-0.355***</td>
</tr>
<tr>
<td></td>
<td>(0.0573)</td>
<td>(0.0568)</td>
</tr>
<tr>
<td>Demog. Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time Trend</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Standard errors (in parentheses) are robust and clustered at the MSA level. Std(Price) is calculated using departures from MSA trend of prices in the first half of the sample, while the second half of the sample is used to estimate the model. Demographics include age, age, race, and education. * denotes significance at the 1% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

\(^a\) Coefficients are average marginal effects.
Table 7: Parameter Estimates

Table 5:

<table>
<thead>
<tr>
<th>Table 4:</th>
<th>α</th>
<th>β</th>
<th>δ</th>
<th>β</th>
<th>δ</th>
<th>β</th>
<th>δ</th>
<th>β</th>
<th>δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>(iii)</td>
<td>0.494</td>
<td>0.853</td>
<td>0.859</td>
<td>0.828</td>
<td>0.885</td>
<td>0.856</td>
<td>0.856</td>
<td>0.829</td>
<td>0.883</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.106)</td>
<td>(0.072)</td>
<td>(0.078)</td>
<td>(0.080)</td>
<td>(0.107)</td>
<td>(0.072)</td>
<td>(0.080)</td>
<td></td>
</tr>
<tr>
<td>(iv)</td>
<td>0.410</td>
<td>0.717</td>
<td>0.879</td>
<td>0.700</td>
<td>0.901</td>
<td>0.720</td>
<td>0.875</td>
<td>0.701</td>
<td>0.899</td>
</tr>
<tr>
<td></td>
<td>(0.138)</td>
<td>(0.097)</td>
<td>(0.129)</td>
<td>(0.071)</td>
<td>(0.138)</td>
<td>(0.097)</td>
<td>(0.129)</td>
<td>(0.072)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Roman numerals refer to specifications in Tables 4 and 5. Standard errors are approximate, as calculated using the delta method. Estimates use the preferred estimate of \((\sigma - \rho) = 16.883\), and the coefficient on \(\frac{d\pi}{ds}\) from Column (iv) of Table 6.
Figure 4: Overpayment Ratio

Panel A: Overpayment Relative to Biased Self

Panel B: Overpayment Relative to Unbiased self

Notes: This figure calculates the ratio between the present values of the most expensive smoking habit that an unaddicted teenager would accept and the least expensive smoking habit that she would refuse. Panel A uses a biased agent in the denominator, while Panel B uses an otherwise-identical agent with $\alpha = 0$, $\beta = 1$. For a perfectly rational consumer (not facing credit constraints), this ratio should equal 1. Prices are fixed during the consumer’s youth (i.e. for $m$ periods) and then allowed to change during her adulthood. Estimates use benchmark results of $\alpha = 0.410$, $\beta = 0.7$, $\delta = 0.9$, $\sigma - \rho = 16.88$. $m$ refers to the remaining periods of “youth”. Present values are taken using the estimated long-run discount factor $\delta$. 

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## Additional Tables

### Table A-2: Demographic Controls

<table>
<thead>
<tr>
<th></th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td>1(Smoker = 1), Linear Probability Model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.00908***</td>
<td>0.00908***</td>
<td>0.01374***</td>
<td>0.01376***</td>
</tr>
<tr>
<td></td>
<td>(0.00318)</td>
<td>(0.00318)</td>
<td>(0.00212)</td>
<td>(0.00212)</td>
</tr>
<tr>
<td>Age^2</td>
<td>-0.00009***</td>
<td>-0.00009***</td>
<td>-0.00016***</td>
<td>-0.00016***</td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
<td>(0.00003)</td>
<td>(0.00003)</td>
<td>(0.00003)</td>
</tr>
<tr>
<td>Education variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>-0.234***</td>
<td>-0.238***</td>
<td>-0.0268***</td>
<td>-0.0261***</td>
</tr>
<tr>
<td></td>
<td>(0.0089)</td>
<td>(0.0089)</td>
<td>(0.0042)</td>
<td>(0.0042)</td>
</tr>
<tr>
<td>College</td>
<td>-0.0366*</td>
<td>-0.0362*</td>
<td>-0.0518***</td>
<td>-0.0510***</td>
</tr>
<tr>
<td></td>
<td>(0.0199)</td>
<td>(0.0198)</td>
<td>(0.0104)</td>
<td>(0.0105)</td>
</tr>
<tr>
<td>More than College</td>
<td>-0.0336</td>
<td>-0.0332</td>
<td>-0.0787***</td>
<td>-0.0776***</td>
</tr>
<tr>
<td></td>
<td>(0.0231)</td>
<td>(0.0230)</td>
<td>(0.0261)</td>
<td>(0.0263)</td>
</tr>
<tr>
<td>Demographic Variables:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>-0.0186*</td>
<td>-0.0186*</td>
<td>-0.0847***</td>
<td>-0.0847***</td>
</tr>
<tr>
<td></td>
<td>(0.0098)</td>
<td>(0.0099)</td>
<td>(0.0268)</td>
<td>(0.0268)</td>
</tr>
<tr>
<td>Black</td>
<td>0.0081</td>
<td>0.0080</td>
<td>0.0081**</td>
<td>0.0088***</td>
</tr>
<tr>
<td></td>
<td>(0.0097)</td>
<td>(0.0090)</td>
<td>(0.0041)</td>
<td>(0.0032)</td>
</tr>
<tr>
<td>Include Non-Urban Sample^b</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>MSA Fixed Effects and Trends</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>N obs.</td>
<td>120,535</td>
<td>120,535</td>
<td>410,729</td>
<td>410,729</td>
</tr>
</tbody>
</table>

Notes: Standard errors (in parentheses) are robust and multi-way clustered by both year and MSA following Cameron, Gelbach and Miller (2006). * denotes significance at the 10% level; ** at the 5% level; and *** at the 1% level.

^a The omitted category is “High School or Less”

^b Non-urban are respondents outside the 31 metropolitan statistical areas used in the main regressions. For statistical purposes here, they are grouped into a single “other” MSA.
### Table A-3: Predicting Current and Future Prices

<table>
<thead>
<tr>
<th>Dependent Variable: $\ln(\text{Price}_t)$</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(\text{Taxes}_t)$</td>
<td>0.3042</td>
<td>0.5006</td>
<td>0.5280</td>
<td>0.4971</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0310)</td>
<td>(0.0315)</td>
<td>(0.0314)</td>
</tr>
<tr>
<td></td>
<td>[0.0621]</td>
<td>[0.0781]</td>
<td>[0.0562]</td>
<td>[0.0756]</td>
</tr>
<tr>
<td>$\ln(\text{KY Burley}_t)$</td>
<td>–</td>
<td>0.1419</td>
<td>–</td>
<td>0.1402</td>
</tr>
<tr>
<td></td>
<td>(0.0155)</td>
<td>(0.0162)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.0480]</td>
<td>[0.0458]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{Budget Gap}_t$</td>
<td>–</td>
<td>–</td>
<td>-0.0246</td>
<td>0.0337</td>
</tr>
<tr>
<td></td>
<td>(0.0537)</td>
<td>(0.0477)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.1360]</td>
<td>[0.1476]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.776</td>
<td>0.827</td>
<td>0.779</td>
<td>0.827</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent Variable: $\ln(\text{Price}_{t+1})$</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(\text{Taxes}_t)$</td>
<td>0.6364</td>
<td>0.6360</td>
<td>0.6080</td>
<td>0.6077</td>
</tr>
<tr>
<td></td>
<td>(0.0446)</td>
<td>(0.0471)</td>
<td>(0.0483)</td>
<td>(0.0508)</td>
</tr>
<tr>
<td></td>
<td>[0.0882]</td>
<td>[0.0879]</td>
<td>[0.0816]</td>
<td>[0.0834]</td>
</tr>
<tr>
<td>$\ln(\text{KY Burley}_t)$</td>
<td>–</td>
<td>-0.006</td>
<td>–</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.0471)</td>
<td>(0.0631)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.1239]</td>
<td>[0.1111]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{Budget Gap}_t$</td>
<td>–</td>
<td>–</td>
<td>0.2655</td>
<td>0.2655</td>
</tr>
<tr>
<td></td>
<td>(0.1091)</td>
<td>(0.1095)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.1786]</td>
<td>[0.1778]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.844</td>
<td>0.853</td>
<td>0.860</td>
<td>0.867</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dependent Variable: $\ln(\text{Price}_{t+1})-\ln(\text{Price}_t)$</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(\text{Taxes}_t)$</td>
<td>0.1110</td>
<td>0.0991</td>
<td>0.0799</td>
<td>0.0761</td>
</tr>
<tr>
<td></td>
<td>(0.0242)</td>
<td>(0.0291)</td>
<td>(0.0268)</td>
<td>(0.0289)</td>
</tr>
<tr>
<td></td>
<td>[0.0688]</td>
<td>[0.0704]</td>
<td>[0.0691]</td>
<td>[0.0696]</td>
</tr>
<tr>
<td>$\ln(\text{KY Burley}_t)$</td>
<td>–</td>
<td>-0.0482</td>
<td>–</td>
<td>-0.0165</td>
</tr>
<tr>
<td></td>
<td>(0.0518)</td>
<td>(0.0441)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.1418]</td>
<td>[0.1319]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{Budget Gap}_t$</td>
<td>–</td>
<td>–</td>
<td>0.2902</td>
<td>0.2882</td>
</tr>
<tr>
<td></td>
<td>(0.0677)</td>
<td>(0.0659)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.1407]</td>
<td>[0.1421]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.102</td>
<td>0.150</td>
<td>0.197</td>
<td>0.225</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses are robust and clustered by MSA. Standard errors in square brackets are robust and multi-way clustered by both year and MSA following Cameron et al. (2006). All specifications include MSA fixed effects.
Table A-4: Price Sensitivity – Alternative Specifications

<table>
<thead>
<tr>
<th>Panel A: Young Smokers (Dependent Variable: $1(\text{Smoker} = 1)$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age &lt; 20</strong></td>
</tr>
<tr>
<td>ln(price$_t$)</td>
</tr>
<tr>
<td>(0.191)</td>
</tr>
<tr>
<td>ln(price$_{t+1}$)</td>
</tr>
<tr>
<td>(0.161)</td>
</tr>
<tr>
<td>(0.142)</td>
</tr>
<tr>
<td>Ratio of Price Coefficients</td>
</tr>
<tr>
<td>(0.108)</td>
</tr>
</tbody>
</table>

**First Stage (Dependent Variable: ln(Price$_{t+1}$))**

| ln(taxes$_t$) | 0.195 | 0.195 | 0.236 | 0.192 | 0.192 | 0.230 | 0.197 | 0.197 | 0.235 |
| (0.052) | (0.052) | (0.057) | (0.051) | (0.051) | (0.058) | (0.050) | (0.051) | (0.057) |
| Budget Gap$_t^{a}$ | 0.298 | 0.350 | 0.298 | 0.297 | 0.343 | 0.298 | 0.290 | 0.338 | 0.290 |
| (0.080) | (0.076) | (0.080) | (0.078) | (0.071) | (0.078) | (0.076) | (0.071) | (0.076) |

N. obs | 5,289 | 5,289 | 5,289 | 5,289 | 11,647 | 11,647 | 11,647 | 11,647 | 17,975 | 17,975 | 17,975 | 17,975 | 17,975 | 17,975

<table>
<thead>
<tr>
<th>Panel B: Mature Smokers (Dependent Variable: $1(\text{Smoker} = 1)$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age &gt; 30</strong></td>
</tr>
<tr>
<td>ln(price$_t$)</td>
</tr>
<tr>
<td>(0.063)</td>
</tr>
<tr>
<td>ln(price$_{t+1}$)</td>
</tr>
<tr>
<td>(0.051)</td>
</tr>
<tr>
<td>ln(taxes$_t$)</td>
</tr>
<tr>
<td>(0.046)</td>
</tr>
<tr>
<td>Ratio of Price Coefficients</td>
</tr>
<tr>
<td>(0.108)</td>
</tr>
</tbody>
</table>

**First Stage (Dependent Variable: ln(Price$_{t+1}$))**

| ln(taxes$_t$) | 0.176 | 0.176 | 0.211 | 0.170 | 0.170 | 0.205 |
| (0.051) | (0.051) | (0.058) | (0.052) | (0.052) | (0.058) |
| Budget Gap$_t^{a}$ | 0.283 | 0.324 | 0.283 | 0.285 | 0.325 | 0.285 | 0.285 | 0.285 |
| (0.074) | (0.068) | (0.074) | (0.075) | (0.068) | (0.075) |

N. obs | 40,436 | 40,436 | 40,436 | 40,436 | 34,775 | 34,775 | 34,775 | 34,775 |

Notes: Standard errors (in parentheses) are robust and clustered at the MSA level. All specifications control for age, age$^2$, race, and education, and include both MSA fixed effects and MSA-specific time trends.

$^a$ Average percentage shortfall in state government budgets within an MSA.