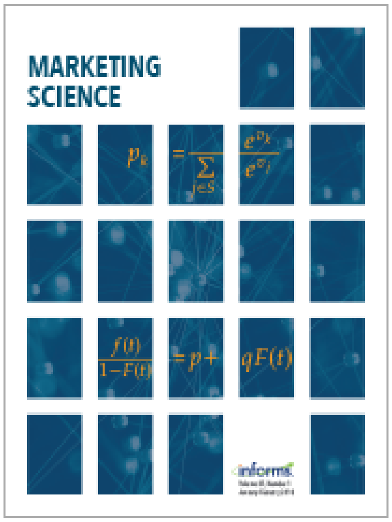

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Smoking Cessation: A Model of Planned vs. Actual Behavior for Time-Inconsistent Consumers

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We offer a simple model of intertemporal choice to characterize how planned versus actual behaviors evolve for time-inconsistent smokers. Our results suggest that smokers' participation and cessation decisions are governed by the interplay between three effects. The *cessation effect* leads smokers to advance their plans to quit smoking, whereas the *procrastination effect* leads them to consecutively revise their planned quitting age upwards. Consequently, the duration of smoking is effectively governed by which one of these two effects is dominant. Finally, for certain consumer segments, a *threshold effect* causes an "all or nothing" type of extreme smoking behavior based on certain critical values of present-biased preferences. Our results provide some preliminary evidence that both marketing efforts by tobacco firms and public policy initiatives can have a significant influence on smoking behavior. In particular, we find that reductions in the age at which individuals start smoking may not only vastly extend their duration of smoking, but also convert potential "never smokers" into lifetime smokers. Finally, we estimate a hazard model using survey data from over 800 smokers to provide evidence in support of our theoretical model.

Key words: rational addiction; time-inconsistent preferences; smoking cessation; hyperbolic discounting; hazard models
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1. Introduction

Thank heaven, I have given up smoking again!... God! I feel fit. Homicidal, but fit. A different man. Irritable, moody, depressed, rude, nervy, perhaps; but the lungs are fine.
—A. P. Herbert

Researchers frequently examine the impact of marketing actions by invoking rational consumers with well-defined and stable preferences (Assunção and Meyer 1993, Rabin 1998, Sun 2005). Preference theory characterizes rationality by postulating that consumers make choices that are optimal with respect to their defined preference ordering (see Shugan 2006 for a discussion[1]). However, the recent literature has advocated departures from rationality such as cognitive limitations, context effects, mental accounting, and time inconsistency of preferences (Dholakia and Simonson 2005, Loewenstein and Thaler 1989). It is not surprising that this debate has also been at the heart of the analysis of addictive behaviors, where a diverse set of models have been proposed based on different assumptions regarding the nature and extent of rationality among consumers (Chaloupka et al. 2000).

The rational addiction model (RAM) of Becker and Murphy (1988) was the first to recognize that addiction, a seemingly irrational and myopic behavior, is consistent with optimization according to stable preferences. In this framework, individuals with perfect foresight choose addiction because the gains from addiction exceed the costs (Gruber and Koszegi 2001, 2004). The essence of the model is that greater past consumption of an addictive good increases the desire for current consumption but decreases the marginal utility of consuming the same good in the future. Although several empirical applications have found support for the RAM for a variety of addictions (Olekalns and Bardsley 1996, Waters and Sloan 1995), the assumption of perfect foresight on part of consumers has been criticized on the grounds that it does not account for the "self-control" problem faced by most consumers of addictive substances (Chaloupka

[1] Shugan (2006) provides a detailed discussion of consumer rationality, including definitions and empirical evidence. He notes that statistical controls appear to provide increasing support for consumer rationality while experimental controls have often found the opposite. Such an apparent conflict, the author argues, is due to the fact that these two perspectives ask different questions.

and Warner 2000, Gruber 2003). The main contribution of the recent literature has been to overcome this limitation of perfect foresight and explicitly incorporate *time inconsistency* in consumer choice (Gruber and Koszegi 2001, 2004; Laibson 1997, 2003; O'Donaghue and Rabin 1999; Wertenbroch 1998, 2003).[2] In the context of smoking behavior, which is the subject of this paper, this inconsistency is generally characterized as the conflict between a smoker's present preferences and future choices. In the present, smokers are very impatient and greatly discount the future costs of smoking relative to its current benefits. Hence, when faced with a choice between the instant gratification from smoking versus the future mortality risks, they prefer to smoke. In contrast, future smokers are very patient and prefer to quit because of the mortality risk. The problem, to the abiding regret of smokers, is that they never reach this future scenario (Gruber 2003). As they move from today to tomorrow, patient future smokers are transformed into impatient current smokers and delay their decision to quit.

The unique features of time inconsistency are the use of precommitment or self-control devices to handle impulsive behavior (Kivetz and Simonson 2002, Thaler and Shefrin 1981) and the inability of time-inconsistent consumers to actualize their desired or predicted future levels of consumption (Gruber and Koszegi 2004). The marketing literature has primarily focused on the former tendency of time-inconsistent consumers to use self-control devices, and a few studies have found that consumers voluntarily and strategically ration their purchase quantities of impulse goods (Hoch and Loewenstein 1991, Wertenbroch 1998). For example, Wertenbroch (1998) found that instead of purchasing cartons, many regular smokers buy their cigarettes by the pack. These smokers knowingly forsake the quantity discounts from cartons in order to curtail smoking, thereby suggesting that precommitment appears to be an important mechanism for controlling time-inconsistent behavior.

The second feature of time inconsistency regarding the differences between planned and actual behavior is also a common feature of stated smoker preferences. According to Burns (1992), 8 of 10 smokers in America express a desire to quit their habit. However, as stated in Gruber and Koszegi (2004):

> Unfortunately, these desires can be interpreted in a number of ways, and *we are not aware of any evidence for adults on their specific predictions or intentions about future smoking behavior*. (p. 1963, italics added)

Here, we focus on this task of characterizing the desired optimal behavior of time-inconsistent smokers. We develop a theoretical model of planned and actual smoking behavior, analyze the implications of this model with regard to smoking participation and cessation, and attempt to validate the model with data collected from a sample of over 800 current and former smokers. Accordingly, §2 presents an economic framework for modeling time-inconsistent behavior and contains the details of our theoretical model. Section 3 contains a numerical simulation of the model where we characterize the conditions under which smoking is initiated and formally analyze the impact of a smoker's penchant for instant gratification and procrastination on the likelihood and timing of cessation. This section also discusses how changes in marketing and public policy variables related to the benefits and costs of smoking impact the planned and effective quitting ages of smokers. Section 4 describes our attempt to validate the theoretical model with survey data on the actual and planned durations of smoking. Because this model cannot be estimated directly, we adopt a three-stage strategy to align it with the empirical setting. First, we use the theoretical model to simulate how the planned and actual duration of smoking varies across a population of consumers who differ from one another in their perceptions of the benefits and costs of smoking. In the second stage, we estimate an empirical hazard model of smoking durations and find that it provides a good fit to the simulated data. In the last stage, we estimate the empirical model on the actual survey data and compare the resulting predicted cessation behavior with the predicted rates from the simulated data. We find that the theoretical model generates distributions of planned and actual smoking durations that are very similar to those that are observed with data from the survey of actual smokers. This led us to conclude that there is strong evidence in favor of the theoretical model. Finally, §5 concludes with the implications of our model, its limitations, and directions for future research.

To summarize, this paper contributes by formally investigating the relationship between planned and actual behavior over the entire life cycle for smokers. Building on the prior work of Laibson (1997) and Gruber and Koszegi (2001, 2004), our theoretical model examines the manner in which time-dependent preferences can cause actual quitting rates to be much lower than planned quitting rates. Also, further to the well-documented procrastination effect (Akerlof 1991; O'Donoghue and Rabin 1999, 2000), our model identifies two additional effects that govern smoking cessation for time-inconsistent consumers: (a) the *cessation effect* refers to our counterintuitive finding that a proclivity for instant gratification causes smokers to actually advance their original plans to quit smoking and (b) the *threshold effect* makes it less likely

[2] Although an early analysis of time-inconsistent discounting can be found in Strotz (1955).

that smokers will start smoking if their present biased preference exceeds a threshold value. As a result, we demonstrate that two consumers with very similar preferences can adopt extremely different smoking behaviors, one of them choosing never to smoke and the other becoming a lifetime smoker. Our analysis also highlights the extreme power that marketing efforts by tobacco manufacturers may have on smoking behavior, not just by affecting the length of smoking, but also by potentially converting some nonsmokers into lifetime smokers. Furthermore, we show that the development of more effective smoking cessation aids may induce lifetime smoking behavior in certain segments of consumers. Finally, our theoretical results have some interesting public policy implications as we demonstrate that even a small increase in the legal smoking age may not just reduce the length of smoking, but also decrease the initiation of smoking. Thus, our theory provides evidence that may lend some support for legislative efforts that attempt to increase the legal smoking age. In particular, California has been at the forefront of these efforts and has recently enacted numerous antismoking measures, including legislative attempts to increase the legal smoking age from 18 to 21. Increasing the legal age beyond 18 years will have the immediate effect of making it harder to market tobacco to high school students and teenagers, thereby potentially saving many of them from a lifetime of addiction.

2. A Model for Individual Smoking Behavior

2.1. Consumer's Maximization Problem

Our model characterizes the smoking horizon of consumers from the time smoking is initiated to the time of their planned and actual quitting behavior. We assume that each consumer's decision to quit (planned quitting age) arises from the perceptions of three types of costs and benefits:

(1) **Direct utility benefit of smoking** (associated with the pleasure of smoking). In order to model this, we define an instantaneous additive utility function for period t as:

$$U_t = u_s(S_t) + u_x(X_t), \tag{1}$$

where S_t takes a value of zero if individuals do not smoke in period t and a value of one if they do, u_s is the direct utility derived from smoking, and u_x is the utility derived from consuming the numeraire or other market goods (X).

The consumer's budget constraint in period t is given by:

$$p_s S_t + X_t = Y_t, \tag{2}$$

where Y_t is the individual's income in period t and p_s is the (relative) price of cigarettes per period. Therefore, the utility level in period t may be characterized as:

$$U_t = u_x(Y_t) \equiv u_x(X_t)$$

if the consumer does not smoke in period t.

$$U_t = u_s(1) + u_x(Y_t - p_s)$$

if the consumer smokes in period t.

We assume that the instantaneous utility from smoking is higher than the instantaneous utility from not smoking (i.e., by consuming only market goods). Otherwise, no one would ever choose to smoke. Accordingly, we call ΔU the *incremental* direct utility derived from smoking (and consuming market goods) versus not smoking, i.e.,

$$\Delta U_t = u_s(1) + u_x(Y_t - p_s) - u_x(Y_t) > 0. \tag{3}$$

(2) **Health cost of smoking** (associated with health and mortality risk). We follow Suranovic et al. (1999) and model the health cost of smoking through a reduction in the consumer's life expectancy. Assume that individuals have the opportunity to start smoking at a given stage of their life cycle. Without any loss of generality, the individuals' age A can be measured from that stage onwards (i.e., we assume that $A = 0$ when the individuals can start smoking).[3] Let $T(A)$ be the remaining life expectancy at age A for a "never smoker" and assume that each year of smoking reduces life expectancy by α ($0 < \alpha < 1$). Then the life expectancy of an individual aged A who has smoked until age I is given by $A + T(A) - \alpha I$. Note that under our assumptions the quitting age is equal to the number of years of smoking.

(3) **Withdrawal cost of smoking** (associated with the suffering and discomfort caused by refraining from smoking until addiction disappears). We model this effect by assuming that smokers bear a utility loss of u_w when they quit smoking (at age I). This term captures the withdrawal effect, which refers to a negative physical reaction and other reductions in utility associated with the cessation of smoking (Chaloupka 1991).

Finally, we note that for each individual, the optimal quitting age also depends on how the individual discounts future utility. A time-consistent consumer discounts the future at a constant discount rate r.

[3] What we are assuming, more precisely, is that there is a minimum age for individuals to start smoking, due to restrictions imposed by family pressure, social norms, or legal rules (e.g., prohibition to sell cigarettes to youngsters).

Such a consumer will face the following dynamic optimization problem:

$$\max_I V = \int_{t=A}^{I} [u_s(1) + u_x(Y_t - p_s)] e^{-r(t-A)}\, dt + \int_{t=I}^{A+T(A)-\alpha I} u_x(Y_t) e^{-r(t-A)}\, dt - u_w e^{-r(I-A)}. \quad (4a)$$

The first term in this equation captures the present value of the total direct utility of smoking from age A to I, whereas the second term reflects the net utility gain from (a) the increased longevity as a result of quitting at I and living until $A+T(A)-\alpha I$, and (b) the concomitant disutility of the withdrawal symptoms associated with quitting. Expression (4a) implicitly assumes that individuals start smoking when they are offered that possibility (at $A = 0$). However, consumers can always choose not to start smoking, in which case they will not have to bear the withdrawal cost u_w. Consequently, for $A = I = 0$ the individual's expected lifetime utility will not be given by (4a), but by:

$$V' = \int_{t=0}^{T} u_x(Y_t)\, e^{-rt}\, dt \quad (4b)$$

Let $I^*(A)$ be the quitting age that maximizes (4a) at age A. Accordingly, $I^*(0)$ is the value of I that maximizes (4a) at the "starting age" ($A = 0$) and $V^*(0)$ is the corresponding value of the objective function (i.e., $V^*(0) = V[I^*(0)]$). Then for any age A, $I^*(A)$ will only be the optimal quitting age if $V^*(0) \geq V'$. We call this condition, which evaluates whether an individual wishes to smoke at the starting age, the "lifetime utility condition" (LUC). Thus, the optimal quitting age at age A, $I^{OPT}(A)$ is:

$$I^{OPT}(A) \begin{cases} = I^*(A) & \text{if LUC is satisfied} \\ = 0 & \text{if LUC is not satisfied.} \end{cases}$$

Having defined the utility function, we turn to a comparative analysis of the optimal quitting age for time-consistent versus time-inconsistent smokers.

2.2. Quitting Age Under Exponential Discounting

The optimal quitting age under exponential discounting can be derived by solving the maximization problem 4(a). The details are contained in the technical appendix, where we characterize the solution and describe the properties of the optimal quitting age. Here, we simply note that under exponential discounting the optimal quitting age is independent of the smoker's current age (see Equation (A4)).

2.3. Quitting Age Under Time-Inconsistent Preferences

The hyperbolic function incorporates time inconsistency by allowing the discount rates to be higher for shorter delay horizons, i.e., the rate of decline in the discount function decreases with the time delay between present and future consumption (Loewenstein and Prelec 1992, Frederick et al. 2002). Under hyperbolic discounting, the discount function for t periods is given by (Ainslie and Haslam 1992; Laibson 1997, 2003):

$$F_t = (1 + \theta t)^{-\beta/\theta}, \quad \beta \geq 0,\ \theta \geq 0. \quad (5)$$

For this function, the rate of decline in the discount function (i.e., the discount rate) decreases as t increases, as desired. Thus, $r(t) = -F'(t)/F(t) = \beta/(1+\theta t)$, and we can see that β represents the discount rate when $t = 0$. Further, as t increases, the discount rate converges to zero. This means that any future period is discounted at a lower rate than the current period. More specifically, the future period discount rate will be lower the higher the value of θ, so that θ represents time inconsistency and a bias towards the present in consumer preferences. Thus, the hyperbolic function captures an important consumer instinct: Any behavior that involves a sacrifice appears less appealing as the moment of sacrifice approaches.

The optimization problem of a time-inconsistent smoker is therefore similar to Equation (4a) and differs only with respect to the discount factor. Modifying (4a) to include hyperbolic discounting, it is possible to derive the following first-order condition (see technical appendix for details):

$$\Delta U_I [1 + \theta(I - A)]^{-\beta/\theta} + \beta u_w [1 + \theta(I - A)]^{-(\beta+\theta)/\theta} = \alpha u_x(Y_{T-\alpha I})[1 + \theta(T - A - \alpha I)]^{-\beta/\theta}. \quad (6)$$

Note that unlike the case of exponential discounting, the optimal quitting age for hyperbolic discounters depends on their current age (A). For a given set of parameter values, each current age (A) yields a different "optimal" quitting age $I^*(A)$. This is the typical behavioral pattern for time-inconsistent consumers. Due to the time inconsistency of their preferences, these smokers keep changing their planned quitting age as they become older. Whether they effectively end up quitting or not at some point during their life depends on factors that are captured in the model parameters. In particular, the individual will effectively stop smoking if there is a solution to Equation (6) such that $I^*(A) = A$. This leads us to the following cessation equation:

$$\Delta U_I + \beta u_w = \alpha u_x(Y_{T-\alpha I})[1 + \theta(T - (1+\alpha) I)]^{-\beta/\theta}. \quad (7)$$

As before, expressions (6) and (7) will only provide the "optimal" and effective quitting ages if the LUC utility condition is satisfied, i.e., if $V^*(0) \geq V'$ where $V' = \int_{t=0}^{T} u_x(Y_t)(1 + \theta t)^{-\beta/\theta}\, dt$ and $V^*(0) = V[I^*(0)]$.

It is worth noting that conditions (6) and (7) may be equivalently expressed in terms of the crossing period n, i.e., the number of periods elapsed at the point where the exponential and hyperbolic discount factors are equal. In this way, the hyperbolic discounting parameter β can be determined endogenously for given values of r, n, and θ (see the technical appendix for details). Solving these equations yields the optimal planned and effective quitting ages. However, because they cannot be solved algebraically for I, we investigate the implications of our model by means of numerical simulations, which are reported in the next section.

3. Numerical Simulations

3.1. Base Simulation

To understand how preference bias affects smoking participation behavior, we ran some numerical simulations of the model under the simplifying assumption of constant income ($Y_t = \overline{Y}$) and the following parameterization:

—utility discount rate under time-consistent preferences $r = 3.5\%$;

—remaining life expectancy when the individuals start to smoke ($A = 0$) $T = 60$;

—direct utility level for a nonsmoker $u_x(\overline{Y}) = 100$;

—direct utility gain from consuming both cigarettes and other goods $\Delta U = 5$;

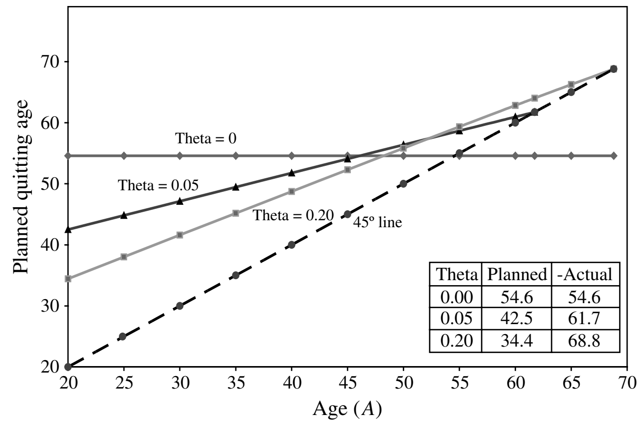
—withdrawal utility loss $u_w = 20$;

—life-expectancy loss from smoking one period $\alpha = 0.12$.

The choice of 3.5% for the discount rate is justified on the basis of a recent study by Chesson and Viscusi (2000), who estimated a discount rate of 3.4% for smokers. The choice of $T = 60$ is governed by the fact that life expectancy in most Western countries is close to 80 years. Thus, setting the life expectancy T to 60 corresponds to implicitly assuming that individuals start smoking at the real age of 20. The choice of 0.12 for the life-expectancy loss parameter α was based on estimates from the epidemiological literature where it has been shown that the loss of life expectancy resulting from lifetime smoking (that is, smoking for approximately 55 years) may be as high as 6.5 years (Shaw et al. 2000). Using this information, we obtain a rough estimate of α as $6.5/55 = 0.12$. Finally, our choice of $u_x(\overline{Y}) = 100$, $\Delta U = 5$, and $u_w = 20$ merely imply that smoking increases instant utility by 5% whereas withdrawal symptoms decrease total utility by 20%.

For these parameter values, the optimal quitting age under exponential discounting, which can be directly computed from Equation (A4) (technical appendix), is $I^* = 34.6$ years. Thus, the model predicts that an individual with time-consistent preferences will smoke for approximately 35 years. If we

Figure 1 **Planned Quitting Age as a Function of Current Age** ($n = 40$)



Theta	Planned	-Actual
0.00	54.6	54.6
0.05	42.5	61.7
0.20	34.4	68.8

assume that the starting age for the onset of smoking is 20 years, this corresponds to an optimal "real" quitting age of 54.6 years. In the rest of this section we report our results in terms of "real age" by adding 20 years to the model results (we perform a sensitivity analysis of this assumption in §3.2).

The hyperbolic discounting case is more complicated because we have two other variables (θ and β or θ and n) that influence $I^*(A)$. Furthermore, $I^*(A)$ is not invariant to the individual's current age (A). We proceeded as follows. First, we fixed the crossing period (n), and starting with a particular value of θ, we solved Equation (A9) (technical appendix) numerically to find the optimal quitting age for different values of A. This was followed by changing the value of θ and repeating the process (recall that an increase in θ implies an increase in the preference bias towards the present). We present our results diagrammatically in Figure 1. It depicts how the planned quitting age (I) varies with the individual's current age (A) for alternative values of θ and a crossing period of $n = 40$.

The intercept of each "planned quitting-age curve" measures the number of years that individuals plan to participate in the market when they start smoking. The figure illustrates the two major competing forces that shape planned and actual quitting behavior: the cessation effect and the procrastination effect. These two effects, along with a third variable that impacts smoking participation (the threshold effect), are discussed in detail below.

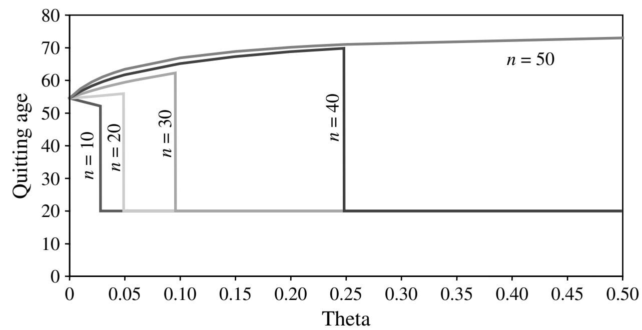
Cessation Effect. We find that the larger the preference bias for the present (i.e., the higher the value of θ), the sooner the individual plans to quit at the starting age.[4] Rather paradoxically, *a proclivity for instant gratification causes smokers to advance their original plans to quit smoking*. In other words, smokers

[4] This is not a completely general result. For particular values of n there may be intervals of θ in which the planned smoking period at the starting age does not increase with θ.

with larger present preference biases are more likely to harbor the illusion that they can quit early. We call this the *cessation effect*. The intuition for this effect is as follows. First, consider the case of rational individuals who start smoking at the age of 20 (period 0). As noted above, these individuals would plan to quit smoking in about 35 years (age 55), because this is when the present value of marginal smoking benefits equal the marginal health costs of smoking for one additional year. However, note that although the marginal benefits are due to occur in 35 years, the marginal health costs are only due to occur in about 56 years.[5] By way of contrast, now consider the impact of increasing the value of θ from 0 to 0.1. The discount factor for 35 years decreases from 0.29 to 0.27, whereas the discount factor for 56 years increases from 0.14 to 0.19.[6] This implies that for the rational smoker the present value of 100 units of smoking benefits is 29 units, but for the hyperbolic smoker it is only 27 units. In other words, hyperbolic smokers *underestimate the benefits of smoking* relative to rational smokers. At the same time, hyperbolic smokers evaluate 100 units of health costs as 19 units (relative to the 14 units for the rational smoker). Consequently, they *overestimate the health cost of smoking*. Taken together, these two effects cause hyperbolic smokers to accelerate their cessation plans at the onset of smoking. Note that the cessation effect increases with θ.

Procrastination Effect. This well-known effect (O'Donoghue and Rabin 2000) leads hyperbolic smokers to successively postpone their planned quitting age. The slope of each planned quitting-age curve in Figure 1 measures the extent of procrastination. For each value of θ, the effective quitting age is given by the intersection between the corresponding planned quitting-age curve and the 45° line ($I^*(A) = A$). For $\theta = 0.05$, these individuals initially plan to quit at the

Figure 2 **Effective Quitting Age as a Function of θ**



age of 42.5. However, they procrastinate and end up quitting only at the age of 61.7, about 7 years later than time-consistent smokers. As is clear from the figure, this procrastination effect is even more pronounced for $\theta = 0.20$.

In Figure 2, we show how the effective quitting age varies with the degree of preference bias (θ) for alternative values of n (crossing period). For example, when $n = 40$, we find that the effective quitting age initially rises with θ. This implies that the procrastination effect dominates the cessation effect. In other words, instead of advancing their plans to quit, these smokers are more likely to postpone cessation. The opposite is true when $n = 10$.

Threshold Effect. Figure 2 also shows that for each n there is a value of θ above which the quitting age suddenly drops to the starting age (20 years), meaning that the time-inconsistent individual will no longer want to initiate smoking. The rationale for this discontinuity is as follows. Consider again the case of $n = 40$. As θ increases, there is a decline in the planned quitting age at the onset of smoking (i.e., the cessation effect).

For example, when θ increases from 0 to 0.20 the planned quitting age drops from 54.6 to 34.4. Similarly, when $\theta = 0.24$ the planned quitting age drops further to 33.5 (and the actual quitting age becomes 68.8, meaning that these individuals would smoke for most of their lives). The drop in the planned quitting age implies that the present value of the withdrawal costs increases, reducing the lifetime utility gain from smoking relative to choosing never to smoke (note that the nonsmoker bears no withdrawal cost). However, when θ is increased to 0.25, the expected lifetime utility of smoking is no longer higher than the expected lifetime utility of *non*–smoking (that is, the lifetime utility condition ceases to be satisfied). At this point θ reaches its threshold level and the effective number of years of smoking suddenly drops to zero. In short, the threshold effect arises because hyperbolic smokers tend to be overly optimistic about their ability to quit early. In turn, this increases their perception of the costs associated with planned quitting and may

[5] Because we assume that the individual loses 0.12 years of life expectancy per year of smoking, if he smokes for 35 years his remaining life expectancy is reduced by 4.2 years, from 60 to about 56 years, or from age 80 to age 76.

[6] This is entirely consistent with the literature, which provides ample evidence that discount rates decline over relatively long time horizons. For example, Thaler (1981) found that the average discount rates across different monetary values were, respectively, 2.01, 0.9, and 0.17 for 1 month, 1 year, and 10 years in the future. Similarly, Cropper et al. (1992) tested discounting in the context of intergenerational choices between two life-saving programs, one involving saving lives today, whereas the other would save lives at fixed points in the future. They found implied discount rates that declined from 16.8% for lives saved in Year 5, to 11.2% in Year 10, to 7.4% in Year 25, 4.8% in Year 50, and 3.8% in Year 100. In a related study, Cropper et al. (1991) conclude that the discount rate used to discount lives from $T = 50$ to $T = 0$ is greater than the discount rate used to discount lives at $T = 100$ to $T = 50$, again suggesting that the discount rate falls over time.

lead them to refrain from ever initiating smoking. Our model indicates that under ceteris paribus conditions, two smokers with very similar preferences (say, θ values of 0.24 and 0.26, respectively) may end up adopting extremely different smoking behaviors, with one choosing never to smoke and the other becoming essentially a lifetime smoker. Thus, our results seem to capture the all or nothing behavior associated with a variety of consumption patterns. The real-world relevance of the threshold effect depends mainly on the extent to which smokers' preferences lie above the threshold or at least close to it (so that a change in exogenous conditions may alter their location relative to the threshold, as discussed below). In addition, it depends on the starting age and the degree to which youngsters realize or are aware of the withdrawal costs when they initiate smoking. For example, consider a group of hyperbolic discounters facing the decision of whether or not to start smoking. As we demonstrate in our sensitivity analysis below, it turns out that older individuals in this group also have a lower threshold value of θ and are therefore more likely to stay above the threshold—i.e., they are less likely to start smoking.

In summary, our simulation highlights three major effects with regard to lifetime smoking behavior for time-inconsistent individuals:

(a) The cessation effect *reduces* the number of periods that individuals plan to smoke when they first engage in cigarette consumption;

(b) The procrastination effect *increases* the amount by which they postpone their planned quitting age with the passage of time;

(c) The threshold effect causes some consumer segments to be "never smokers" and others to indulge in a lifetime of smoking.

3.2. Effects of Parameter Changes

We now discuss how changes in marketing- and policy-related variables impact the planned and effective quitting ages of smokers. Specifically, we consider the impact of (a) an increase in the perceived direct utility of smoking, (b) an increase in the perceived health costs of smoking, (c) a reduction in the perceived withdrawal costs, and (d) a decrease in the age at which a consumer starts smoking. We note that marketing, promotion, and public policy messages targeted towards potential and actual smokers directly impact these four factors. According to Kilbourne (1999), image advertising has been especially effective on young people and some of the themes developed in cigarette ads are particularly seductive, such as the linking of tobacco with maturity, sophistication, sex, rebelliousness, and athletic ability. Empirical research has shown that smoking and alcohol advertising and other less direct forms of communication (such as associating smoking with youthful vigor, good looks, and high socioeconomic status in movie scenes), tend to increase individuals' perception of the benefits of consumption (Pechman and Shih 1999, MacKinnon and Lapin 1998, Pollay et al. 1996).

The results obtained from solving the model numerically, with variations in parameter values relative to the base scenario, are shown in Table 1 and discussed in detail below.

Increase in the Perceived Direct Utility Gain of Smoking (ΔU)

Tobacco companies can impact the direct utility gain of smoking through pricing, advertising, and promotion decisions. From Table 1 we see that increasing the direct utility of smoking (ΔU) by 20% (from five to six) has the following effects:

1. Rational smokers ($\theta = 0$) increase their quitting age by about 4 years (from 54.6 to 58.7 years)
2. Time-inconsistent individuals who were smokers in the base scenario (interval $0 \leq \theta \leq 0.25$) increase their actual quitting age by less than 4 years. For example, for $\theta = 0.1$ the effective quitting age increases by only 2.5 years (from 65.2 to 67.7).
3. Some time-inconsistent individuals who were "never smokers" in the base scenario (for whom

Table 1 Effective and Planned Quitting Ages as a Function of θ (for Parameter Variations from Reference Scenario)

	Base		$\Delta U = 6$		$\alpha = 0.15$		$u_w = 10$		$T = 65$	
θ	Plan	Actual	Plan	Actual	Plan	Actual	Plan	Actual	Plan	Actual
0	54.6	54.6	58.7	58.7	48.1	48.1	53.0	53.0	54.0	54.0
0.01	50.4	56.7	55.0	60.6	43.8	50.0	48.9	54.8	49.1	56.1
0.05	42.5	61.7	47.6	65.0	36.3	55.1	40.9	59.1	39.9	61.2
0.1	38.3	65.2	43.3	67.7	—	—	36.7	62.2	35.1	64.6
0.2	34.4	68.8	39.1	70.4	—	—	32.9	65.7	30.7	68.3
0.3	—	—	36.8	71.8	—	—	30.9	67.7	28.5	70.1
0.5	—	—	34.2	73.0	—	—	28.8	70.1	—	—
0.75	—	—	32.4	73.6	—	—	—	—	—	—
1	—	—	—	—	—	—	—	—	—	—
Threshold	0.249		0.936		0.074		0.675		0.313	

θ ranges from 0.25 to 0.94), not only start smoking but also do so for essentially all their lives (effectively quitting after the age of 70).

As this example illustrates, our model provides interesting insights for the marketing of cigarettes. Due to the discontinuity in the smoking duration function, *minor price reductions or advertising campaigns that have only a small impact on perceptions of smoking benefits may convert a "never smoker" into a lifetime smoker*. Note that this result is not simply due to the addictive property of cigarettes, but mainly due to time inconsistency in consumers' preferences. Thus, our model captures the extreme power that marketing and policy decisions can have in shaping the behavior of some segments of smokers.

Increase in the Perceived Health Costs of Smoking (α)

Antismoking campaigns often call consumers' attention to the detrimental effects of smoking on human health, trying to prevent them from underestimating those effects. In Table 1, we demonstrate the effect of a 25% increase in the perceived health costs of smoking. Basically, this change has the opposite effect relative to what was observed with increasing the direct utility of smoking:

1. For low values of θ (interval $0 \le \theta \le 0.07$), the effective quitting age declines by approximately seven years.

2. The threshold level of θ declines from 0.25 to 0.07. Therefore, long-time smokers (i.e., smokers between 45 and 49 years in the base scenario) whose value of θ lies in the 0.07–0.25 interval, will now no longer want to start smoking.

Thus, increasing the perceived health costs of smoking has a significant role to play in smoking cessation behavior. Of course, these results depend on the ability of public campaigns to actually convince smokers of the health costs associated with smoking.

Reduction in the Perceived Withdrawal Costs

The addictive nature of cigarettes has led to the development of numerous cessation aids (such as nicotine replacement therapy). Many of these products are designed with the specific intention of helping smokers to better cope with the withdrawal symptoms associated with quitting. Table 1 illustrates the effect of a 100% reduction in these perceived withdrawal costs (from 20 to 10):

1. For rational or time-inconsistent individuals who are smokers in the base scenario (interval $\theta \le 0.25$), the effective quitting age decreases by a relatively small amount (the reduction increases with θ, from 1.9 to 3.2 years).

2. However, as the threshold level of θ increases from 0.25 to 0.68, individuals whose value of θ lies in this interval (never smokers in the base scenario) will end up smoking for about 50 years (i.e., they become smokers as a result of lower withdrawal costs).

In short, by reducing the withdrawal costs, these products help smokers to quit earlier. However, if such products also change the perceptions of potential smokers regarding the difficulty of quitting, then they may cause some time-inconsistent individuals to initiate smoking and continue doing so for many years.

Reduction in the Starting Age

In our model, the starting age is set at zero (for simplification) and the parameter T (remaining life expectancy at the starting age) is set in accordance with the assumed real starting age. A real starting age of 20 corresponds to $T = 60$. However, T increases from 60 to 65 for individuals who have the opportunity to start smoking 5 years earlier (at the age of 15). The results of this change are also shown in Table 1. Reducing the starting age has two main effects:

1. Those consumers that choose to smoke in the base scenario ($\theta \le 0.25$) will smoke for about 4.4 more years. More specifically, the model indicates that if hyperbolic smokers are given the opportunity to start smoking 5 years earlier, they will also advance their initial plans to quit. Unfortunately, however, they will end up quitting almost at the same age as they would have done had they started to smoke five years later.

2. The threshold level of θ increases from 0.25 to 0.31. This means that some individuals who would never smoke if they were prohibited from doing so until the age of 20 may become lifetime smokers if they are given the opportunity to start smoking at the age of 15.

These results have interesting public policy implications. For example, they suggest that efforts to target adolescents can have significant payoffs for tobacco companies. First, these efforts are directed at "vulnerable" consumers who tend to harbor the illusion that they can quit smoking soon, even if they are aware of the addictive properties of cigarettes and of the difficulty of quitting (due to the cessation effect). In fact, Gruber (2002) found that youths dramatically underestimate the addictive nature of cigarettes. Second, the procrastination effect tends to extend the smoking duration of younger smokers relative to those who start smoking later in life. Finally, the threshold effect may induce lifetime smoking habits among certain segments of smokers who would otherwise never initiate smoking. Consequently, there may be a strong case for public policy officials to restrict cigarette advertising and promotion activities that attempt to target youths. This is particularly salient in light of the recent study by Pearce et al. (1998), which estimated that 34% of all cigarette experimentation among adolescents in California between 1993 and 1996 could be attributed to tobacco promotional activities. Nationally, this implies that over 700,000 adolescents each year are potentially susceptible to a lifetime of smoking because of being targeted at an early age.

4. Empirical Application

4.1. Empirical Strategy

In the previous section we saw that our theoretical model generated two types of results: (a) predictions about the conditions under which people decide to initiate smoking and (b) predictions about smokers' planned and actual behavior regarding smoking cessation. Whereas the first result is determined by the threshold effect, the second is governed by the interplay between the cessation and procrastination effects. However, the lack of a closed-form solution for the theoretical model makes it difficult to derive and estimate an empirical model directly. Moreover, none of these effects are directly observable. Rather, all that can be observed are the overt smoking behaviors (planned and actual duration of smoking) that are caused by these effects. Hence, a sensible approach is to measure the observed durations of these overt behaviors in a population of smokers and use an empirical modeling procedure that can capture these differences between planned and observed smoking durations as predicted by the theoretical model. Hazard models are an obvious choice due to their explicit focus on modeling durations (see Helsen and Schmittlein 1993 for a review and the appendix for brief details).

Accordingly, we estimate smoking persistence functions $S(t)$, indicating the percentage of smokers who did not quit (continued to smoke) after t periods of consumption.[7] This is similar to the approach used by Douglas (1998) and Douglas and Hariharan (1994) in estimating the initiation and duration of smoking. To test the theoretical model, we adopted the following strategy. First, we used the theoretical model to simulate the planned and actual quitting rates for a heterogeneous group of hypothetical smokers. Second, we estimated our proposed hazard model with these simulated data. This allowed us to demonstrate the manner in which the interaction between the cessation and procrastination effects manifests itself in the planned and actual quitting behavior of these hypothetical smokers. Third, to assess the validity of the theoretical model, we estimated this hazard model using real data on planned and actual smoking behavior from a survey of current and former smokers and compared these estimates with the predicted rates from the simulated data. The smoking behavior predicted by the simulated data (from the theoretical model) matched the observed behavior in the real data, thereby constituting an empirical validation of the cessation and procrastination effects in the theoretical model. Finally, to provide empirical evidence for the threshold effect, we demonstrated the existence of lower accumulated rates of quitting (higher percentages of smokers) for those consumers who started smoking at very young ages compared to those who initiated smoking when they were older. In other words, we found evidence that certain segments tend to be "forever smokers" if they are enticed into smoking at a relatively young age.

4.2. Distributions of Smoking Duration from Simulated Data

This section describes the first two steps of our empirical strategy. To illustrate the implications of our theoretical model regarding the distribution of smoking durations, we performed an additional set of simulations where population heterogeneity was introduced in the model. More specifically, we simulated the planned and actual behavior of 350 artificial smokers who differed from one another in terms of both the direct utility gain derived from smoking (ΔU) and the withdrawal costs (u_w).[8] We first considered the case where smokers are hyperbolic discounters and set θ and n at 0.1 and 40, respectively. For each individual we solved the model for: (a) planned quitting age when smoking is initiated (i.e., age 18), (b) planned quitting age 10 years later, and (c) actual quitting age. Then we considered an alternative scenario in which individuals discount the future exponentially. Here, consumers plan consistently so that their planned and actual smoking behaviors coincide.

With these simulated data of planned and actual smoking durations in hand, we used hazard models to estimate the corresponding distributions. As we report later, in every case the Weibull specification outperformed alternative specifications. The main results of estimating this specification on the simulated data are shown in Figure 3a, where we report the survivor or persistence rates (i.e., the conditional probability of *not* quitting) for both exponential and hyperbolic discounters.

[7] The term "survival function" is commonly adopted in the literature on hazard models. In this particular context, however, the survival function indicates the percentage of early smokers who continue smoking after a certain number of periods. Therefore, in this sense the "survivors" are exactly those consumers whose corporeal survival is most threatened. To avoid potential confusion, we adopt the term "smoking persistence" instead of "survival."

[8] More specifically, we assumed that the parameters ΔU and u_w are uniformly distributed within the population in the [1, 6] and [5, 25] intervals, respectively, and that individuals start smoking at the age of 18. The intervals were chosen such that they included the values for ΔU and u_w from the original simulation. The remaining model parameters were kept at their base levels.

Figure 3a Smoking Persistence Functions for Simulated Time-Consistent and Time-Inconsistent Smokers

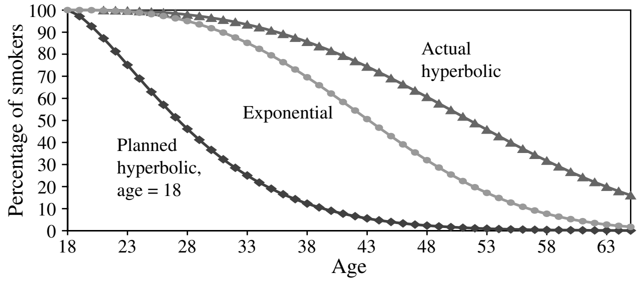
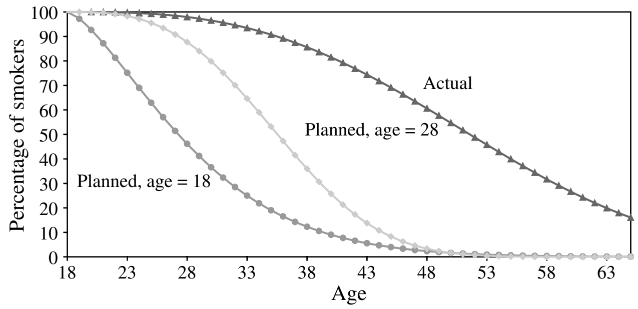


Figure 3b Planned and Actual Smoking Persistence Functions for Simulated Time-Inconsistent Smokers



The middle curve indicates that under the chosen parameterization, 85% of time-consistent (exponential) smokers would still be smoking at the age of 33, whereas 32% would be smoking at the age of 48. If, on the other hand, smokers discount the future hyperbolically, their planned smoking behavior would be very different. As the curve on the lower left demonstrates, only 25% of the smokers who started smoking at the age of 18 would have plans to be smoking at the age of 33 (and only 2% would plan to smoke at age 48). *The difference between the lower-left and middle curves captures the magnitude of the cessation effect*, i.e., the hyperbolic smokers' proclivity to advance their plans to quit smoking.

However, these plans of time-inconsistent smokers are not fulfilled, leading them to remain smokers for longer than initially planned, as shown by the curve on the upper right. Here we can see that 93% would be smoking at the age of 33 and 61% would be smoking at the age of 48. *Thus, the difference between the lower-left and upper-right curves* (*planned versus actual*) *reflects the magnitude of the procrastination effect*, i.e., hyperbolic smokers' inability to keep to their original plans. In this particular simulation, the actual persistence function of hyperbolic discounters lies above the corresponding function for exponential discounters, indicating that for most individuals (although not for all) the procrastination effect dominates the cessation effect.

Figure 3b shows the results of investigating the planned persistence function of hyperbolic smokers at age 28 (i.e., 10 years hence) and compares it with both their previous plans and their actual behavior.

Here we see that after a period of 10 years (at age 28), due to the fact that the *procrastination effect* has started to operate, smokers change their plans relative to the ones they had earlier. Whereas a decade earlier, 25% of the smokers planned to be smoking at the age of 33, now this has increased to 65%. Consequently their planned smoking persistence function has become closer to the "true" persistence function. In summary, the above simulations illustrate that (a) hyperbolic discounting produces a gap between intended and actual quitting rates and (b) this gap diminishes with older cohorts.

We now proceed to the estimation of the distributions of planned and actual smoking duration from our survey of smokers.

4.3. Distributions of Smoking Duration from Survey Data

This section describes the third step of our empirical strategy—the estimation of hazard models of (planned and actual) smoking duration from survey data. Under ideal circumstances, empirical estimation of planned and actual smoking durations would be made based on longitudinal data. This would allow a comparison of planned and actual behavior through the life cycle for a random sample of individuals of the same cohort (as was done in the previous section with the simulated data obtained from the theoretical model). However, such data are not available, and we must rely on information from cross sections of individuals from different cohorts.

To measure the distribution of *planned duration* of smoking, we conducted 500 face-to-face interviews in a number of public places that are frequented by smokers. Respondents (smokers aged 18–54 who started smoking between the ages of 16 and 21[9]) were told that these interviews were being conducted as part of a university research project, leading to a response rate of approximately 65%. We selected respondents based on systematic random sampling and then screened them via a set of questions pertaining to their current age, current smoking behavior, and the age at which they started to smoke. Finally, we collected information regarding their plans for future smoking participation, whether they had attempted to quit in the previous five years, attitudes towards smoking, perceived health status, and key sociodemographic variables. The sample details are reported later in Table 2. The plans for future smoking were elicited through a multiple bounded dichotomous choice type of format commonly used

[9] A smoker was defined as somebody who typically smokes more than five cigarettes per day.

Table 2 Sample Characteristics

Control variables	Planned duration survey (smokers)	Actual duration survey (smokers and ex-smokers)
% female (%)	49.8	55.8
Average education (years)	11.80 (3.74)	11.45 (4.24)
Perceived health status	2.09 (0.62)	2.20 (0.68)
Average age (years)	32.37 (9.64)	39.61 (12.36)
Daily cigarette consumption	17.33 (9.18)	16.07 (7.97)

Note. Standard deviations in parentheses.

in contingent valuation studies (Hanemann et al. 1991, McFadden 1994, Mitchell and Carson 1989). More specifically, we asked them about their intention to smoke at various points in the future (1 year hence, 5 years, 10 years, and those who were younger than 40 were also queried about their smoking intentions at the age of 40).[10] Each respondent's answers to these questions were combined with information on their current age to obtain lower and upper bounds for the number of years that they planned to smoke. For example, consider an individual aged 25 years who started smoking regularly at the age of 18. If this respondent expects to still smoke in five years but not in ten years, we may conclude that he plans to smoke for a period of between 12 years and 17 years. Call the lower and higher bounds of smoking duration t_L and t_H, respectively.[11] This information can be used to characterize the distribution of planned smoking duration. The probability of an individual quitting smoking between periods t_L and t_H is given by:

$$\Pr(t_L \leq T \leq t_H) = F(t_H) - F(t_L) = S(t_L) - S(t_H). \quad (8)$$

However, we must bear in mind that our data are truncated, because we do not observe individuals who have already quit smoking before their current age. Therefore, we must consider the probability of respondents planning to quit smoking between periods t_L and t_H, given that they have already smoked for t_0 periods. Then the likelihood function for respondent i is given by:

$$L_i = \frac{F^{pd}(t_{Hi}) - F^{pd}(t_{Li})}{1 - F^{pd}(t_{0i})} = \frac{S^{pd}(t_{Li}) - S^{pd}(t_{Hi})}{S^{pd}(t_{0i})}, \quad (9)$$

where the superscript pd refers to planned duration (as opposed to actual duration) of smoking. Thus, the log-likelihood function for the whole sample of n respondents is given by:

$$\operatorname{Log} L = \sum_{i=1}^{n} \operatorname{Log} \frac{S^{pd}(t_{Li}) - S^{pd}(t_{Hi})}{S^{pd}(t_{0i})} \quad (10)$$

At this stage it is worth noting that empirical models, where a single planned smoking persistence function $S(t)$ is estimated for all cohorts, implicitly assume that (a) individuals plan their smoking behavior consistently through time and (b) smokers' preferences do not vary across cohorts. The former assumption legitimizes the use of data from smokers of different ages in order to estimate functions that are invariant to the age at which the plan is made. However, as shown in the previous section, this assumption is only valid for exponential discounters and may be inappropriate for hyperbolic smokers. With respect to the second assumption, if the preferences of different cohorts differ, then they will exhibit different plans even if smokers are time consistent. In such a scenario, plans and behavior would coincide for each cohort but they would still differ across cohorts. Thus, to relax these limiting assumptions we also estimated an alternative specification, where we allow the persistence function to vary across cohorts, i.e., we assume that the parameters of $S(t)$ vary with the respondents' current age.

We now turn to the estimation of duration models for *actual* behavior. For this purpose, we conducted 347 smaller interviews with randomly selected smokers and ex-smokers aged 18–64 who had also started smoking between the ages of 16 and 21. In these interviews, conducted in the same manner and with similar survey response rates as before, we collected information on actual smoking duration behavior, such as the age at which the respondents had started smoking regularly, whether they had already quit and, if so, the actual quitting age (a significant event that is usually recalled with a great ease and accuracy by ex-smokers). Although the previous sample was restricted to smokers, this sample included both current and former smokers, with current smokers comprising 60.2% of the sample. As before, information was also collected on key sociodemographic variables and perceived health status. Summary statistics are reported in Table 2, based on which we find that the two sample distributions (i.e., this sample regarding actual smoking and the previous one regarding planned smoking and consisting only of smokers) are very similar in terms of the key demographic characteristics.

For example, a z-test for differences in gender revealed a test statistic of 1.71 and failed to reject the

[10] In fact, there were two versions of this question, in accordance with the recommended procedures in contingent valuation studies. In the other version, respondents were asked about whether they would still smoke: (i) in 3 years; (ii) in 8 years; (iii) in 15 years; (iv) at the age of 50 (if they were currently younger than 50). Each version was applied to about half of the sample.

[11] For computing t_L and t_H we made the following assumptions: (i) it was assumed that the respondents started smoking regularly at the age of 18 (whereas we knew that they have in fact started between the ages of 16 and 21); (ii) for respondents who provided a "yes" answer to all questions, the higher bound was set at 62 years (that is, we assumed that such respondents would not smoke after the age of 80, which is above the average life expectancy at birth).

hypothesis that the sample proportions were the same ($p = 0.18$). For education, a nonparametric Mann-Whitney U test ($z = 0.906$, $p = 0.365$) fails to provide evidence that the two samples differ in terms of the probability distributions for educational background. Because this was not a clinical study, we were unable to collect objective measures related to respondents' health. However, there is some evidence to suggest that self-reported health indicators are valid indicators of health status and well-being, particularly for young and middle-aged individuals (Kahneman 1999, Miilunpalo et al. 1997). Thus, in an effort to control for such differences, we asked respondents to rate their perceived health status. The Mann-Whitney U test ($z = 2.18$, $p = 0.03$) suggested that the population with both former and current smokers had a slightly more positive perception of its health status, which was only to be expected, given that it included former smokers. However, a test of group mean differences for health status failed to reject the hypothesis that the means for former and current smokers were equal ($t = -2.28$, $p = 0.98$). Regarding age, the appropriate statistical tests indicated that the populations of both surveys had different age distributions ($z = -4.8$, $p = 0.00$). This difference between the two samples was expected (because the second sample included respondents in the 55–64 age group) and suggests the importance of controlling for these age differences in the analysis. In our analysis for actual quitting durations, we were careful to do so, and estimated a varying parameter model that allows the model parameters to vary with age. Finally, we controlled for the number of cigarettes consumed daily by the smokers in the two samples. We found that the test statistics ($z = -1.135$, $p = 0.18$) failed to provide any evidence for differences in the two distributions. Thus, because these two samples appear to be fairly similar in terms of these control variables, any observed differences in smoking behaviors between them are unlikely to be on account of their demographic characteristics.

For each respondent, we computed the number of years of regular smoking, t_i. For current smokers, our measurement of t_i reflected the smoking duration for smokers who are currently active but who may choose to quit at some future unobserved date. The censored nature of these data is captured by means of the following likelihood function (Greene 2000):

$$\ln L = \sum_{i=1}^{n} (1 - Smk) \ln \lambda^a(t_i) + \sum_{i=1}^{n} \ln S^a(t_i), \tag{11}$$

where Smk is a dummy variable that takes the value of one for current smokers and the value of zero for ex-smokers, the superscript a stands for actual (as opposed to planned) duration of smoking, and $\lambda(t)$ and $S(t)$ represent the smoking hazard and persistence functions. As mentioned earlier, the estimation of a single persistence function for actual behavior from data of various cohorts of consumers rests on the implicit assumption of similar preferences across cohorts. If this were not the case, different cohorts would exhibit differences in their actual persistence functions. To incorporate this possibility and to control for differences between the two samples in terms of age distributions, we used a varying parameter specification in which the model parameters are allowed to vary with the respondents' current age. As was the case in the simulation reported in the previous section, we estimated the likelihood functions in (10) and (11) using parametric hazard models. As before, the Weibull model outperformed the other specifications and provided the best fit to the data at hand.[12]

Table 3 contains the results of estimating the Weibull specification for both the fixed parameter and varying parameter models of planned and actual duration of smoking. The fixed parameter specification of the smoking persistence function is given by:

$$S(t) = e^{-(\lambda t)^p} \tag{12}$$

λ and p are the parameters of the Weibull model. For both the planned duration and actual duration, the fixed-parameter estimates have the expected positive sign and are statistically significant. However, there are large differences between the estimates of both models, implying that the smoking persistence functions for planned and actual duration differ significantly. For example, under the additional simplification that individuals start smoking at the age of 18 (we know that they did so between the ages of 16 and 21), the model based on the respondents' planned behavior indicates that only 21% of those who start smoking at the age of 18 would still be regular smokers at the age of 30. However, the model fitted to actual behavior indicates that the true percentage is as high as 80%. These results indicate the existence of a gap between planned and actual behavior, appearing, therefore, to provide evidence in favor of time-inconsistent preferences.

[12] For *Planned Durations*, the log likelihood (and Akaike information criterion) for the Weibull and log-logistic distributions were −454.51 (915.02) and −481.09 (968.18), respectively (for the fixed parameter model), and −450.83 (909.65) and −464.38 (936.76), respectively (for the varying parameter model). Similarly, for *Actual Durations*, the log likelihood (and Akaike information criterion) for the Weibull and log-logistic distributions were −653.72 (1313.4) and −655.59 (1317.2), respectively (for the fixed parameter model), and −648.59 (1305.2) and −650.16 (1308.3), respectively (for the varying parameter model). These diagnostics clearly suggest that the Weibull outperforms the log-logistic specification in every case.

Table 3 Estimates of Smoking Duration Models

	Fixed-parameter models		Varying parameter models	
Parameters	Planned duration	Actual duration	Planned duration	Actual duration
λ	0.1431 (0.0313)	0.02842 (0.0019)	—	—
θ_0	—	—	0.8564 (0.3634)	2.9601 (0.3161)
θ_1	—	—	0.0517 (0.0087)	0.0124 (0.0063)
p	0.8193 (0.0737)	1.3920 (0.0962)	—	—
β_0	—	—	0.8641 (0.2587)	−0.1191 (0.2682)
β_1	—	—	−0.0301 (0.0084)	−0.0073 (0.0058)
Weibull log-likelihood	−454.51	−653.72	−450.83	−648.59
n	500	347	500	347

Note. Standard errors in parentheses.

However, if the smokers' plans are not consistent through their life cycle, then the fixed-parameter specification is not appropriate, and we should allow those plans to vary with age. This is done in the varying-parameter specifications, where the following expressions are adopted for λ and p:

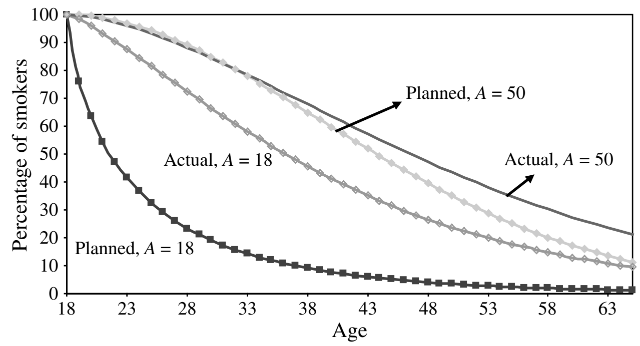
$$\lambda = e^{-\theta_0-\theta_1 A} \tag{13}$$

$$p = e^{-\beta_0-\beta_1 A}. \tag{14}$$

Again we find that most of the parameter estimates are significant at the 95% level of confidence and have expected signs. We note that the fixed-parameter model is nested within the varying-parameter model and can be obtained by restricting the two parameters to zero (i.e., $\theta_1 = \beta_1 = 0$). The estimates of θ_1 and β_1 are significant for the *planned* duration model, whereas in the *actual* duration model only the θ_1 parameter is significant. Likelihood ratio tests also confirm the rejection of the restrictions $\theta_1 = \beta_1 = 0$ for both models (p-values $= 0.025$ and 0.006 for the planned and actual duration models, respectively).

These results reaffirm that the persistence functions vary with age. Such variation is particularly strong for planned duration, meaning that the planned hazard rate for any future age depends significantly on the planner's current age. To further explore the empirical results and compare them with the predictions of the theoretical model, Figure 4 shows the estimated smoking persistence functions of planned and actual duration for respondents aged 18 and 50. It illustrates that the planned persistence functions for younger and older respondents clearly differ from one another,

Figure 4 Estimated Smoking Persistence Functions for Varying-Parameter Duration Models



with the younger cohort planning to quit much earlier than what may be inferred from the plans of the older cohort.

Such a large difference between the planned behaviors of the two cohorts does not necessarily imply time-inconsistent preferences. As stated above, different cohorts could have different lifetime smoking plans due to different preferences on smoking and health. However, if both cohorts planned consistently, then we should observe that the difference in cohort plans is matched by a similar difference in actual behavior. The gap between the two curves for actual behavior ($A = 18$ and $A = 50$) confirms that there are different patterns of actual quitting across the cohorts. More precisely, young cohorts tend to effectively quit smoking at faster rates than older cohorts did at corresponding ages. However, although they are quitting earlier than are their older counterparts, younger smokers are still quitting much later than they had initially planned. This is evident from the gap between the planned and actual curves for the 18-year-olds. In fact, although the plans of those who are 18 today indicate that 77% of them would quit in 10 years, our estimate is that only 28% will have actually done so. Consequently, we find that for each cohort there is a gap between intended and actual quitting rates of success, as implied by the theoretical model. Although they provide lower estimates of actual quitting rates, our results for adults are in general agreement with those reported in Gruber (2003) for youths. The second implication regarding the diminishing gap between intended and actual quitting rates for older cohorts is also readily apparent from Figure 4. Indeed, the planned and actual survival functions for 50-year-olds are very similar.

Finally, there is the matter of whether the threshold effect is empirically supported. Because it relates to consumers whose time inconsistency leads them to never smoke, such an effect cannot be directly investigated with data on smokers (or former smokers). However, it seems possible to obtain indirect evidence by considering some differential age-based sensitivity implications of our model. More specifically, note that our results of §3.2 suggest that due to the threshold effect we would expect to find a larger proportion of lifetime smokers among early starters. We present empirical confirmation of this in the appendix. Although the reported evidence cannot be regarded as an empirical test of the threshold effect, it is clearly consistent with its implications. Taken together, these empirical results provide strong support for our theoretical model regarding planned and actual smoking behavior under time-inconsistent preferences. In particular, they demonstrate the crucial role of the cessation and procrastination effects in determining smoking behavior.

4.4. Alternative Explanations

We now investigate the possibility that there may be alternative reasons for our empirical results. For example, it may well be that smokers underestimate the magnitude of the withdrawal symptoms when they begin smoking, so that the rational thing to do may be to continue smoking despite wanting to quit.[13] In our model, an underestimation of u_w by time-consistent smokers ($\theta = 0$) would lead them to reduce their planned quitting age. Having reached that planned age, some smokers would attempt to quit in every period. This attempt would make them aware of the true withdrawal cost, leading them to revise their planned quitting age upwards. Consequently, the underestimation of withdrawal costs by younger smokers may cause the gap between planned and actual smoking behaviours, as well as a narrowing of that gap with older cohorts, just as we observed empirically. However, our own analysis suggests that this is unlikely to be the main explanation for our empirical results. This is so for two reasons. First, our model simulations suggest that even a severe underestimation of the true cost of quitting would cause a much smaller gap between planned and actual behavior compared to what we observe empirically. For example, in comparing the base scenario with the case of $u_w = 10$ in Table 1, we can see that even this severe underestimation in u_w (50% reduction) would cause a gap of only 1.6 years between the planned and effective quitting ages (53.0 and 54.6, respectively) of a time-consistent smoker. Second, and more crucially, we reestimated our model using data from those respondents who had made a serious attempt to quit over the previous five years. Specifically, we included a dummy variable for attempted quitters as a determinant of parameters λ and p in our empirical models of planned duration. If the results were being driven by the difficulty of quitting, we would expect differences in the planned quitting durations between the attempted quitters and the remaining smokers. However, we found that the coefficients of the dummy variable were nonsignificant in both the fixed and the varying parameter specifications.[14] Therefore, we can conclude that the large gap between planned and behavior persists even when the likelihood of a significant underestimation of the costs of quitting is eliminated.

Another possible explanation for our results is based on the idea that, rather than being time inconsistent, young consumers underestimate the future detrimental effects of smoking. This estimation error could cause a narrowing of the gap between planned and actual behavior. However, in this case the gap would be the opposite of what we observe empirically. For example, suppose the true health cost is 0.15, but the time-consistent smokers start by estimating it to be 0.12. Table 1 shows that these smokers initially plan to quit at the age of 54.6. If, later in life, they become more aware of the true health costs of smoking, they revise the planned quitting age downwards (from 54.6 to 48.1). Therefore, time-consistent smokers would end up quitting earlier (not later) than they had previously planned. Furthermore, we find that younger smokers tend not to underestimate the health cost of smoking relative to older individuals. In our survey we asked respondents to provide us with an estimate of the average number of years of life that are lost due to lifetime smoking. We compared the mean stated estimates for young and old smokers (below and above 30, respectively) and found no significant differences ($t = 0.677$, $p = 0.499$).

5. Conclusions and Directions for Future Research

In this paper we investigated smoking participation decisions in the context of a simple dynamic consumer model that may incorporate rational or imperfectly rational preferences. Our results suggest that there are three major effects governing the smoking behavior of time-inconsistent individuals. The cessation effect leads smokers to reduce their planned quitting age at the moment they initiate consumption. In particular, the cessation effect is based on the tendency of the hyperbolic consumer to overestimate the health costs and underestimate the direct benefits of marginally increasing the smoking horizon.

[13] We are grateful to an anonymous reviewer for suggesting this alternative explanation.

[14] For the fixed-parameter model, λ and p are given by: $\lambda = \lambda_0 + \lambda_1 * D$ and $p = p_0 + p_1 * D$, where D is the dummy variable for attempted quitters. The obtained p-values for λ_1 and p_1 were -0.093 and -0.400, respectively. Similarly, for the varying parameter model: $\lambda = e^{-\theta_0-\theta_1 A-\theta_2 D}$ and $p = e^{-\beta_0-\beta_1 A-\beta_2 D}$, p-values for θ_2 and β_2 were 0.130 and 0.073, respectively.

The procrastination effect leads them to consecutively revise their planned quitting age upwards. Finally, the threshold effect causes an "all or nothing" type of smoking behavior.

Furthermore, our numerical simulations provided a number of additional interesting insights. First, we found that time-inconsistent individuals have a smaller *planned* smoking horizon relative to rational smokers. Second, the interplay between the three effects stated above can result in a variety of *actual* behaviors, ranging from never smoking to lifetime smoking. Finally, we found that marketing efforts by tobacco firms and public policy initiatives may have a significant influence on smoking behavior. For example, advertising and other forms of enhancing the consumers' perceived benefits of smoking tend to extend the duration of smoking and may even turn some nonsmokers into lifetime smokers. Similarly, our model indicates that reducing the age at which individuals have the initial opportunity to engage in smoking by n years causes them to smoke almost n years longer. Furthermore, such a reduction may convert a potential "never smoker" into a lifetime smoker. This provides a case for public policy intervention to impose restrictions on the legal age for smoking and prevent tobacco firms from targeting young individuals with advertising and promotional campaigns. Recently, legislative efforts have been made in California to increase the legal age from 18 to 21 years. The rationale for this is the contention that the number of adult smokers could be reduced dramatically by preventing impressionable teens from smoking or chewing tobacco.

> Recruiting new teen smokers is key to the tobacco industry's survival, said state Sen. Joe Dunn, D-Santa Ana. "If you're not smoking by the age of 18, the likelihood of you being a lifelong customer of that industry is small," (Ed Fletcher, Scripps Howard News Service, 3/24/2004)

Our model provides support for this contention.

In the second part of the paper we estimated various models of smoking duration based on survey data pertaining to both the planned and actual participation behavior of smokers. Our empirical results were fully consistent with the predictions of our theoretical model and demonstrated the crucial role of the cessation and procrastination effects in determining smoking behavior. Coincidentally, our study also provided clear evidence, obtained through a different methodology compared to previous empirical studies, that smoking decisions are mainly motivated by imperfect rationality and contributed to the substantial set of additional evidence that "is needed before the time-inconsistent model will be accepted as the appropriate formulation of preferences" (Gruber and Koszegi 2004, p. 1963). Finally, our empirical results can be interpreted as providing additional support for public policy measures that constrain the smokers' consumption decisions.

A fruitful direction for future research would be to investigate the manner in which (positive or negative) advertising affects consumers' perceptions of the costs and benefits of smoking and their plans for smoking participation. One would expect positive advertising to increase the planned quitting age by increasing the perceived direct benefit/pleasure of smoking (ΔU) and negative advertising to decrease the planned quitting age by increasing the perceived health cost of smoking (α). However, both types of advertising could also change the planned quitting age by affecting the individual's discount rate. Such results could provide a basis for resolving some of the debates regarding the efficacy of public service advertising. For example, prior work by Pechmann et al. (2003) and Pechmann and Ratneshwar (1994) has investigated the impact of antitobacco advertising on smoking among adolescents. They found that the most effective messages were those that enhanced adolescents' perceptions that smoking poses severe social risks, in that it could lead to social rejection and/or social sanctions, whereas nonsmoking could lead to social acceptance and respect. Our results suggest that it is important to consider the relative effects of both positive and negative advertising via their impact on the direct utility of smoking and the disutility of withdrawal and mortality.

In addition, our result that hyperbolic smokers may actually be less likely to initiate smoking under certain conditions has interesting welfare implications that may be worthy of further investigation. For example, the lower smoking rates among young smokers may provide only a partial picture of smoking incidence because it might mask the fact that those who do smoke may do so for longer periods. This presents an interesting dilemma from a social welfare perspective.

A possible limitation of our model is that our analysis of time inconsistency did not distinguish between the behavior of *sophisticated* consumers who foresee the inability of their future acts to accord with their current plans (also known as a self-control problem) and *naïve* consumers who are unable to foresee this problem. It may very well be the case, as argued by O'Donoghue and Rabin (2000), that there are elements of both sophistication and naiveté in the manner that consumers anticipate future behavior. The literature has uncovered partial support for sophisticated behavior on the part of many consumers in a variety of situations, based on their desire to use self-commitment devices (Wertenbroch 2003). For example, Ariely and Wertenbroch (2002) noted that students were willing to self-impose deadlines to overcome procrastination even when failure to meet the deadlines involved penalties. Our results and those of Gruber (2003) suggest that it is unlikely that smokers are capable of behaving in such a sophisticated manner during adolescence, when the decision to start smoking typically takes place. Nevertheless, it may be worth exploring how, in a more general scenario, our analysis could incorporate sophisticated time-inconsistent smokers. Finally, it is worth noting that although our analysis was conducted in the context of an addictive good, the latter represent merely one setting with negative internalities, i.e., where today's consumption causes harm tomorrow (Gruber 2002). The implications of present-biased preferences are likely to be similar for nonaddictive goods that also exhibit negative internalities such as junk food and the many harmful but nonaddictive drugs (Rabin 1998).

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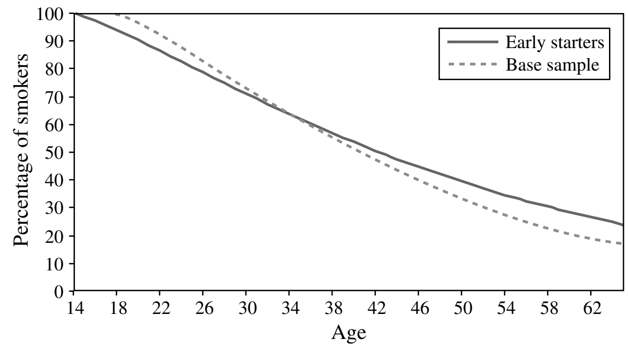
Appendix. Some Empirical Evidence for the Existence of the Threshold Effect

We compare our original sample of smokers and exsmokers (347 individuals) with an additional subsample of early starters (191 individuals who started smoking before the age of 16). Our results regarding the threshold effect (from §3.2) show that we can expect early starters to also quit smoking at an earlier age than the other smokers (even if just slightly earlier, depending on the level of preference bias). Therefore, for any given advanced age, we would expect the proportion of still-smokers to be lower among early starters. However, note that the threshold effect can reverse this—there is a subset of lifetime smokers among the early starters who would be "never-smokers" had they refrained from smoking at very young ages. If this subgroup is large enough, at advanced ages we should observe lower accumulated rates of quitting (higher percentages of smokers) among early starters than among those who have started later.

To investigate this relationship, we estimated a new specification of the actual varying-parameter duration model on the extended sample, where a dummy capturing the starting period was also included as a covariate (in addition to the current age). More specifically, λ and p are given

Figure A.1 **Smoking Persistence Functions for Early Starters and for Base Sample**



Notes. 1. Variable A is set at $A = 30$. 2. For representation purposes the starting ages are set at the mean levels of the corresponding subsamples (14 years for the early starters and 18 for the base sample).

by $\lambda = e^{-\theta_0-\theta_1 A-\theta_2 Dum}$ and $p = e^{-\beta_0-\beta_1 A-\beta_2 Dum}$, where Dum is the abovementioned dummy variable (Dum equals zero for early starters and one for members of the base sample).

We omit the detailed results for the sake of brevity, but suffice it to say here that the parameter associated with the starting period dummy was significant ($\theta_2 = -0.24$, s.e $= 0.11$, p-value $= 0.028$). This confirms that the smoking persistence function is different for the two groups. Figure A.1 contains a graphic representation of these functions. It shows that the percentage of lifetime smokers is considerably higher among early starters. These consumers start smoking four years earlier (on average), but tend to extend their duration of smoking by significantly more than four years relative to the smokers in the base case. For example, our estimates indicate that 28% of the (30-year-old) early starters will still smoke at the age of 60, against 21% of those who started between the ages of 16 and 21. As argued above, these results are entirely consistent with the threshold effect, and while not constituting a proof of the existence of a threshold effect, provide at least some indirect evidence in its favor.

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