Rational Addiction and Rational Cessation: A Dynamic Structural Model of Cigarette consumption*

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Comments welcome.

Abstract

Much of the existing empirical literature on smoking addiction takes a reduced form approach. While interesting and simple to implement, this approach only allows a restricted range of possible policy experiments, usually in the form of price changes. This paper builds and estimates a dynamic structural model of rational addiction and cessation using longitudinal data from a smoking cessation study. A new methodological framework is presented that explains quitting and smoking behavior, and allows interesting and pertinent policy experiments that existing models have difficulty analyzing. This model allows us to consider the effects of regulating the level of nicotine in cigarettes, subsidizing quitting behavior, finding a cure for lung cancer as well as temporal changes in prices. It explicitly models the unobserved addiction and health process. Using additional data from medical studies, I exogenously identify the health generating process and incorporate it into the model. The paper shows that the addition of health effects into a model of rational addiction is important in explaining smoking dynamics.

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1 Introduction and Motivation

There is a long history of empirical research modeling cigarette addiction. Much of the existing empirical literature takes a reduced form approach that attempts to explain observed smoking and quitting behavior using past (and future[1]) behavior, prices, and demographic characteristics. While interesting and easy to implement, this approach has not been able to look at some of the policy experiments that this paper considers. This is an empirical study of smoking using a model of rational addiction. It presents a framework that explains smoking and quitting behavior, and allows us to consider a variety of policy experiments that the existing empirical literature has difficulty analyzing. More importantly, it provides a practical and intuitive way of incorporating health when modeling smoking addiction. While there has been much medical evidence showing the negative health effects of smoking and the health benefits of smoking cessation,[2] formal empirical modeling of the dynamic health process and the way it interacts with smoking and quitting behavior has not been attempted. This is largely because of the difficulty of observing the health status of individuals. The data used in this paper have similar limitations. This paper introduces a stochastic health process using external medical data and shows that health effects are important in explaining quitting behavior. I first discuss the limitations of the existing literature and then explain what this paper has to offer.

The traditional reduced form approach of modeling cigarette consumption estimates a generalized linear model and uses it to evaluate the effectiveness of excise tax policies[3] or other regulatory policies[4] on smoking. This approach typically requires either individual or aggregate level data on observed consumers' responses to policy changes in order to estimate an empirical relationship between individuals' behavior as a function of the policy instrument of interest. This methodology only allows us to evaluate the effects of policy experiments that have already been conducted. As such, these models will have

[1] In the existing empirical rational addiction literature including Chaloupka (1991) and Becker, Grossman, and Murphy (1994), lead consumption and prices are also included as regressors in the linear model.

[2] Examples of references include US Dept. of Health of Human Services (1989) and (1990).

[3] Examples include Lewit and Coate (1982), Wasserman, Manning, Newhouse, and Winkler (1991), Becker, Grossman, and Murphy (1994) and Chaloupka (1991).

[4] Some papers that analyze policies other than prices include Hu, Sung, and Keeler (1995), Barnett, Hu, Sung, and Keeler (1995), which looked at the effectiveness of antismoking media policies in California, and Chaloupka and Wechsler (June, 1997), which looked at control policies on youth smoking.

difficulty analyzing policy experiments that have not yet been conducted. Examples of these policy experiments include analyzing the impact of regulating the level of nicotine in cigarettes, the effects of subsidizing quitting behavior, and the impact of finding a cure for lung cancer. Even though these policy experiments have never been conducted, they remain options for both state and federal regulators interested in regulating smoking.

Second, traditional models have not focused on explaining the patterns of smoking and quitting behavior observed in data. Empirical evidence suggests that quitting usually occurs '*cold turkey*', with many quitters often relapsing to the level they were smoking before they quit for good. Smokers who continue smoking smoke a relatively stable number of cigarettes. Traditional models have difficulty generating and explaining these extreme behaviors: small changes in consumption amongst continuing smokers and large discrete changes among quitters. The attractive feature about a generalized linear model is that the error term can take any value on the real line. Hence, it can be fitted to all observed behaviors, even though upon simulation these models do poorly at replicating behaviors seen in data.

The morbidity associated with smoking addiction has been well documented. Evidence suggests that many smokers begin to experience the negative consequences from a lifetime of smoking when they reach middle-age (Behrman, Sickles, and Taubman (1990) and (2000)). Studies have also shown that health concerns and health events become important initiators of smoking cessation among smokers of this age group (Falba (2000)). While much is known about the health consequences of cigarette smoking, there has been little formal empirical modeling of the health process and quantifying its importance in observed quitting dynamics.[5]

The empirical rational addiction literature (like Chaloupka (1991) and others that follow) often uses the influential model of Becker and Murphy (1988) as the theoretical base for the empirical application. These papers make a functional form assumption on the individual's utility function that generalizes the Euler equation to a simple linear model. This simplification allows the implications of the rational addiction model to be tested in an empirically tractable way. However, these derivations usually ignore the binding constraint that quitting behavior poses on the first order condition of a utility maximizing individual. As such, the empirical moment conditions taken to data no

[5]Notable references that looks at the importance of health in smoking cessation include Jones (1994) and Hu, Ren, Keeler, and Bartlett (1995).

longer accurately represent the first order conditions implied by the rational addiction model. Further more, these papers do not try to estimate the structural parameters that are of significant policy interest. These include the parameters of the utility function and those that govern the evolution of the state variables.[6] See Section 7.1 of the Appendix for an example of the derivation of the Euler equation for a habit formation model that correctly account for the binding constraint on the choice set.

This paper attempts to remedy the aforementioned limitations. It develops a dynamic structural model of rational addiction and cessation, and estimates it using longitudinal data from a National Cancer Institute (NCI) study into smoking cessation. The paper explicitly models the individuals smoking and quitting behavior using a utility maximising framework with uncertainty while taking into account the effects the individual's behavior has on the addiction and health process. It expicitly puts a dynamic structure on the stochastic addiction and health process.[7] I make structural assumptions about the decision making process, the beliefs of the individual, the nature of the stochastic addiction and health process, and the manner in which it affects the individual's well-being. These assumptions drive the estimation of the structural parameters. Having these parameter estimates provides us with additional degree of freedom when looking policy experiments.

This paper has two main goals. The first is to present a framework that allows us to consider a larger variety of experiments than currently possible. This is accomplished by providing a structural model of rational addiction and cessation that can be taken to data. It is the structural parameters of the model that allow us to consider the new variety of policy experiments that traditional models have difficulty analyzing. This paper allows us to consider, for example, the effects of regulating the level of nicotine in cigarettes, subsidizing quitting behavior, finding a cure for lung cancer, and temporal changes in prices.

[6]The Euler equation that accounts for this choice constraint will have to assume that the smoker who quits will resume smoking sometime in the future in order to arrive at a compensating change needed for the first order conditions to hold for an optimizing individual. Hence, an implicit assumption underlying the moment condition approach is that a smoker would never permanently quit.

[7]Many addictions typically involve an unobserved addiction process that affects current behavior and behaviors in the future. Putting a dynamic structure on how this unobserved state evolves is important when making long run predictions of policy changes. A policy change, like a price increase, will cause smokers to alter their short-run behavior. These short run behavioral changes will affect the way the addiction process evolves. Existing models that do not explicitly model the changes to this unobserved addiction process may give misleading long run predictions, even for policy experiments for which there are data.

The second goal is to provide a model that explains smoking and quitting behavior. I show that the specification of a simple habit formation model with the stochastic addiction stock being the only unobserved state, is not sufficiently rich to explain the dynamics observed in data. Instead, a model that incorporates a health process is shown to be able to explain the discrete jumps associated with *cold turkey* quits and relapse. This health process, which incorporates the morbidity of smoking addiction, is identified using data from an external medical study (into diseases associated with tobacco use). I show through simulation that the addition of health effects to a simple habit formation/rational addiction model is important in explaining smoking and quitting dynamics.

Finally, the framework presented also has applications outside cigarette addiction. The natural extension would be in modeling other forms of addiction (like gambling, alcohol and drug addiction, etc.) or clinical experiments involving an addiction process.[8] This model can also be extended to situations where individuals or firms repeatedly engage in an activity that has dynamic consequences. Possible applications in empirical industrial organization include modeling repeated retail purchases of a consumer good with habit or taste formation, or a firm's advertising or investment expenditure contributing to an unobserved state like goodwill[9] or firm's productivity.

The paper is organized as follow. Section 2 provides a brief review of related literature. A description and preliminary analysis of the data is provided in section 3. Section 4 defines the model and provides a brief outline of the intuition behind its setup. Monte Carlo simulation is presented in Section 5 and Section 6 concludes.

2 Existing Literature

Economists have long been puzzled by the many inconsistencies of addiction. The main distinguishing feature being individuals repeatedly engaging in an activity that provides immediate gratication and pleasure, while knowingly ignoring its adverse consequences in the future. Non-addicts do not face this impulsive need and are able to stay away from these activities. Economic models that analyze addiction fall into two

[8]The current specification of the model assumes that addiction only contributes to a *reinforcement effect*, which is not a reasonable approximation of all addictions. This is something I intend to relax in future extensions of this research.

[9]A recent empirical industrial organization paper by Hitsch (2000) has this feature in his model.

broad categories.

One response has been to ignore the rational choice framework and develop models of irrational behavior. An exhaustive review on this sizeable body of theoretical literature is beyond the scope of this paper.[10] Some themes emphasized in this literature include the compulsiveness of addictive consumption (Shefrin (1984)), self control and myopia (*e.g.* Thaler and Shefrin (1981) and O'Donoghue and Rabin (1999)), and timing inconsistencies (Akerlof (1991) and Ainslie and Haslam (1992)). For example, Ainslie and Haslam (1992) provide evidence of timing inconsistencies, and consider the implications if time discounting is hyperbolic rather than the exponential as assumed in standard rational choice theory. Thaler and Shefrin (1981) and Shefrin (1984) explain compulsiveness and myopia by allowing the individual to have multiple sets of preferences that may be conflicting. Identifying and testing the behavioral predictions of these models has been restricted to experimental studies.

The other response is to explain these apparently irrational behaviors using the standard assumptions of the rational choice framework. The seminal paper of Stigler and Becker (1977) and Becker and Murphy (1988), argued that addictive consumption is consistent with rational, forward looking, utility maximizing behavior. Becker and Murphy (1988) relax the intertemporal separability assumption of utility by allowing current consumption to add to a consumption capital that lowers overall utility, while increasing the marginal utility from the good in the future. The model explains the *reinforcement, tolerance*, and *withdrawal* features of addiction and is able to motivate binging and *'cold turkey'* quitting behavior. This model has been praised as well as criticized for being inconsistent with observed addictive behavior. A number of papers have introduced modifications to this model to arrive at more realistic predictions. Dockner and Feichtinger (1993) allow for a more general addiction process where the addictive good accumulates to two different stocks of consumption capital. Their modification allows for a variety of cyclical consumption profiles over time. Orphanides and Zervos (1995) allow for individual uncertainty about the addictive nature of the consumption good. The authors explain rational addiction in terms of learning through experimentation. Their followup paper, Orphanides and Zervos (1998), allow for state dependent discount rates. Introducing this general discount rate reconciles myopic behavior amongst addicts and

[10] Rabin (1998) provides a nice discussion of many of the ideas in behavioral economics, not necessarily related to addiction.

optimizing far-sighted behavior amongst non-addicts within the rational choice framework.

A number of empirical papers have taken Becker and Murphy's (1988) rational addiction model to data. Papers like Chaloupka (1991) and Becker, Grossman, and Murphy (1994) use a discrete time version of Becker and Murphy's (1988) model with the assumption that the utility function takes a quadratic form. This linearizes the first order condition and can be estimated using a general method of moments procedure. Chaloupka (1991) applies this to individual level data to test the implications of the rational model. As mentioned earlier, this and subsequent paper using the Euler condition ignore the binding constraints quitting behavior places on the choice set. Furthermore, these papers do not try to estimate the structural parameters and have not focused on trying to explain actual smoking and quitting behavior.[11]

A growing body of empirical papers have looked at the effects of health on smoking and quitting behavior. Jones (1994) uses survey data from Britain's Health and Lifestyle Survey to investigate the effects that various measures of health status, social interaction and addiction have on the likelihood that a smoker attempts and succeeds at quitting. Using current health status to proxy for past health, he finds the interesting result that poor health is associated with a lower likelihood of cessation, while smokers with long standing disability or illness have a higher likelihood of quitting. Using data from the Health and Retirement Study (HRS), Falba (2000) looks at the effects that a new diagnosis of an acute illness and decline in functionality have on smoking cessation in middle aged married couples. The author finds that the new diagnosis of an acute or chronic illness is a strong motivator for smoking cessation. Other studies include Wray, Herzog, Willis, and Wallace (1998) that looked at the effects heart attack has on continued smoking, and Smith et al. (2000) uses the HRS panel to assess how health events change the life expectations of smoker and non-smokers. These papers highlight the importance of morbidity in determining quitting behavior amongst middle-aged smokers.[12]

As a further example of the importance of health status in smoking and quitting decisions, participants of the COMMIT study, (used in this paper and to be described in Section 3) were asked to give their reasons for attempting to quit in the final inter-

[11] Section 7.1 of the Appendix provides a derivation of the Euler condition that correctly reflect the bounded choice set.

[12] Quitting has been posed as either a *curative* or *preventive* measure taken by a smoker when faced with the prospect of increase health problems in the future from continual smoking. See Jones (1994).

view. The results, taken from another study using the same data are shown in Table 2. The most common reasons given were concern over health and the expense associated with smoking. In this paper, I extend this idea further by formally putting a dynamic structure to the health process and integrating this into a rational choice framework.

Insert Table 2 here. Note that some tables are left to the end of the paper.

3 The Data

This section provides a brief description of the data sets used in this paper. Some details on the sampling process of this study have been left to Section 7.2 of the Appendix. The main longitudinal dataset comes from a NCI funded project entitled 'The Community Intervention Trial for Smoking Cessation' (COMMIT hereafter). This project was created to investigate the effectiveness of community wide interventions in helping smokers achieve and maintain long-term smoking cessation. The project began in 1989 and lasted till 1993. It was conducted in 11 matched pairs of communities, 10 pairs in the US, and the remaining pair in Canada. A community is broadly defined to include a portion of a major metropolitan area or two small cities in the same geographical location. There is a distinct geographical boundary separating these communities to ensure independence of intervention activities and minimize contamination. These selected communities were matched for general socio-demographic characteristics, like population size, demographic profile, (such as age and income distribution, ethnicity), smoking prevalence rate, access to intervention channels, etc. Table 3.1 shows some general statistics on the communities enrolled under COMMIT. One of the communities in each pair was randomized into an intervention group. The intervention activities were organized around four task forces that include health care providers, work sites and organizations, cessation resources and services, and public education.

Insert Table 3.1 here

Table B1 describes the selection process used to generate the final dataset for this analysis. A total of 20,347 smokers were recruited from the 11 pairs of communities, 66 percent of this sample completed the final survey in 1993, and 30 percent were lost to follow-ups and could not be located in the final period. Some 2.5 percent of the sample passed away and 1.5 percent refused to continue with the study. After dropping observations with incomplete information, a total of 7,765 observations are included for the final sample.

The COMMIT dataset provides no direct information on the health status of these smokers. To proxy the health process, I use the individual specific information from COMMIT together with external data from a cancer study to generate an estimate of the individual's health status. In particular, I use data from two well-known studies sponsored by the American Cancer Society, entitled the **Cancer Prevention Study I** and **II** (henceforth CPS-I and CPS-II respectively). These studies remain the largest longitudinal mortality study of diseases caused by tobacco use. CPS-I, formerly termed the 25 State Study began in October 1959 and ended in October 1972. Over 1 million men and women, representing 3 percent of the population over the age of 45 were recruited for this 12 years study. The second study, CPS-II, was instituted in September of 1982 and continued through 1988. It recruited 1.2 million persons from all the 50 US states. These studies have been extremely important in formulating the findings of the Surgeon General Report of the 1960's and 1980's and played a critical role in establishing a causal link between smoking and several diseases. The data covered a wide spectrum of diseases.[13]

Table B1 Selection of data

	No. of obs	Percentage
Sample at base survey in 1989.	20,347	
Sample that completed the final survey in 1993.	13,415	65.93
Sample that cannot be located in 1993.	6,124	30.10
Sample that deceased by 1993. (260 individuals unaccounted for.)	495	2.43
Sample that refused to be followed.	313	1.54
Sample that completed all 5 surveys.	8,361	41.10
Sample with incomplete information.	596	2.93
Current sample.	7,765	38.17

For this paper, I use the information on all-cause mortality by number of cigarettes

[13]Interested readers should refer to US Dept. of Health of Human Services (1989) and National Cancer Institute (1997) for more details on these studies and their findings.

smoked, attained age and duration of smoking to parameterize the relationship between the mortality risk ratio for current smokers and these individual specific characteristics.[14] A polynomial log model of smokers characteristics is fitted over these data. Table 3.2 compares the risk ratio estimates with that reported in National Cancer Institute (1997) for the study CPS I for two consumption levels. The log model gives a reasonable overall fit to the data. This model is used together with the mortality rates from the 1991 Life Tables (for a non-smoker) to estimate the mortality rates for the COMMIT data.

Insert Table 3.2 here

3.1 Preliminary Analysis of the Data

This section provides some descriptive statistics. An observation at year t is the average number of cigarettes smoked per day by the enrolled individual during the time of the annual interview.[15] I define *quit* to mean that the smoker reported zero consumption on the day of the interview.[16] Table B2 shows the quit dynamics of the data. All individuals upon enrolment are smokers. The mean for the sample at the start of the study is about 23 cigarettes smoked per day.

Table B2 shows that 18 percent of the sample reported quitting in the first period, 1990, and this percentage gradually increases to 31 percent of the sample in the final period, 1993 (as shown by figures in the first column). Around a third of those that quit in 1990 relapse in the second period, 1991. In the sample of continuing smokers in 1990, 10 percent of these individuals will report zero consumption in 1991 and so on. This table help illustrate the quitting dynamics in the data. A dynamic model of smoking should be able to generate these dynamics of quits and relapses. Out of the entire sample, 58 percent never quit over the period of the study while 11 percent successfully quit for all four periods as shown in the last row.

[14] The mortality risk ratio is the ratio of the death rate of a smoker (usually expressed in number of deaths per 100,000 persons), over that of a non-smoker.

[15] This average was constructed using the reported cigarettes smoked on a weekday and that smoked during the weekend.

[16] This definition is obviously very loose and potentially problematic since the smoker could have just attempted to quit and resumed smoking the day after the interview. The NCI used a stronger requirement in that the individual has to stop smoking for at least six months to attain the *quit* status. As such, the dataset does provide information on whether the smoker was smoking six months prior to the date of the interview but not the actual amount the smoker was consuming. I have decided to ignore this censored information for now as it complicates much of the econometrics in the modelling section. I hope to include this additional information in future revisions of the paper.

Table B2 : Quitting Dynamics on full sample.

<table>
<tr><th>Year
% that quit</th><th colspan="8">Total sample
n=7765</th></tr>
<tr><td>1990
18.49%</td><td colspan="4">18.49%
(1436)Q</td><td colspan="4">81.51%
(6329)S</td></tr>
<tr><td>1991
22.64%</td><td colspan="2">13.19%
(1024)Q</td><td colspan="2">5.31%
(412)S</td><td colspan="2">9.45%
(734)Q</td><td colspan="2">72.05%
(5595)S</td></tr>
<tr><td>1992
26.58%</td><td>11.90%
(924)Q</td><td>1.29%
(100)S</td><td>1.47%
(114)Q</td><td>3.84%
(298)S</td><td>6.04%
(469)Q</td><td>3.41%
(265)S</td><td>7.17%
(557)Q</td><td>64.88%
(5038)S</td></tr>
<tr><td>1993
31.06%</td><td>11.06%
(859)Q</td><td></td><td></td><td></td><td></td><td></td><td></td><td>57.64%
(4476)S</td></tr>
</table>

S and Q denotes the subsamples that smoke and quit respectively.

Most of the numbers for 1993 have been omitted for space considerations.

Table B3 shows some statistics comparing the various quit samples. The sample that stopped smoking over the entire length of the study are on average older, and of higher average income compared to the sample that never quits, or that which quit for only a single period. This sample also smoke a smaller amount on average upon enrolment in the study and started smoking at a later age. Further analysis of these data also show that the subsample that successfully quit the entire period of the study are on average more educated and hold more 'white collar' jobs. This feature of the data also arises in reduced form regressions with these demographic characteristics. Of the sample that never quit, I find that these smokers tend to smoke a relatively constant amount throughout the study period. Smokers usually remain in the cigarette bracket that they started with upon enrolment in the study.

One of the features of the dataset that is not ideal is the absence of any information about the purchasing behavior of the smoker or the price that they pay for their cigarettes. Cigarettes are differentiated mainly by unobserved taste and some observable attributes like length, size, nicotine and tar content, advertising, etc. Firms set a national wholesale price, on which the state and federal government levy an excise tax followed by the retailer's and wholesaler's markup. The classic argument in a differentiated products framework for instrumenting for price even when using individual level data is the unobserved product quality is most likely correlated with price.

Table B3 : Descriptive Statistics on various sub-samples

Variables	Sub-sample that: never quits ($n = 4467$)	quit for 4 periods ($n = 858$)	quits for 1 period ($n = 1183$)	Full sample ($n = 7752$)
Mean Age	41.0	42.5	40.8	41.2
in 1989.	(10.2)	(11.2)	(10.4)	(10.5)
Mean cig.	25.1	19.4	22.4	23.2
smoked in 1989.	(12.1)	(12.7)	(12.3)	(12.5)
Mean	17.8	18.6	18.1	18.0
starting age	(4.1)	(4.4)	(4.3)	(4.2)
Median daily	93.92	101.50	100.35	96.80
Income† 1990 US$	(57.1)	(58.4)	(58.1)	(57.6)

Std. error in parenthesis. † Median income is calculated for each respective income groups, measured in 1990 US$.

Intuitively, we expect price to be high when the unobserved component of demand is high hence generating this correlation. The natural remedy would be to instrument for price using cost shifters. Moreover in this scenario where price information is unobserved, there is an additional problem of measurement error. In the regressions that follow, I have chosen to instrument for price to remedy these econometric problems. The price series used is the weighted average retail price for the state, measured in 1990 US$.[17] This is instrumented on average hourly earnings in the state, average price for Burley and Flue-cured tobacco[18], state and federal taxes measured in 1990 US$, and state and time dummies.

Insert Table 3.3 here

[17] The price data is the nominal weighted average price for a pack of cigarettes for the state taken from Table 13a Tobacco Institute (1994), The Tax Burden on Tobacco, compiled by the now defunct Tobacco Institute. This prices include state and federal levied excise tax but does not include municipal or county excise tax nor sales tax. The data for 1990 to 1994 takes into account the generic brand category of cigarettes. These data is subsequently deflated by the CPI.

[18] This is taken from the USDA Tobacco website.

Table 3.3 shows two stage least squares (2SLS henceforth) cross-sectional regressions for three periods of the sample. The dependendent variable $ln(1 + C_t)$, is regressed on instrumented log prices, $ln(\hat{P_t})$, and individual demographic characteristics. In the first period of the study 1989, we find that the coefficient on price is not significantly different from zero. The estimates suggest that smokers in states with higher prices are not on average smoking less than smokers in states with lower cigarette prices. In the regressions for 1991 and 1993, we find that the coefficient on price becomes significant. Quitting behavior is crucial in identifying the price coefficients. These estimates indicate that quitting rate is higher in states with higher average prices confirming its role as an effective regulatory instrument. The price elasticities of 0.25 to 0.37 also fall in the range obtained by previous empirical work using similar forms of analysis.

Insert Table 3.4 here

The estimates on the remaining variables suggest the following empirical facts about the various covariates: smokers who are older, started smoking later, more educated and of higher income group are on average more likely to quit; female smokers on average smoke less than male smokers; smokers who hold 'blue collar' jobs are less likely to quit. This empirical features of the data also arise in Table 3.4 which shows cross-sectional probit regressions for the period 1990 and 1993. The indicator for an intervention community from both these sets of regressions do not seem to be a major explanatory variable for quitting behavior.

This preliminary analysis of the data helps highlight some facts about smoking cessation. Statistically significant predictors of quitting behavior include higher income, higher education, older age, later starting age and being male. This is in line with the findings in other papers.[19]

4 The Model

This project began with a much simpler habit formation model, with prices and the addiction stock as the only state variables. This model could not capture much of the dynamics of the data. In particular, it underpredicts the proportion of quits and provides unrealistic estimates of the price elasticity. A discussion of this preliminary model is included in Section 7.3 of the Appendix. In this section, I will provide a general

[19] See Wasserman, Manning, Newhouse, and Winkler (1991) and Hu, Ren, Keeler, and Bartlett (1995)

overview of the main model (that incorporates the health process as a state variable), and the estimation approach. This will be followed by an outline of the assumptions in Section 4.2 and the estimation procedure in Section 4.4.

4.1 Overview of the model and the estimation procedure

The smoker is assumed to have a set of well defined preferences (represented by a static utility function), which is time separable and does not change over time. The individual maximizes the sum of discounted expected utility, in a manner consistent with his preferences and beliefs about the states that affects well-being. Addiction is modeled as a unobserved '*stock*' that accumulates stochastically. Current consumption provides instantaneous utility to the smoker and also adds linearly to this stock, which depreciates at a constant rate. This stock variable affects the marginal utility of future consumption, capturing the *reinforcement* feature of addictive consumption. The accumulation process is stochastic in that a random component also adds linearly to this unobserved addiction stock. This disturbance summarizes other unobserved factors that influence the smokers decision each period.

Health is approximated by a discrete state variable.[20] For now, the individual is assumed to be in one of three possible states, either high, low or an absorbing terminal state of health. This discrete process evolves according to a first order Markov process. The realization of next period's health state depends on its current realization, the vector of current states, the individual's characteristics, and the individual's action this period.

The characteristics that influence how health evolves, like age, gender, and smoking history (as represented by the duration of smoking and the amount the individual smokes on average), is summarized by two statistics, the individual's *mortality rate* and *mortality risk ratio*. I assume that a smoker is endowed with these two statistics at the beginning of the program. These statistics are computed using data from CPS I and the 1991 Life Tables, and are a source of individual heterogeneity. The mortality risk ratio measures the excess mortality incurred by the smoker from his history of smoking.[21]

[20]In reality, health status obviously does not take discrete values and is influenced by many factors that are dynamic. However, to model this complex process in a computationally tractable way, I resort to this simple first approximation.

[21]This is measured by the ratio of the death rate of a smoker with the defined characteristics and smoking

The probability that the individual enters the terminal state next period is determined by the mortality rate. The probablity that the smoker draws a low health state next period depends on these two statistics and his decision in the current period.

Smoking increases the probability that a worse health state occurs next period and indirectly increases the likelihood of entering the terminal state sooner. This cost where continual smoking brings the smoker closer to an undesired state, is factored into the smoker's decision each period. The notion of a lower state of health is purely academic and need not be associated with the occurrence of any serious smoking associated illnesses, rather it is meant to capture either a lower state of well-being, or a realization that the smoker is closer to an absorbing terminal state as a results of his addiction, hence creating an incentive to quit. This incentive however is weakened by the fact that the individual gets utility from smoking and from accumulating the addictive stock.

This model also allows the cost incured at the low health state to vary according to the individual's demographic characteristics. Quitting in this model can be a *preventive remedy* that lowers the probability that a worse health state occurs, hence improving the smoker's health prospects in the future. In the event that a worse health state actually occurs, quitting in this model can also be *curative remedy*, where it increases the probability that the smoker improve his or her health status in the future.

Estimation is based on the likelihood of a sample path of observed behavior conditional on the initial values of the observed behavior and vector of states. To assign a likelihood to any observed path, the model is first solved numerically at the observed realization of prices, individual characteristics, and all possible realizations of the health status. The solution procedure entails numerically computing the value function[22] and the policy rule as a function of the states. Certain functional form restrictions allow us to compute the values of the unobserved states associated with observed behavior. A likelihood can then be assigned to the observed consumption path.[23] This is followed by standard maximum likelihood procedures.

history, over that of a non-smoker with similar characteristics. The mortality rate for that individual is simply the product of this risk ratio and the mortality rate of non-smoker with the same characteristics.

[22]Which represents the lifetime total present discounted expected utility.

[23]An detailed discussion of the intuition behind the estimation methodology is provided in Pakes (1996) for the case of modelling the investment decision of a firm where the unobserved state is the firm's productivity. The approach is also similar to that used by Timmins (2000) where the author models the pricing decision of the municipal owned water utilities; the unobserved state in that problem is the net marginal revenues in the water utilities' profit function.

4.2 Assumptions and Definitions

A representative smoker at each period t decides whether to quit or continue smoking c_t cigarettes so as to maximise the sum of discounted expected utilities. The decision space is bounded and is denoted by $\mathbb{D} = [0, \bar{C}]$. The agent is infinitely lived with the possibility of entering an absorbing terminal state. The individual is concerned about a vector of four **state variables**, $\{\mathrm{H}_t, \mathbb{I}_{t-1}, \mathbb{I}_t, , a_t\}$. I will first explain these state variables.

The agent's **smoking status in the previous period** is denoted by $\mathbb{I}_t \in \{0, 1\}$. It takes a value of 1 if he quits in the previous period and 0 otherwise. This indicator summarizes information about the agent's smoking history and directly affects the evolution of the health process, $\mathrm{H_t}$.[24]

The agent's instantaneous marginal utility from consumption depends on **a stock of addictive substance**, a_t, which is known to the smoker but unobserved by the economic analyst. Like c_t, this state variable is also bounded, $a_t \in [0, \bar{A}]$. It decays stochastically over time and the smoker's current consumption adds linearly to it as shown in Equation 4.1.

$$a_{t+1} = \begin{cases} (1+\delta_0)a_t + \delta_1 c_t + \xi_{t+1}, & : \quad \xi_{t+1} \sim N(0, \sigma_\xi^2) \quad \text{if} \quad 0 \leq a_{t+1} \leq \bar{A} \\ \bar{A} \text{ or } 0 & : \quad \text{otherwise} \end{cases} \tag{4.1}$$

The rate of decay is denoted by δ_0, where $\delta_0 \in (-1, 0)$. a_t is a measure of the smoking history of the individual and needs to be recovered so as to assign a conditional likelihood to any observed consumption, c_t. $\mathbf{\Lambda}$ denotes the set of parameters defining the stochastic process of a_t, that is,

$$\mathbf{\Lambda} = \{\delta_0, \delta_1, \sigma_\xi\}.$$

The state variable, H_t, represents **the health status of the agent** at period t. It takes three discrete values, $\mathrm{H}_t \in \{\mathrm{h^H}, \mathrm{h^L}, \mathrm{h^T}\}$ and evolves according to a Markov decision process. The state, $\mathrm{h^H}$, denotes a good state of health, $\mathrm{h^L}$ denotes a bad state, which can be thought of as a negative health event, and $\mathrm{h^T}$, the terminal state. The agent, for now, is assumed to have a constant discount factor $\beta \in (0, 1)$, which does not depend on either state or choice variables.[25]

[24] For now, both $\mathbb{I}_t$ and $\mathbb{I}_{t-1}$ are assumed to have no direct effect on the smoker's intantaneous utility.

[25] The framework is sufficiently flexible to allow for state dependent discount factor as well as hyperbolic discounting. This is a feature I will consider when performing policy experiments.

The **state vector** for this model is denoted by $\boldsymbol{s}_t = \{\mathrm{H}_t, \mathbb{I}_{t-1}, \mathbb{I}_t, , a_t\}$, it lives in a state space $\mathbb{S} = \{\mathrm{h}^{\mathrm{H}}, \mathrm{h}^{\mathrm{L}}, \mathrm{h}^{\mathrm{T}}\} \times \{0,1\} \times \{0,1\} \times [0, \bar{A}]$.

Each smoker i is endowed with a **characteristics vector** denoted $\boldsymbol{x}_i = \{m_i, P, Y_i, r_i, \alpha_i,\ g_i,\ z_i\}$

α_i: Mortality rate if individual i were a non-smoker.[26]

r_i: Relative risk ratio reflecting smoker's i smoking history and characteristics.[27]

m_i: Mortality rate for smoker i, where $m_i = r_i \times \alpha_i$.

P: Price.

Y_i: Real Income (in 1990 US $) for smoker i.

g_i: Average age of smoker i.

z_i: other individual specific characteristics.

These variables are assumed to be constant over time with the exception of price, P. The smoker takes price as given and does not expect it to change. Even though the agents are assumed to be naive about prices, the estimation will involve solving the model at each observed price. This simplication does not in any way compromise the analytic power of the model. I estimated an earlier model that considers price as a state and found that this does not contribute much to the prediction of smoking and quitting behavior[28].

The factors that influence the health process change over time and depend on the smoker's decision each period. Introducing these various individual characteristics as actual states variables that influence the health process would be computatationally very expensive. Given the short time period of the data and the fact that all individuals are 'seasoned' smokers, I will assume that the smokers are endowed with a risk ratio, r_i, and a mortality rate, m_i, that does not change over the periods of the sample. In effect, the risk ratio and mortality rate become sufficient statistics for the individuals' characteristics and smoking history. The health process depends on the endowed risk ratio, mortality rate and the smokers decision to smoke or quit. The mortality rate of the smoker, m_i, is given by the product of this relative risk ratio, $(r_i,)$ and mortality rate of a non-smoker with the same age and individual characteristics profile (α_i).[29]

[26] This is calculated from 1991 Life Tables.

[27] This is estimated using CPS I and II.

[28] I have included description of this earlier model in Section 7.3 of the Appendix.

[29] Given the assumption that the factors influencing the mortality rates are constant over time, the

The health state variable evolves according to a first order Markov process with a probability transition matrix, $\mathbf{H}(\cdot)$, given by Equation 4.2 below.

$$\mathbf{H}(m_i,\ c_t,\ \mathbb{I}_t,\ \mathbb{I}_{t-1},\ z_i,\ \mathbf{\Pi}) =$$
$$\begin{bmatrix} (1-m_i)\frac{\exp(\boldsymbol{\psi}_{it})}{1+\exp(\boldsymbol{\psi}_{it})} & (1-m_i)\frac{1}{1+\exp(\boldsymbol{\psi}_{it})} & m_i \\ (1-\lambda m_i)\frac{1}{1+\exp(\boldsymbol{\omega}_{it})} & (1-\lambda m_i)\frac{\exp(\boldsymbol{\omega}_{it})}{1+\exp(\boldsymbol{\omega}_{it})} & \lambda m_i \\ 0 & 0 & 1 \end{bmatrix} \tag{4.2}$$

The transition probability depends on c_t and all elements of the state vector except for the actual stock of addiction, a_t. Given that both a_t and H_t are both unobserved, this assumption ensures that the joint distribution of these states take a simple form. This will be futher explained in Section 4.4. I will use the conventional Markov chain notation, $\mathbf{P}_{\mathrm{HL}}$, to denote the probability of the event $\mathrm{H}_{t+1} = \mathrm{h}^{\mathrm{L}}$, given that $\{\mathrm{H}_t = \mathrm{h}^{\mathrm{H}}, r_i,\ m_i,\ \mathbb{I}\{c_t > 0\},\ \mathbb{I}_t,\ \mathbb{I}_{t-1}\}$, that is,

$$\begin{aligned} \mathbf{P}_{\mathrm{HL}} &= \mathbb{P}\{\mathrm{H}_{t+1} = \mathrm{h}^{\mathrm{L}} \mid \mathrm{H}_t = \mathrm{h}^{\mathrm{H}}, r_i,\ m_i,\ \mathbb{I}\{c_t > 0\},\ \mathbb{I}_t,\ \mathbb{I}_{t-1},\ \mathbf{\Pi}\} \\ &= \frac{1-m_i}{1+\exp(\boldsymbol{\psi}_{it})} \end{aligned}$$

The terms $\boldsymbol{\psi}_{it}$ and $\boldsymbol{\omega}_{it}$ in the logit probabilities are linear functions of the variables $\{r_i,\ m_i,\ \mathbb{I}\{c_t > 0\},\ \mathbb{I}_t,\ \mathbb{I}_{t-1}\}$. The term $\boldsymbol{\psi}_{it}$ in the logit probabilities takes the form,

$$\boldsymbol{\psi}_{it} = \psi_0 + \psi_1 r_i + \psi_2 m_i + \psi_3 \mathbb{I}\{c_t > 0\} + \psi_4 \mathbb{I}_t + \psi_5 \mathbb{I}_{t-1} + \psi_6 \mathbb{I}_{t-1}\mathbb{I}_t. \tag{4.3}$$

Intuitively, the probability of a negative health event, h^{L}, is increasing if the individual continues to smoke. It is also increasing in the duration of smoking and the age of the smoker. This would be reflected by a large value of m_i, and r_i. Introducing both these terms allows us to differentiate between two individuals of the same mortality rate, m_i, but different age, and smoking history. These differences are reflected by different risk ratios, r_i. The terms r_i, m_i, and $\mathbb{I}\{c_t > 0\}$, capture the morbidity of smoking addiction. The likehood of a negative health incident is decreasing in $\mathbb{I}_t$ and $\mathbb{I}_t$, capturing the health

individually endowed mortality rates, are calculated at the average age of the individuals in the study.

benefit to quitting.[30] The interaction term represented by the parameter ψ_6 captures the health gains associated with quitting for consecutive periods.

The term $\boldsymbol{\omega}_{it}$ has a similar functional form,

$$\boldsymbol{\omega}_{it} = \omega_0 + \omega_1 r_i + \omega_2 m_i + \omega_3 \mathbb{I}\{c_t > 0\} + \omega_4 \mathbb{I}_t + \omega_5 \mathbb{I}_{t-1} + \omega_6 \mathbb{I}_{t-1}\mathbb{I}_t. \tag{4.4}$$

$\boldsymbol{\omega}_{it}$ captures the opposite effect to $\boldsymbol{\psi}_{it}$. It is increasing in r_i, m_i, and $\mathbb{I}\{c_t > 0\}$ and decreasing in $\mathbb{I}_{t-1}$ and $\mathbb{I}_t$. The morbidity of smoking and the health benefits to cessation is a multi-faceted and complex process that depends on many factors.[31] Accounting for these different factors will be computationally infeasible and will put unrealistic demands on what the data can provide. The above representation is chosen to an intuitive first approximation of the health process that capture some of the main features of smoking and quitting. This specification can be made richer given more detailed data. The vector $\mathbf{\Pi}$ denotes the parameters of the health process H_t, where,

$$\mathbf{\Pi} = \{\lambda, \psi_0, \ldots, \psi_6, \omega_0, \ldots, \omega_6\}$$

The agent's **single period utility function** is denoted by $\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) = \mathbf{u}_t$. It is additively separable and stable over time. The functional form for $\mathbf{u}_t$ is chosen such that it is well-defined and bounded over the state space $\mathbb{S}$ and decision space $\mathbb{D}$. It takes the following form,

$$\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) = \begin{cases} \boldsymbol{\tau}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) & : \quad c_t \geq 0, \quad \mathrm{H}_t \in \{\mathrm{h^H}, \mathrm{h^L}\} \\ 0 & : \quad \forall\, c_t, \qquad \mathrm{H}_t \in \{\mathrm{h^T}\}. \end{cases}$$

The utility in the terminal state, $\mathrm{H}_t = \mathrm{h^T}$, has been normalized to zero. For $c_t > 0$ and $\mathrm{H}_t \in \{\mathrm{h^H}, \mathrm{h^L}\}$, the function $\boldsymbol{\tau}(.)$, takes the following form.

$$\begin{aligned} & \boldsymbol{\tau}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) \\ = \; & \gamma_0 \ln(1 + c_t) + \gamma_1 a_t \ln(c_t) + \gamma_2 P c_t + \gamma_3 \ln(Y) + \gamma_4' g_i + \gamma_5 \\ + \; & \mathbb{I}\{\mathrm{H}_t = \mathrm{h^L}\}(\zeta_0 \ln(1 + c_t) + \zeta_1 a_t \ln(1 + c_t) + \zeta_3 \ln(Y_i) + \zeta_4' g_i + \zeta_5). \end{aligned} \tag{4.5}$$

[30] As supported by a large body of medical evidence, examples include US Dept. of Health of Human Services (1989) and US Dept. of Health of Human Services (1990)

[31] US Dept. of Health of Human Services (1990) provides a discussion of the benefits of smoking cessation.

The smoker gets instantaneous utility, $\gamma_0 \ln(1 + c_t)$, from smoking c_t; the term γ_1, captures the *reinforcement effect* arising from the addictive stock, a_t. γ_2 represents the disutility experienced from paying P for each unit of consumption. The term γ_5, captures the mean utility level while not in the terminal state. The parameters γ_3, and γ_4, capture the contributions of individual income, Y_i, and age, g_i, to the mean utility. The identification of the parameters, γ_3, γ_4 and γ_5 comes from the dynamics of quitting amongst heterogenous individuals. For example, individuals with higher income will have a higher mean utility level while not in the terminal state. As such the identification of γ_3, for example, would come from individuals with higher income group quitting more often. When a lower state of health h^{L} is encountered, the individual experiences an instantaneous disutility represented by the set of parameters $\{\zeta_0, \zeta_1, \zeta_5\}$. A smoker who smokes more and is more addicted will experience a much larger disutility represented by ζ_0 and ζ_1 respectively. This serves to proxy for a more severe negative health event typically encountered among heavier smokers. The terms ζ_3 and ζ_4 capture the effect income and age have on the disutility from being in the lower health state.[32] The set of parameters $\boldsymbol{\Theta}$ is defined as

$$\boldsymbol{\Theta} = \{\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \zeta_0, \zeta_1, \zeta_3, \zeta_4, \zeta_5\}. \tag{4.6}$$

4.3 The Single Agents Problem

The representative agent's optimization problem is to choose an optimal stationary decision rule $\mathbf{c}^* = \{c^*_{i0}, c^*_{i1}, \dots c^*_{i\infty}\}$ to solve the dynamic program,

$$\max_{\mathbf{c}^*} \mathbb{E}\left\{ \sum_{t=0}^{\infty} \beta^t \mathbf{u}(c_{it}; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) \mid c_0, \boldsymbol{s}_0, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi} \right\}.$$

If $\mathbf{V}_t$ denotes the lifetime total discounted expected utility from employing the stationary optimal policy $\mathbf{c}^*$ when the initial state and characteristics vector is $\{\boldsymbol{s}_t, \boldsymbol{x}_i\}$, and the

[32] The model currently does not allow the instantaneous disutility from the negative health event to differ whether the individual smokes or not. Certain illnesses like emphysema or bronchial related diseases would be aggravated or worsen if the smoker continues to smoke. The specification of the model is sufficiently flexible to allow for this.

parameters set at the values $\{\boldsymbol{\Lambda},\ \boldsymbol{\Theta},\ \boldsymbol{\Pi}\}$, that is, $\mathbf{V}_t = \mathbf{V}_{\mathbf{c}^*}(\boldsymbol{s}_t \mid \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi})$, the Bellman's operator for this single agent's problem is then given by,

$$\mathbf{V}_t = \max_{\mathbf{c}^*}\{\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) + \beta\, \mathbb{E}(\mathbf{V}_{t+1} \mid c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi}))\}. \tag{4.7}$$

The assumptions made in Section 4.2 satisfy the sufficient conditions for the Contraction Mapping Theorem to apply.[33] This ensures that there exists a unique fixed point to the Bellman's operator and that a non-empty stationary policy rule, $\boldsymbol{\chi} : \mathbb{S} \mapsto \mathbb{D}$, exists and is of the form shown in Equation 4.8. Using the properties of the contraction mapping, the fixed point $\mathbf{V}_t$ can be solved by *successive approximation* methods and the policy rule can be solved numerically by *policy improvement* techniques.

$$\begin{aligned} \mathbf{c}_t^* &= \arg\max_{\mathbf{c}_t^*}\{\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) + \beta\, \mathbb{E}(\mathbf{V}_{t+1} \mid \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi})\} \\ &= \boldsymbol{\chi}(\boldsymbol{s}_t \mid \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi}) = \boldsymbol{\chi}_t, \quad \text{where } \mathbf{c}_t^* \in \mathbb{D}, \end{aligned} \tag{4.8}$$

Given the definition of the Markovian state variables, the expectation in the Bellman's oparator can be written in the following separable form,

$$\begin{aligned} &\mathbb{E}(\mathbf{V}(\boldsymbol{s}_{t+1} \mid c_t, \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi})) \\ = &\int_{\mathrm{H}}\int_a \mathbf{V}(\boldsymbol{s}_{t+1}) \cdot \wp_\xi(a_{t+1} \mid \mathrm{H}_{t+1}, c_t, \boldsymbol{s}_t, \boldsymbol{\Theta}, \boldsymbol{\Lambda}) \cdot \wp_{\mathbf{H}}(\mathrm{H}_{t+1} \mid c_t, \boldsymbol{s}_t, \boldsymbol{\Pi})\; da_{t+1}\; d\mathrm{H}_{t+1} \\ = &\sum_{\mathrm{H}_{t+1} \in \{\mathrm{h^H}, \mathrm{h^L}\}} \wp_{\mathbf{H}}(\mathrm{H}_{t+1} \mid c_t, \boldsymbol{s}_t, \boldsymbol{\Pi}) \cdot \int_a \mathbf{V}(\boldsymbol{s}_{t+1}) \cdot \wp_\xi(a_{t+1} \mid \mathrm{H}_{t+1}, c_t, \boldsymbol{s}_t, \boldsymbol{\Theta}, \boldsymbol{\Lambda})\, da_{t+1}\,. \end{aligned}$$

4.4 Estimation

I now outline the estimation strategy that I adopt in this paper. I have borrowed heavily from theories and numerical methods employed in solving and estimating mixed discrete and continuous Markov Decision Process. These areas have been heavily researched and interested readers should refer to Pakes (1996), Rust (1994), Timmins (2000) for more in depth discussion.

A *Nested Fixed Point Maximum Likelihood Estimation* method is used to estimate the parameters of this model. This algorithm comprise of two loops. An outer loop

[33]Interested readers should refer to Ross (1970), Lucas and Stokey (1989), and Rust (1996)

solves for the parameter that maximise the likelihood of the sample of data. An inner loop solves for the fixed point of the value function, the policy rule, and calculates the implied conditional likelihood corresponding to a set of parameter values. A modified policy iteration method is adopted to solve for the fixed point to the Bellman Equation 4.7 conditional on $\{\hat{\mathbf{\Theta}}, \hat{\mathbf{\Lambda}}, \hat{\mathbf{\Pi}}, \boldsymbol{x}_i\}$. This is used together with the Brent's numerical method that solves for the mixed discrete and continuous optimal control. This is carried out on a discretized state space.

These dynamic programming numerical procedures solve for the policy rule $\boldsymbol{\chi}(.)$, as a function of the state vector, $\boldsymbol{s}_t$. The maximum likelihood estimation approach requires that a likelihood be assigned to the tuple $\{c_t,\ \boldsymbol{s}_t\}$ conditional on $\{c_{t-1}, \boldsymbol{s}_{t-1}, \boldsymbol{x}_i, \mathbf{\Lambda}, \mathbf{\Theta}, \mathbf{\Pi}\}$. This means that we need to recover the unobserved states, $\{a_t, \mathrm{H}_t\}$, from the solved policy rule $\boldsymbol{\chi}_t$. The static one period utility is defined to be non-decreasing in the unobserved state a_t, holding everything else constant. This condition would ensure that the the policy function is also non-decreasing in a_t.[34] This restriction on the utility function provides an invertibility condition that allows the recovery of the unobserved state, $a_t = \boldsymbol{\chi}^{-1}(c_t = \mathbf{c}^*; \mathrm{H}_t, \mathbb{I}_{t-1}, \mathbb{I}_t \mid \boldsymbol{x}_i, \mathbf{\Lambda}, \mathbf{\Theta}, \mathbf{\Pi})$. This condition states that every vector $\{\mathbf{c}^*, \mathrm{H}_t, \mathbb{I}_{t-1}, \mathbb{I}_t\}$ is only associated with a single value of the unobserved state a_t.

This approach precludes the introduction of the *tolerance effect* in the manner considered in existing theoretical model of rational addiction like Becker and Murphy (1988). Allowing the policy rule to be non-monotonic in a_t creates a non-uniqueness complication that would make the estimation problem not tractable. I believe that this restriction is not an unreasonable approximation of the cigarette addiction process. However, there are many examples of addiction like that of alcohol and cocaine addiction where this assumption is unrealistic. In these forms of addiction, there are significant negative health effects associated with accumulating the addiction stock. In future extension of this paper, I intend to relax this assumption by resorting to alternative estimation methods. A minimum distance estimation approach in which the metric is the euclidean norm between the implied and observed moment conditions is a possible alternative. The potential complication in that approach is the choice of moment conditions. This will be a topic of further extensions of this paper.[35]

[34] A formal statement and proof of this result is given in *Lemma 3* of Pakes (1996).

[35] There is also the added issue that the state H_t is also unobserved and the defined invertibility condition requires this state to be an element of the conditioning vector $\{\mathbf{c}^*, \mathrm{H}_t, \mathbf{I}_{t-1}, \mathbf{I}_t\}$. I will consider two

FIGURE 4.1: ILLUSTRATION OF A STYLISED POLICY FUNCTION.

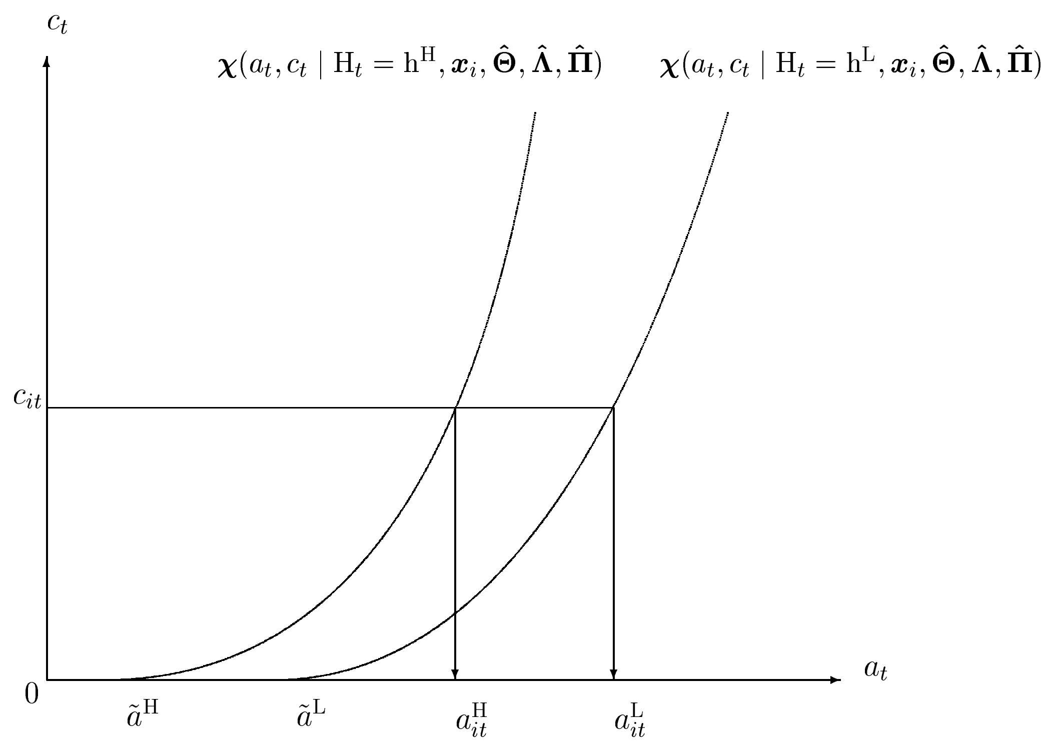


Figure 4.1 illustrates a stylized policy function, conditional on a set of parameter values, characteristics vector and states $\{\mathbb{I}_t, \mathbb{I}_{t-1}, \mathrm{H_t}\}$. The monotonicity property allows the unobserved a_i, corresponding to the observed $c_i > 0$, to be solved through simple interpolation. The diagram shows that the amount of cigarettes smoked, c_t, is increasing with the level of addiction, a_t, holding the remaining states fixed. The amount consumed conditional on an addiction stock a_t is lower when $\mathrm{H}_t = \mathrm{h}^{\mathrm{L}}$.

In a sample of T observations, the estimation algorithm defines a likelihood for the sample path, $\{c_{i2}, \boldsymbol{s}_{i2}, \ldots, c_{iT}, \boldsymbol{s}_{iT}\}$, conditional on the observation vector, $\{c_{i1}, \boldsymbol{s}_{i1}\}$, at period $t = 1$. Given the definition of the stochastic process H_t in Equation 4.2, where the realization of H_{t+1} depends only on $\{m_i,\ c_t,\ \mathbb{I}_t,\ \mathbb{I}_{t-1},\ z_i,\ \boldsymbol{\Pi}\}$, the joint distribution of

alternative ways of dealing with this initial condition problem. The first would be to naively assume that $\mathrm{H}_t = \mathrm{h}^{\mathrm{H}}$ at the beginning of the sample. The second would be to calculate the stationary distribution associated with the irreducible portion of the Markov chain and assign individuals to this health state according to this distribution.

the two unobserved states have a simple separable form,[36]

$$\begin{aligned}
&\mathbb{P}(c_{i2}, \boldsymbol{s}_{i2} \mid c_{i1}, \boldsymbol{s}_{i1}, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi}) \\
= &\sum_{\mathrm{H}_{i2} \in \{\mathrm{h^H}, \mathrm{h^L}\}} \mathbb{I}\{c_{i2} = \boldsymbol{\chi}_2,\ \mathrm{H}_{i2}\} \cdot \wp_{\xi}(a_{i2} = \boldsymbol{\chi}_2^{-1} \mid \mathrm{H}_{i2}, c_{i1}, \boldsymbol{s}_{i1}, \boldsymbol{\Theta}, \boldsymbol{\Lambda}) \cdot \wp_{\mathbf{H}}(\mathrm{H}_{i2} \mid c_{i1}, \boldsymbol{s}_{i1}, \boldsymbol{\Pi})
\end{aligned}$$

The data tracks the behavior of smokers over a period of 5 years, each smoker i starts in period $t = 1$ smoking some positive amount, $c_{i1} > 0$. I will suppress the index for individual smokers for now. Consider the case where an individual smokes a positive amount throughout the entire sample period, the likelihood of observing $\{c_2, \boldsymbol{s}_2\}$ will be,

$$\begin{aligned}
&\ell(c_2, \boldsymbol{s}_2 \mid c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}, \hat{\boldsymbol{\Pi}}) \\
= &\sum_{\mathrm{H}_2 \in \{\mathrm{h^H}, \mathrm{h^L}\}} \mathbb{I}\{c_2 = \boldsymbol{\chi}_2,\ \mathrm{H}_2\} \cdot \wp_{\mathbf{H}}(\mathrm{H}_2 \mid c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Pi}}) \\
\cdot\ & f_{\xi}(\boldsymbol{\chi}_2^{-1} - (1 + \hat{\delta}_0)\boldsymbol{\chi}_1^{-1} - \hat{\delta}_1 c_1 \mid \mathrm{H}_2, c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}})
\end{aligned}$$

where $f_{\xi}(\ldots)$ denotes the normal density. The corresponding likelihood for the entire consumption path for periods $t = 2, \ldots, T$ of a smoker who never quits would be,

$$\begin{aligned}
&\ell(c_2, \ldots, c_T, \boldsymbol{s}_2, \ldots \boldsymbol{s}_T \mid c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}, \hat{\boldsymbol{\Pi}}) \\
= &\prod_{t=2}^{T} \Bigg\{ \sum_{\mathrm{H}_t \in \{\mathrm{h^H}, \mathrm{h^L}\}} \mathbb{I}\{c_t = \boldsymbol{\chi}_t,\ \mathrm{H}_t\} \cdot \wp_{\mathbf{H}}(\mathrm{H}_t \mid c_{t-1}, \ldots, c_1, \boldsymbol{s}_{t-1}, \ldots, \boldsymbol{s}_1, \hat{\boldsymbol{\Pi}}) \\
\cdot\ & f_{\xi}(\boldsymbol{\chi}_t^{-1} - (1 + \hat{\delta}_0)\boldsymbol{\chi}_{t-1}^{-1} - \delta_1 c_{t-1} \mid \mathrm{H}_t, c_{t-1}, \ldots, c_1, \boldsymbol{s}_{t-1}, \ldots, \boldsymbol{s}_t, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}) \Bigg\}
\end{aligned}$$

The dynamics in this smoking behavior(holding P fixed) are driven by the stochastic process determining H_t and a_t. In Figure 4.1, these threshold levels of addiction are denoted by $\tilde{a}^{\mathrm{H}}$ when the individual is in the good state of health and $\tilde{a}^{\mathrm{L}}$ when he gets a negative health shock. If a_t falls below this threshold, the smoker stops smoking for

[36]For example, the probability of observing $\{c_{i2}, \boldsymbol{s}_{i2}\}$ conditional on $\{c_{i1}, \boldsymbol{s}_{i1}\}$, where $\mathrm{H}_{i1} = \mathrm{h^H}$, will be

$$\begin{aligned}
&\mathbb{P}(c_{i2}, \boldsymbol{s}_{i2} \mid c_{i1}, \boldsymbol{s}_{i1}, \boldsymbol{x}_i, \boldsymbol{\Lambda}, \boldsymbol{\Theta}, \boldsymbol{\Pi}) \\
= &\ \mathbb{I}\{c_{i2} = \boldsymbol{\chi}_2, \mathrm{H}_{i2} = \mathrm{h^H}\} \cdot \wp_{\xi}(a_{i2} = \boldsymbol{\chi}_2^{-1} \mid \mathrm{H}_{i2} = \mathrm{h^H}, c_{i1}, \boldsymbol{s}_t, \boldsymbol{\Theta}, \boldsymbol{\Lambda}) \cdot \mathbf{P}_{\mathrm{HH}} \\
+ &\ \mathbb{I}\{c_{i2} = \boldsymbol{\chi}_2, \mathrm{H}_{i2} = \mathrm{h^L}\} \cdot \wp_{\xi}(a_{i2} = \boldsymbol{\chi}_2^{-1} \mid \mathrm{H}_{i2} = \mathrm{h^L}, c_{i1}, \boldsymbol{s}_t, \boldsymbol{\Theta}, \boldsymbol{\Lambda}) \cdot \mathbf{P}_{\mathrm{HL}}.
\end{aligned}$$

that period t. As such, quitting, even after conditioning on the unobserved H_t, creates an indeterminacy of the stock of addiction for that period. The likelihood for that individual requires that the indeterminate a_t be integrated out. To illustrate, consider the case where a smoker is smoking in period one, quits in period $t = 2$, relapses in period three and continue smoking the remaining periods. The likelihood of this consumption path would be,

$$
\begin{aligned}
& \ell(c_2, \ldots, c_T, \boldsymbol{s}_2, \ldots, \boldsymbol{s}_T \mid c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}, \hat{\boldsymbol{\Pi}}) \\
= & \prod_{t=4}^{T} \Bigg\{ \sum_{\mathrm{H}_t \in \{\mathrm{h}^{\mathrm{H}}, \mathrm{h}^{\mathrm{L}}\}} \mathbb{I}\{c_t = \boldsymbol{\chi}_t,\ \mathrm{H}_t\} \cdot \wp_{\mathbf{H}}(\mathrm{H}_t \mid c_{t-1}, \ldots, c_1, \boldsymbol{s}_{t-1}, \ldots, \boldsymbol{s}_1, \hat{\boldsymbol{\Pi}}) \\
\cdot \ & f_\xi(\boldsymbol{\chi}_t^{-1} - (1 + \hat{\delta}_0)\boldsymbol{\chi}_{t-1}^{-1} - \delta_1 c_{t-1} \mid \mathrm{H}_t, c_{t-1}, \ldots, c_1, \boldsymbol{s}_{t-1}, \ldots, \boldsymbol{s}_t, \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}) \Bigg\} \\
\cdot \ & \sum_{\mathrm{H}_3} \sum_{\mathrm{H}_2} \mathbb{I}\{c_3 = \boldsymbol{\chi}_3,\ \mathrm{H}_3\} \cdot \mathbb{I}\{c_2 = \boldsymbol{\chi}_2,\ \mathrm{H}_2\} \cdot \wp_{\mathbf{H}}(\mathrm{H}_3 \mid c_2, c_1, \boldsymbol{s}_2, \boldsymbol{s}_1, \hat{\boldsymbol{\Pi}}) \cdot \wp_{\mathbf{H}}(\mathrm{H}_2 \mid c_1, \boldsymbol{s}_1, \hat{\boldsymbol{\Pi}}) \\
\cdot \ & \int_{-\infty}^{\tilde{\xi}_{\mathrm{H}_2}} f_\xi(\boldsymbol{\chi}_3^{-1} - (1 + \hat{\delta}_0)\boldsymbol{\chi}_2^{-1} \mid c_2 = 0, \boldsymbol{\chi}_2^{-1} \leq \tilde{a}_{\mathrm{H}_2}, \boldsymbol{s}_2, c_1, \boldsymbol{s}_1; \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}) \\
\cdot \ & f_\xi(\boldsymbol{\chi}_2^{-1} - (1 + \hat{\delta}_0)\boldsymbol{\chi}_1^{-1} - \hat{\delta}_1 c_1 \mid c_1, \boldsymbol{s}_1; \hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}})) d\, \boldsymbol{\chi}_2^{-1}. \qquad (4.9)
\end{aligned}
$$

$$
\begin{aligned}
\text{where} \quad & \tilde{\xi}_{\mathrm{H}_2} \in \left\{ \tilde{a}^{\mathrm{H}} - (1 + \hat{\delta}_0)a_1 - \hat{\delta}_1 c_1,\ \tilde{a}^{\mathrm{L}} - (1 + \hat{\delta}_0)a_1 - \hat{\delta}_1 c_1 \right\} \\
\text{and} \quad & \tilde{a}_{\mathrm{H}_2} \in \left\{ \tilde{a}^{\mathrm{H}}, \tilde{a}^{\mathrm{L}} \right\}
\end{aligned}
$$

Hence each quit observation would generate an integral in the likelihood calculation. There is a total of sixteen possible likelihood formulations (depending on the quitting patterns observed) and another sixteen possible permutations of the health state for the sample of five periods used in this paper. I have chosen to leave these various likelihood formulation out of the paper, they are available on request from the author. The likelihood for the entire sample would simply be the product of all the individual likelihood functions, that is,

$$
\mathcal{L}_n = \prod_{i=1}^{n} \ell(c_{i2}, \ldots, c_{iT}, \boldsymbol{s}_{i2}, \ldots, \boldsymbol{s}_{iT} \mid c_{i1}, \boldsymbol{s}_{i1}, \boldsymbol{\Theta}, \boldsymbol{\Lambda}, \boldsymbol{\Pi}) \qquad (4.10)
$$

5 Monte Carlo Simulations

This section discusses the Monte Carlo simulation of the structural model described in Section 4.2. It illustrates the kind of dynamics that the model can generate and provides a prima facie test of whether the model can explain data. Table 5.1 shows the parameters values used in the simulation. The ζ's have been set to zero. The values for the terms, γ_0, γ_1 and γ_2, are set close to those obtained from the estimation of a preliminary model.[37] The remaining parameters are set by trial and error. The probability transition matrix of H_t at this parameter values for two combinations of the state vector are given below,

$$\mathbb{P}(\mathrm{H}_{t+1} \mid \mathrm{H}_t, \mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0, c_t > 0, \mathbf{\Pi}) = \begin{bmatrix} 0.674 & 0.321 & 0.005 \\ 4.2 \times 10^5 & 0.800 & 0.200 \\ 0.000 & 0.00 & 1.000 \end{bmatrix}$$

$$\mathbb{P}(\mathrm{H}_{t+1} \mid \mathrm{H}_t, \mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0, c_t = 0, \mathbf{\Pi}) = \begin{bmatrix} 0.676 & 0.319 & 0.005 \\ 0.420 & 0.380 & 0.200 \\ 0.000 & 0.000 & 1.000 \end{bmatrix}$$

Insert Table 5.1 here.

The parameters of the health process are chosen such that a smoker in the good state ($\mathrm{H}_t = \mathrm{h}^H$), has approximately 30 percent chance of a negative health event next period.[38] In the event of a negative health shock, quitting is essentially necessary for the smoker to have a reasonable chance of returning to the high health state.[39] With the values of ζ's set to zero, a negative health event does not bring instantaneous disutility but it does bring the individual closer to the absorbing terminal state.

The characteristic vector for the representative agent is set to the mean value for the Massachusetts. The mean age is 41, the average daily consumption is a pack (20 cigarettes), and the average duration of smoking is 18 years. The relative risk ratio, r_i, for a smoker with these mean characteristics is around 2, and the corresponding mortality

[37]A discussion of this model is included in Section 7.3 of the Appendix. This preliminary model is estimated using a sub-sample from the state of Massachusetts.

[38]For example, the first matrix shows that an individual who continues to smoke has a 32.1 percent chance of drawing a bad state next period. Someone who quits has a slightly lower chance, 31.9 percent, of incurring a bad state next period.

[39]So from the first transition matrix, someone in a bad state of health who continues to smoke has a narrow chance of covering back to the good state, (0.004 percent,) and 20 percent of entering the terminal state next period. If the individual quits, he has a 42 percent of recovering back to the good state.

rate, m_i, is around 0.005. The model is first solved at the parameter values and observed cigarette prices for the period 1989 to 1993. The model is then simulated starting from the observed empirical distribution of consumed cigarettes for the year 1989. Random numbers for ξ_t and H_t are drawn according to the predefined stochastic processes. The time path of the smokers' decisions are then computed according to the solved policy rule.

Figure 5.1 : Value Function and Policy Rule
for the simulated sample.

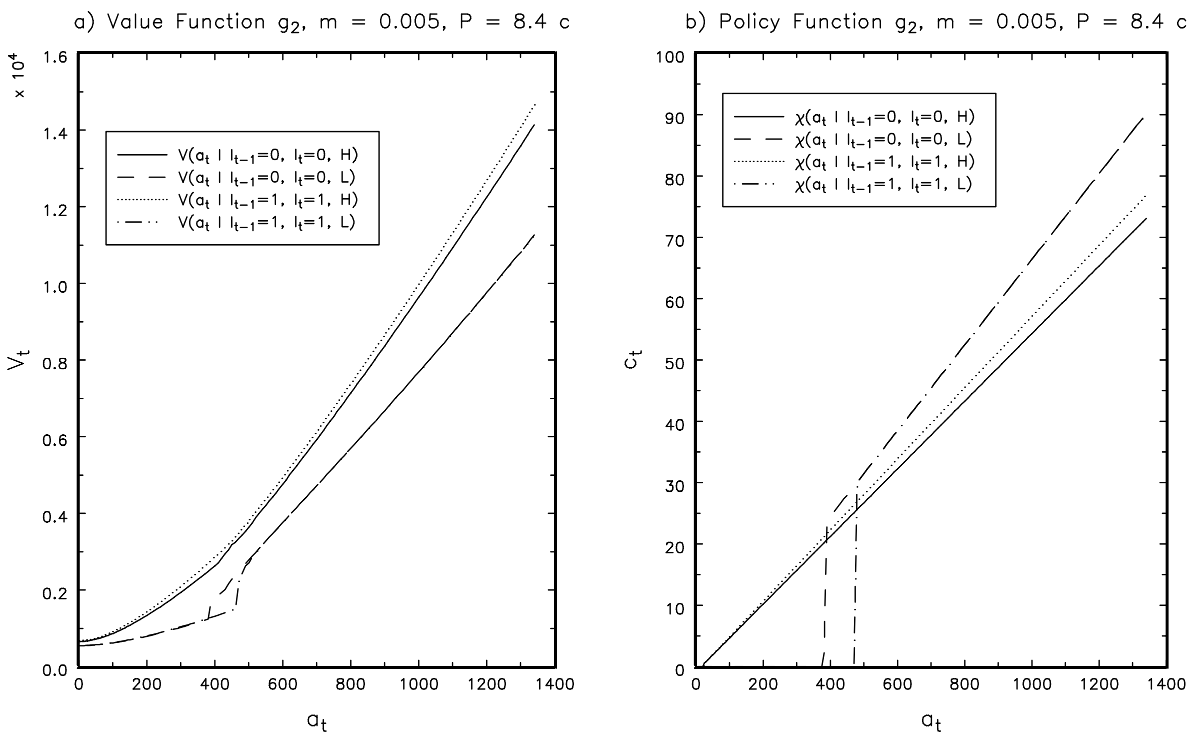


Figure 5.1 shows the value function and policy rule at some combination of the state vector for the year 1991. Figure (a) illustrates the solved value function as a function of the addiction stock, a_t, at the two health states, and the quitting history $\{\mathbb{I}_t = 1, \mathbb{I}_{t-1} = 1\}$ and $\{\mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0\}$. As expected, the value function for an individual in the good health state who has not smoked in the previous two periods, $\mathbf{V}(a_t \mid \mathrm{h^H}, \mathbb{I}_t = 1, \mathbb{I}_{t-1} = 1)$, is greater than if he smoked the previous two periods, $\mathbf{V}(a_t \mid \mathrm{h^H}, \mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0)$. Quitting lowers the chance that a negative health event occurs next period and hence increases the sum of discounted expected utility.[40] The

[40] By the same logic, the value function at the low state of health, $\mathrm{h^L}$, is also lower than the corresponding value functions at $\mathrm{h^H}$, holding everything else equal.

kink in the value functions at h^L corresponds to the kink in the policy function at h^L shown in Figure (b). The transition probabilities are defined to depend only on the current decision of whether to smoke or quit, and not on the actual level of consumption. As such, when the stock of addiction gets to a critical level where it pays to resume smoking, the smoker will consume up to a level that conpensates him for the loss in lifetime utility as a result of the increased probability from entering the terminal state. This generates the kink in the policy function.

By construction, the policy rules are weakly increasing in the addiction stock. Interestingly, $\boldsymbol{\chi}(a_t \mid h^H, \mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0)$, is lower than $\boldsymbol{\chi}(a_t \mid h^H, \mathbb{I}_t = 1, \mathbb{I}_{t-1} = 1)$. That is, conditional on a level of addiction stock, smokers at the high state of health and who have not smoked in the previous two periods, smoke more than a smoker with the same level of addiction but who has smoked the last 2 periods. A negative health event enlarges the range of the addiction stock for which the smoker chooses not to smoke. At these levels of the addiction stock, the increase in lifetime utility from smoking and further accumulating the addiction stock is not offset by the utility decrease from being closer to the terminal state.

Table A1 : Statistics of obs. and sim. sample for state of MA. ($n = 654$)

	obs. P	% quits		sub-sample of smokers, $c_t > 0$			
years	in cents	sim.	obs.	mean(s)	stdev(s)	mean(o)	stdev(o)
1989	8.03	-	0.00	-	-	24.05	12.46
1990	8.16	19.11	21.16	22.56	11.77	22.77	13.45
1991	8.44	29.51	26.79	18.83	10.64	22.46	11.27
1992	8.41	33.64	31.96	15.26	9.85	21.88	10.99
1993	8.62	37.77	35.16	12.02	7.94	21.49	10.84

Table A1, compares some general statistics of the simulated and observed sample. The second column shows the observed price, P, and the third and fourth column show the simulated and observed percentage of quits. The model generates quit percentages that are in the range observed in the data. The current parameterization seems to over predict the number of quits in 1991, and this appears to have a carry-over effect for the subsequent years. This most likely results from demand being too sensitive to price[41].

[41] Coupled with the likely inaccurate parameterization of the health process.

There is a large increase in price in 1991 relative to the previous years and the current parameterization over-predicts the number of quits in that period. The remaining four columns show statistics for the sample of smokers in each period. The distribution of the simulated sample of smokers appears to have means and variances that are well below what is observed in data. The mean consumption level also seems to be decreasing over time. This is a feature of the model that estimation will likely improve upon.

Table A2: Simulated Quitting Dynamics for sample from MA

(observed percentage in parenthesis)

Year % that quit	Total sample n=654							
1990								
19.11	19.11				80.89			
(21.16)	(21.16)Q				(78.84)S			
1991								
29.51	9.33		9.79		20.18		60.70	
(26.79)	(15.83)Q		(5.33)S		(10.96)Q		(67.88)S	
1992								
33.64	4.13	5.20	2.29	7.50	9.32	10.86	17.89	42.81
(31.96)	(14.76)Q	(1.07)S	(1.83)Q	(3.5)S	(7.31)Q	(3.65)S	(8.07)Q	(59.82)S
1993								
37.77	3.06							28.75
(35.16)	(13.39)Q							(52.66)S

S and Q denotes the subsamples that smoke and quit respectively.

Table A2 compares the proportions of the simulated and observed sample that quits and relapses each period. The observed percentages are shown in parenthesis. The first column shows the percentage of observed and simulated quits percentages for each year of the sample (as previously shown in Table A1). The second row shows that 20 percent of the sample of smokers quit in the year 1990 of the study. The model predicts that one-half of this subsample will continue not smoking in the following year (9.3 percent of the full sample). In contrast, in the observed data, around three-fourths of the first period quitters remain quitters (15.8 percent of the original sample). Similarly, the model predicts that one-fourth of the smokers in 1990 will quit in 1991, which is around 20 percent of the full sample. According to the data, only one-eighth of the sample of smokers in 1990 quits 1991. The current parameterization seems to overpredict the proportion of quitters that will relapse and the proportion of continuing smokers who will quit in the next period. This is something I expect actual estimation will improve upon. Tables A1 and A2 highlight a very important feature of the model: its ability to to generate both quitting and smoking dynamics as observed in data.

FIGURE 5.2 : VALUE FUNCTION AND POLICY RULE
VARYING MORTALITY RATE m_i.

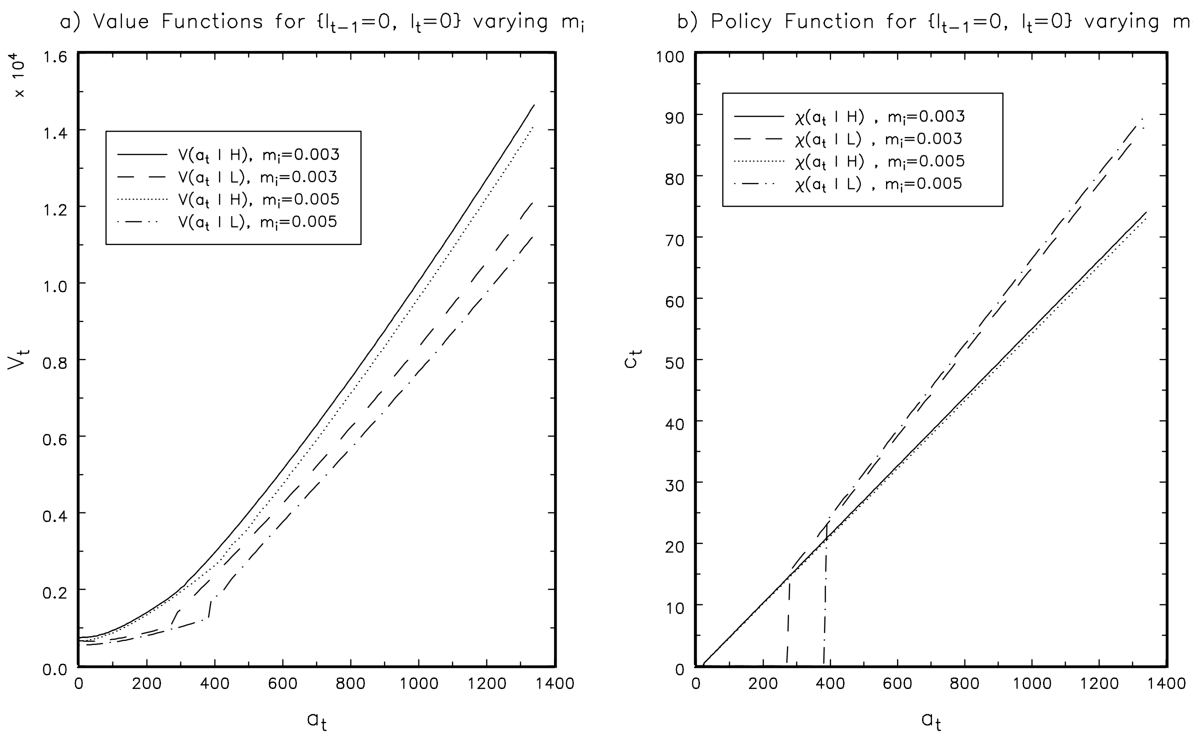
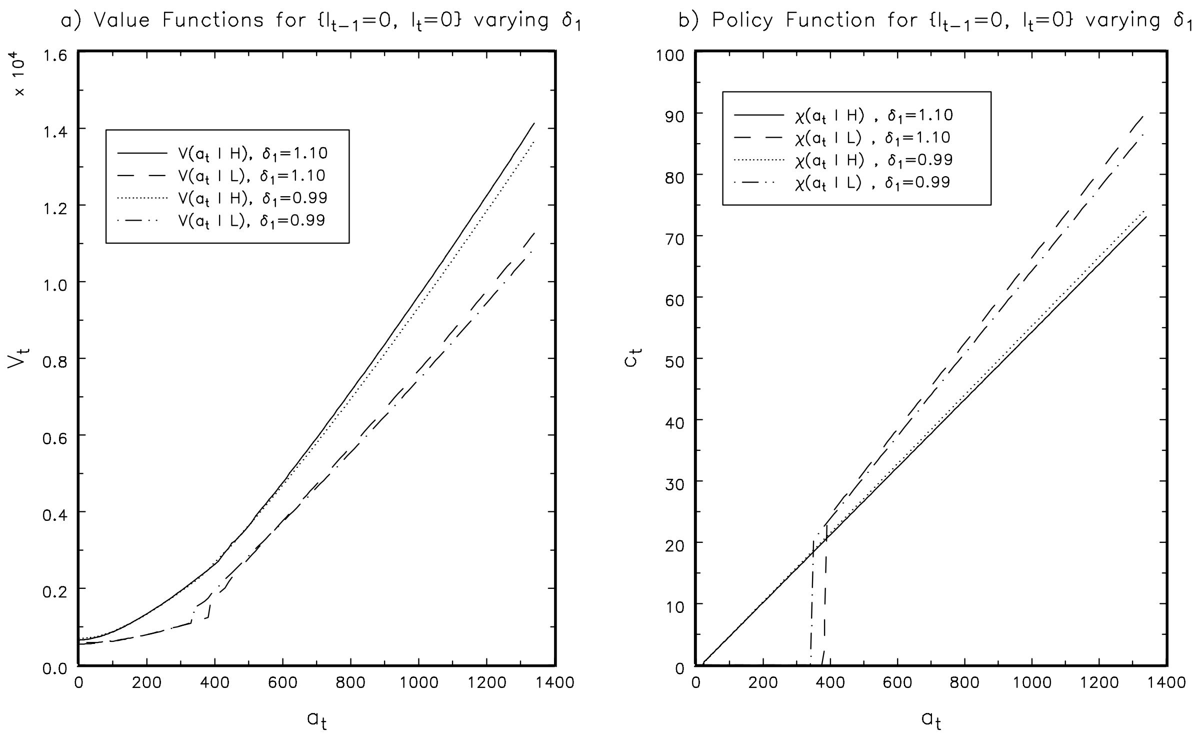


Figure 5.2 compares the policy rules and value functions at the two health states, for two different mortality rates, $m = 0.003$, and $m = 0.005$. The quit indicators are set to $\{\mathbb{I}_t = 0, \mathbb{I}_{t-1} = 0\}$. As expected, the value function at $m = 0.003$ lies above that at $m = 0.005$ (holding everything else constant). The policy functions suggest that the individual with the lower mortality rate is less likely to quit in the event of a negative health shock. A smoker with a higher mortality also smokes more in event of health shock holding the addiction stock fix.

Figure 5.3 : Value Function and Policy Rule varying mortality rate δ_1.



To illustrate the kinds of policy experiments possible with this model, consider a scenario where we lower the amount of nicotine in cigarettes. This is equivalent to varying the parameter δ_1 in the stochastic accumulation Equation 4.1. Table A3 shows statistics from the Monte Carlo simulation of this experiment carried out for five periods and Figure 5.3 shows the corresponding value functions and policy rules. Prices is held fixed at 8.44 cents, which is the level observed in Massachusetts for 1991. The set of numbers in the first three columns shows general statistics for the sample when $\delta_1 = 1.10$. The first column gives the percentage of the sample that quits each period. The second and third columns give the mean and standard deviation of the subsample of smokers in each period. The second set of columns shows statistics in the experiment where we lower the amount that current consumption adds to the addiction stock by 10 percent which is equivalent to setting $\delta_1 = 0.99$.

Table A3 : Simulation statistics from the policy experiment of lowering nicotine content

Period	Baseline simulation $\delta_1 = 1.10$			Policy Change $\delta_1 = 0.99$		
	quit %	mean	std dev.	quit %	mean	std dev.
1	-	24.05	12.46	-	24.05	12.46
2	17.74	22.70	11.73	16.97	22.39	11.50
3	27.83	19.87	10.97	27.22	19.58	10.61
4	33.49	15.79	10.23	34.10	15.55	9.83
5	37.46	13.00	8.68	38.07	12.61	8.29

We find in the first two periods, the percentage of quits actually drop, but increase in the last two periods of the simulation. This counterfactual simulation suggest that lowering nicotine level has a short run effect of lowering the the proportion of quitters but an overall long run effect of increasing the overall sample of quitters. Granted that one should be cautious in interpreting this numbers given the nature of the parameter used in this simulation. Nonetheless, it demonstrates the kind of policy experiments we can conduct with this model.

5.1 Other Possible Policy Experiments

- **Prices:** The dynamic setup of the model allows us to consider a variety possible pricing scenarios. For example, we can compare the impact of a one time, single period increase in price of 20 percent with one that spreads this price increase over two or three periods. The longitudinal nature of the data also allows us to compare the in-sample and out-of-sample predictions of this dynamic model with those of a reduced form model. The predictions of these different scenarios have implications on how a regulator could effectively get smokers to quit as well as how a monopolist cigarette producer could establish a pool of addicted consumers[42].

[42] This paper takes price as given and implicitly assume that there is a single producer of cigarettes. This is obviously an extreme approximation of an oligopolistic industry. Future extensions of this paper would model the supply side of this industry more realistically.

- **Subsidy for quitting:** I will assume that each individual has access to healthcare and that Y in the model is the amount of disposable income (net of taxes and health care contributions). The form of the utility function allows us to introduce a quitting subsidy through a deduction to health care contributions, which correspond to an increase in income in the utility function if the smoker quits. We can compare the effects of a subsidy of $\$x$ spread over the entire lifetime and a subsidy of equal value $\$\frac{x}{1-\beta}$ spread evenly over five periods.

- **Medical cure to smoking related illnesses:** The model allows us consider experiments that effects the excess mortality rate attributed to smoking denoted by $\alpha_i(r_i - 1)$. For example, we can investigate the impact that a cure to lung cancer would have by manipulating the actual excess mortality rate and seeing how quitting rate change accordingly.

This paper comprise of the first two chapters of my dissertation. The first provides general analysis of the data and motivates the dynamic addiction model. The second develops a model of rational addiction, outlines the estimation procedure and demonstrates through Monte Carlo simulation that it can explain the data. The third chapter which discusses the estimation results and the policy predictions is currently in progress.

6 Conclusion

This paper has two primary goals. The first is to build a model of smoking and quitting behavior that allows a variety of policy experiments existing literature has difficulty analyzing. This is achieved by developing a dynamic structural model of rational addiction and cessation. A feasible estimation procedure is outlined that allows us to estimate the structural parameters of the model. It is these structural parameters that allows us to consider the new variety of policy experiments. The second goal is to present a model that captures the quitting and smoking behavior observed in data.

An important contribution of this research is the addition of a health state to a rational addiction model. This stochastic process is identified using external data from studies of tobacco use related illnesses. I demonstrate through Monte Carlo simulation that this addition is important in explaining much of the dynamics in the data. It also provides a practical way of incorporating health when modeling smoking behavior.

The first extension of this research is to modify the choice set of the smoker to allow for choice between premium and generic cigarettes. The COMMIT data provides detailed information regarding smoker's preferences over these types of cigarettes. Aside from unobserved taste attribute, and price, these two tiers of cigarettes are differentiated by the amount of nicotine and tar. Explicitly modeling this choice will provide a more realistic characterization of smoking addiction and perhaps shed some light on smokers' conpensating behavior in the face of increasing prices and the availability of cheaper options that have higher tar and nicotine content. It also means that we need to formally model prices for these two tiers of cigarettes. This will broach the question of how do we model firm's behavior in an industry where consumption has a habit formation or addiction component and how do we integrate a supply side into the model of rational addiction.[43]

I am also currently investigating alternative estimation techniques that would help relax the functional form restrictions used in the present model. Relaxing these assumptions will extend the scope of possible application of this structural model. In particular, the minimum distance approach, which minimizes the norm between implied and observed moment condition. The obstacle to be summounted before this approach can be used is finding a parsimonious set of moment conditions that will work for this model.

7 Appendix

7.1 Euler equations for a stylized rational addiction model with binding constraint on the choice set.

Consider a simple version of the model presented in the paper where the consumer's optimization problem is to choose an optimal stationary decision rule $\mathbf{c} = \{c_0, c_1, \dots c_\infty\}$ to solve the dynamic program,[44]

$$\max_{\mathbf{c}} \mathbb{E}\left\{\sum_{t=0}^{\infty} \beta^t \mathbf{u}(c_t, a_t)\right\} \qquad \text{where} \qquad \beta \in (0,1), \text{ and } \quad c_t \in [0, \bar{C}].$$

Assume that the single period utility $\mathbf{u}()$ is bounded, increasing in both arguments, and twice continuously differentiable. Let the notation $\mathbf{u}_t$ denote the $\mathbf{u}(a_t, c_t)$. The state a_t

[43] A number of papers have looked at the firm's behavior in market's with rational habit persistence. See Fethke and Jagannathan (1996) and Showalter (1999).

[44] The exposition in this section closely mirrors that of Pakes (1996)

is also bounded and evolves according to a stochastic accumulation process as described in the paper, that is,

$$a_{t+1} = \begin{cases} (1-\delta)a_t + c_t + \xi_{t+1}, & : \quad \xi_{t+1} \sim N(0, \sigma_\xi^2) \quad \text{if } 0 \le a_t \le \bar{A} \\ \\ \bar{A} \text{ or } 0 & : \quad \text{otherwise} \end{cases}$$

The Bellman equation for this problem would take the simple form,

$$\mathbf{V}(a_t) = \max_{\mathbf{c}} \left\{ \mathbf{u}(c_t, a_t) + \beta \int \mathbf{V}(a_{t+1}) \, \wp_\xi \left(a_{t+1} \mid a_t, c_t\right) da_{t+1} \right\}$$

Euler condition Ignoring binding constraint.

Consider the simplest case where individual's optimal policy involves consuming positive amounts for all time periods[45]. An alternative policy $\mathbf{c}^*$ involving a perturbation by amount ϵ to c_t is given be

$$\begin{aligned} c_t^* &= c_t + \epsilon & \Rightarrow \qquad a_{t+1}^* &= a_{t+1} + \epsilon \\ c_{t+1}^* &= c_{t+1} - (1-\delta)\epsilon & \Rightarrow \qquad a_{t+2}^* &= a_{t+2} \end{aligned}$$

This alternative policy is constructed to have a one period deviation of the continuous control from t to $t+1$, keeping the remaining policies, $c_{t+\tau}^* = c_{t+\tau}$, for all $\tau \ge 2$. A necessary condition for the policy rule $\mathbf{c}$ to be optimal is that,

$$\frac{\partial \mathbf{u}_t}{\partial c_t} + \beta \int \left\{ \frac{\partial \mathbf{u}_{t+1}}{\partial a_{t+1}} - (1-\delta) \frac{\partial \mathbf{u}_{t+1}}{\partial c_{t+1}} \right\} \wp_\xi \left(a_{t+1} \mid a_t, c_t\right) da_{t+1} = 0.$$

A linearized version of this Euler equation formed in this way typically becomes the moment condition used in method of moments framework. However, the quitting behavior creates a substantial change to this first order condition. Next we consider the effects that a binding constraint on the choice set has on the Euler equation.

Euler condition allowing for the binding constraint.

Consider now an individual who smokes at t and $t+2$, but quits for one period at $t+1$. Because of the zero constraint on the choice set at $t+1$, we cannot rely on compensating pertubations in adjacent periods like that shown in the previous equation

[45] In the context of smoking, this is equivalent to assuming that an individual never quits over the course of the sample (in other words, cigarette consumption is always positive).

to derive the Euler equation. Instead we need to consider a weaker requirement where we consider a compensating perturbation in future periods when the choice constraint is not longer binding. The choice of when to evolke the compensating variation is random, the most natural start would be the first period when the individual resumed smoking. The alternative program that we compare present discounted utility is,

$$\begin{aligned} c_t^* &= c_t + \epsilon & \Rightarrow \quad a_{t+1}^* &= a_{t+1} + \epsilon \\ c_{t+1}^* &= c_{t+1} = 0 & \Rightarrow \quad a_{t+2}^* &= a_{t+2} + (1-\delta)\epsilon \\ c_{t+2}^* &= c_{t+2} - (1-\delta)^2\epsilon & \Rightarrow \quad a_{t+3}^* &= a_{t+3} \end{aligned}$$

Unlike the first proposed alternative program, this second program differs from the optimal for two periods, t and $t+2$, and is identical for remaining periods. One possible Euler condition implied by the optimal program $\mathbf{c}^*$ is given by,

$$\frac{\partial \mathbf{u}_t}{\partial c_t} + \mathbb{E}_t \left\{ \beta \frac{\partial \mathbf{u}_{t+1}}{\partial a_{t+1}} + \beta^2 (1-\delta) \frac{\partial \mathbf{u}_{t+2}}{\partial a_{t+2}} - \beta^2 (1-\delta)^2 \frac{\partial \mathbf{u}_{t+2}}{\partial c_{t+2}} \right\} = 0.$$

More generally, if an individual remained smoke-free for τ periods and we consider the compensating perturbation in the first period he resumes smoking, the corresponding Euler condition for that time path would be,

$$\frac{\partial \mathbf{u}_t}{\partial c_t} + \mathbb{E}_t \left\{ \sum_{j=1}^{\tau+1} \beta^j (1-\delta)^{j-1} \frac{\partial \mathbf{u}_{t+j}}{\partial a_{t+j}} - \beta^{\tau+1} (1-\delta)^{\tau+1} \frac{\partial \mathbf{u}_{t+\tau+1}}{\partial c_{t+\tau+1}} \right\} = 0.$$

Provided that the relapse at period $t+\tau+1$ occurs in the length of the panel, this would be a moment condition for the rational addiction model for an individual who quit for τ periods. The difficulty with the moments condition approach is the implication that the individual cannot permanently quit smoking and needs to resume smoking at some time for a valid moment condition to hold. These are issues that traditional empirical literature on rational addiction using the method of moments approach have ignored.

7.2 Further Description of the COMMIT Data

Prior to randomization, a baseline survey was conducted in each of these communities in January 1988. This was conducted using modified random digit dialing technique with geographic screening methods to identify households in targeted areas. The purpose of this survey is to measure the prevalence rate in these communities as well as to identify resident smokers who will be tracked by the study.[46] Groups of 500 heavy smokers and 500 light smokers between the age of 25 to 64 were identified in each community. A *smoker* is defined as an individual who has smoked at least a hundred cigarettes at the time of the survey and who is currently smoking. A *heavy smoker* is defined as someone who smokes more than 25 cigarettes a day. A *light smoker* is someone who smoke less than 25 cigarettes a day.

A random sample of 400 heavy and 400 light smokers in each community were assigned to the *end-point cohort*[47]. Individuals enrolled in the *end-point cohort* were contacted briefly by telephone each year to determine their smoking status and update tracking information. These individuals were asked a detailed set of questions again at the end the study.

The remaining 100 smokers of each group, together with approximately 100 recent quiters and 100 nonsmokers were assigned to the *evaluation cohort*. This cohort was asked detailed questions about their awareness, receptivity, and participation in the COMMIT program and their perception of social attitudes towards smoking at three periods over the course of the study. All the analysis in this paper are conducted using the *end-point cohort*.

7.3 Estimation of the Preliminary Model

This project began with a simple habit formation model that ignores the randomness of the health process. The model is a discrete time variant of the Becker and Murphy's (1988) model of rational addiction, omitting the *tolerance effect* for the computational reasons already discussed in Section 4.4. This preliminary model has many shortcomings that the current model addresses. What follows is a summary of the estimation results of this preliminary model.

Setup of Preliminary Model

[46] Interested readers should refer to the following references for a more in depth discussion about this project; COMMIT Research Group (1996),COMMIT Research Group (February 1995), and National Cancer Institute (1995).

[47] Cohort members were not explicitly informed of their status but were told that annual contacts would occur.

A representative smoker decides whether to quit smoking or continue smoking c_t cigarettes so as to maximize the sum of discounted expected utilities. The decision space is denoted by $\mathbb{D} = [0, \bar{C}]$. The agent is infinitely lived and is concerned about three **state variables**,$\{\mathbb{I}_t, P_t, a_t\}$, which directly affect her instantaneous utility.

The agent's **smoking status in the previous period** is denoted by $\mathbb{I}_t \in \{0, 1\}$. It takes a value of 1 if she quits in the previous period and 0 otherwise.

The **price** of a unit of consumption is denoted by $P_t \in [0, \bar{P}]$. It evolves according to the following simple stationary autoregressive process given by Equation 7.1. The smoker takes price as given and forms her expectation of future prices according to this process.

$$P_t = \begin{cases} \rho_0 P_{t-1} + \eta_t, & : \quad \eta_t \sim N(0, \sigma_\eta^2) \quad \text{if } 0 \leq P_t \leq \bar{P} \\ \bar{P} \text{ or } 0 & : \quad \text{otherwise} \end{cases} \tag{7.1}$$

The agent's static utility depends on **a stock of addictive substance**, a_t, which affects the instantaneous marginal utility from consumption. This addictive stock is known to the smoker but unobserved by the economic analyst. Like P_t, it is also bounded, $a_t \in [0, \bar{A}]$, it decays stochastically over time and the agent's current consumption adds linearly to it as shown in equation 7.2 below.

$$a_{t+1} = \begin{cases} (1+\delta_0)a_t + \delta_1 c_t + \xi_{t+1}, & : \quad \xi_{t+1} \sim N(0, \sigma_\xi^2) \quad \text{if } 0 \leq a_t \leq \bar{A} \\ \bar{A} \text{ or } 0 & : \quad \text{otherwise} \end{cases} \tag{7.2}$$

The rate of decay is denoted by δ_0, where $\delta_0 \in (0, 1)$. Λ denotes the set of parameters defining the stochastic process of these state variables, that is,

$$\boldsymbol{\Lambda} = \{\rho_0, \sigma_\eta, \delta_0, \delta_1, \sigma_\xi\}. \tag{7.3}$$

I assume that the agent's discount factor β is constant, where $\beta \in (0, 1)$, and does not depend on either state or choice variables. The state vector for this model is denoted by $\boldsymbol{s}_t = \{\mathbb{I}_t, P_t, a_t\}$, it lives in a state space $\mathbb{S} = \{0, 1\} \times [0, \bar{P}] \times [0, \bar{A}]$.

The agent's single period utility function is denoted by $\mathbf{u}(c_t, \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) = \mathbf{u}_t$. It is additively separable and stable over time . The functional form for $\mathbf{u}_t$ is chosen such that it is well-defined and bounded over the entire state and choice space of the dynamic program. The vector $\boldsymbol{x}_i$, denotes the smokers characteristics as defined in Section 4.2, which are assumed not to change over time. $\boldsymbol{\Theta}$ denotes the set of parameters in the utility function that are to be estimated.

The single period utility function takes the following form,

$$\mathbf{u}(c_t, \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) = \left\{ \begin{array}{lcl} \boldsymbol{\kappa}(\mathbb{I}_t, a_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) & : & c_t = 0 \\ \boldsymbol{\tau}(c_t, \boldsymbol{s}_i, \boldsymbol{x}_i, \boldsymbol{\Theta}) & : & c_t > 0 \end{array} \right\},$$

where a smoker receives utility given by Equation 7.4 if she quits at period t, and Equation 7.5 if she smokes $c_t > 0$.

$$\boldsymbol{\kappa}(\mathbb{I}_t, a_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) = \gamma_5 + \gamma_6 \mathbb{I}_t, \tag{7.4}$$

$$\begin{aligned} \boldsymbol{\tau}(c_t, \boldsymbol{s}_i, \boldsymbol{x}_i, \boldsymbol{\Theta}) &= \gamma_0 \ln(1 + c_t) + (\gamma_1 + \nu_1 \mathbb{I}_t) a_t \ln(1 + c_t) \\ &+ (\gamma_2 + \nu_2 \mathbb{I}_t) P_t c_t + \gamma_3 \ln(Y) + \gamma_4 \ln(Y) P_t. \end{aligned} \tag{7.5}$$

The set of parameters $\boldsymbol{\Theta}$ is defined as

$$\boldsymbol{\Theta} = \{\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7, \gamma_8, \nu_0, \nu_1, \phi\}.$$

The representative agent's optimization problem is to choose an optimal stationary decision rule $\mathbf{c}^* = \{c_0^*, c_1^*, \ldots c_\infty^*\}$ to solve the dynamic program,

$$\max_{\mathbf{c}^*} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \beta^t \mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) \mid c_0, \boldsymbol{s}_0, \boldsymbol{x}_i, \boldsymbol{\Theta} \right\}.$$

If $\mathbf{V}_t$ denotes the lifetime total discounted expected utility from employing the stationary optimal policy $\mathbf{c}^*$ when the initial state is $\{\boldsymbol{s}_0\}$, and the parameters set at the values $\{\boldsymbol{x}_i, \boldsymbol{\Theta}, \boldsymbol{\Lambda}\}$, that is, $\mathbf{V}_t = \mathbf{V}_{\mathbf{c}^*}(\boldsymbol{s}_t \mid \boldsymbol{x}_i, \boldsymbol{\Theta}, \boldsymbol{\Lambda})$, the Bellman's operator for this single agent's problem is then given by,

$$\mathbf{V}_t = \max_{\mathbf{c}^*} \{\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) + \beta\, \mathbb{E}(\mathbf{V}_{t+1} \mid c_t, \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}, \boldsymbol{\Lambda}))\}.$$

According to the Constraction Mapping Theorem, there exist a unique fixed point of the Bellman's operator and that a non-empty stationary policy rule, $\boldsymbol{\chi} : \mathbb{S} \mapsto \mathbb{D}$, exist of the form shown in Equation 7.6. Using the properties of the contraction mapping, we can solve for the fixed point $\mathbf{V}_t$ by *successive approximation* methods and the policy rule by *policy improvement* techniques.

$$\begin{aligned} \mathbf{c}_t^* &= \arg\max_{\mathbf{c}_t^*} \{\mathbf{u}(c_t; \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}) + \beta\, \mathbb{E}(\mathbf{V}_{t+1} c_t, \boldsymbol{s}_t, \boldsymbol{x}_i, \boldsymbol{\Theta}, \boldsymbol{\Lambda})\} \\ &= \boldsymbol{\chi}(\boldsymbol{s}_t \mid \boldsymbol{x}_i, \boldsymbol{\Theta}, \boldsymbol{\Lambda}) = \boldsymbol{\chi}_t, \quad \text{where } \mathbf{c}_t^* \in [0, \bar{C}], \end{aligned} \tag{7.6}$$

For each realization of the state vector $\boldsymbol{s}_t \in \mathbb{S}$, the agent optimizes by comparing the total lifetime expected utility from quitting versus continueing smoking. As with discrete choice models, any identification has to come from utility difference arising from this two discrete options. The estimation cannot identify the actual level of utility from either smoking or quitting but only the difference. The mean utility level in $\boldsymbol{\tau}(.)$ is normalized to zero and the difference in mean utility is given by γ_5. γ_6 captures the utility difference arising from quitting the previous period. The term γ_1 picks up the reinforcement effect of addiction and together with γ_0 contributes to the marginal utility from consumption. γ_2 captures the disutility associated with price P_t. The variable $\log(Y)$ is introduced to capture the empirical fact higher income group individuals are more likely to quit. The interaction term $P_t \log(Y)$ captures price sensitivity across different income groups. The remaining $\nu' s$ parameters allow for marginal effects resulting from quitting in the previous periods.

Estimation

The estimation strategy for this model is similar to that used in Section 4.4. A Nested Fixed Point Maximum Likelihood Estimation method is used to estimate the parameters of this model. The fixed point to the Bellman equation conditional on a set of parameter estimates $\{\hat{\boldsymbol{\Theta}}, \hat{\boldsymbol{\Lambda}}, \boldsymbol{x}_i\}$ is numerically computed using a modified policy iteration method. The mixed discrete and continuous optimal control is then solved using Brent's numerical method over a discretized state space. Conditional on this set of parameters, a likelihood is assigned to an entire path of observed consumption conditional on the observation in the first period. The structural restriction that the single period utility function described in the previous section ensures that the policy funtion is weakly monotonic in the unobserved a_t. The monotonicity property allows the unobserved a_i, corresponding to the observed $c_i > 0$, to be solved through simple interpolation. Here, I omit the details already discussed in Section 4.4. Readers should refer to that section for a complete discussion of the estimation procedure.

Table D1 : MLE Estimates for preliminary model

Parameters	Estimates	Std. Error
γ_1	0.557	0.045
γ_2	−153.733	12.296
γ_3	0.029	1.295
γ_4	−0.073	5.960
γ_5	0.093	10.490
γ_6	0.237	13.269
ν_1	−0.054	4.471×10^{-3}
ν_2	0.125	0.063
δ_0	−0.096	3.313×10^{-5}
σ_ξ	13.389	3.901×10^{-3}
Parameters exogenously estimated		
ρ_0	1.026	0.0128
Fixed parameters		
β	0.9	

Results

Table D1 shows the parameter estimates and their standard errors. These estimates are for a subsample of smokers from the state of Massachusetts(MA). The parameter estimates on most of the variables of interest conform to what we expect from the model. The coefficient representing the reinforcement effect γ_1 is positive as expected and significantly different from zero. The coefficient on price, γ_2, is significant and negative. The mean difference in utility level from quitting denoted by γ_5 (and γ_6 if the individual quit the previous period) is not significantly different from 0. These estimates suggest that there is no significant difference in mean utility level from quitting and smoking. Reiterating the point made earlier, addiction in this preliminary model is a desired 'good' that improves the marginal utility from future units of consumption. The only reason why an individual would want to quit is the disutility he or she experience from the prices, and the negative draw to the stochastic shock ξ_t that lowers the stock of addiction such that continued smoking is no longer as attractive.

The policy rule and the value function corresponding to these estimates are shown in Figure 7.1. The policy rule is increasing in the level of addiction (a_t), while holding prices constant and decreasing in prices (P_t) holding the addictive stock constant, as shown in the Figure 7.1(c) and 7.1(e). Similarly, the shape of the value function also follows what we intuitively expect. It is increasing in the addictive stock and decreasing in prices as shown in Figures 7.1(d) and 7.1(f).

Insert Figure 7.1 here

To test this model consider how well it predicts the behavior observed in the data. Table D2 below shows the bootstrap predictions of quit proportions for two income groups in the state of Massachusetts. These predictions are calculated by drawing a bootstrap sample from the observed empirical distribution for 1989. The observed behaviors are then simulated according to the estimated policy rules and stochastic processes of the model. The model under-predicts the proportions of quits each period by a large margin. Though the predicted proportions increase over time, it does not reflect the behaviors observed in the data.

Table D2 : Boot-strap quit predictions in % for income gp. Y_2 and Y_4

Years	Income gp. 2		Income gp. 4	
	Predicted	Observed	Predicted	Observed
1990	0.87	21.82	2.05	26.19
1991	1.23	24.24	2.45	30.95
1992	1.35	33.33	2.53	37.14
1993	1.53	33.94	2.70	43.33

Aside from this, the model also provides unrealistic estimates of the short-run price elasticities. Table D3 shows the estimated short-run elasticities implied by the bootstrap simulation. The two columns shows the implied elasticity arising from a given price change in two separate scenarios. The figures in the first column show the elasticity at $t = 1989$ holding the distribution of cigarette consumption and stock of addiction constant for individuals in the second income group, Y_2.

Table D3 : Short Run price elasticity estimates at $t = 1989$ for Y_2

% price change	Elasticity Estimates	
	holding a_t constant	allowing a_t to change
2	-9.03	0.02
3	-8.64	-5.29
5	-7.50	-6.45
10	-4.85	-4.53
15	-3.62	-3.45

The second considers a similar experiment allowing the stock of addiction to adjust according to the estimated accumulation process. These elasticities are obviously incorrect. The existing empirical literature has accepted the demand price elasticity for smoking to be in the range of -0.4 to -0.8.

The data for the state of MA shows that around 25 percent of the smokers quit in the first period and this proportion increases in each year of the sample. To match this observed data, the model has to rely on ξ_t to generate the distribution of consumption each period and match the proportions of quits. The specification of only two sources of unobservables, η_t that creates uncertainty about prices and ξ_t that generates randomness in the accumulation process, is not sufficient to account for the dynamics in the data. Because accumulating a_t only results in increased costs, smokers have little incentive to quit. Instead the model predicts that smokers will gradually decrease consumption as real prices increase over time. It attributes all of the decrease in smoking to the price increases. The model reconciles the underprediction of quit percentages by underpredicting the overall consumption of smokers, and gives estimates of mean cigarette smoked that is well below what is observed. Because the model predicts that smokers will gradually decrease consumption each period and attributes this to prices, it generates upward biased elasticity estimates.

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Table 2.1:

REASONS FOR QUITTING AMONG THOSE WHO MADE A SERIOUS ATTEMPT TO QUIT BETWEEN 1988 AND 1993 (IN PERCENT)

REASONS	CONTINUING SMOKERS (n = 5807)	SUCCESSFUL QUITERS (n = 3214)	TOTAL (n = 9021)
Concern for current and future health	90.2	90.2	90.2
Expense associated with smoking	64.4	52.8	60.7
Concern for the effect of ETS on others	57.4	52.2	55.8
Setting a good example	56.4	52.4	55.1
Bad breath, smell or taste	49.5	42.8	47.3
Pressure from family, friends or co-workers	46.7	37.3	43.7
Advice from doctor or dentist	44.0	33.7	40.7
Illness or death of a friend or relative	22.3	17.8	20.9
Smoking restriction at work	22.2	14.4	19.7

Source: Table taken from Hymowitz, Cummings, Hyland, Lynn, Pechacek, and Hartwell (1997) in Tobacco Control 1997 Vol. 6 Supp. 2.

Table 3.1:

Smoking Prevalence and Quit
Rates from Sample Survey (Jan. 1988)

Community Area	Smoking Prev. rate	Percentage that Quit the last 5 yr.	Percentage that Quit more than 5 yr. ago	Sample that smoked 100 cigs.	Sample Size
Hayward CA	23.5	19.8	28.3	4801	10504
Vallejo CA ♣	23.4	20.3	28.0	4854	10628
Peterborough, Ontario CAN	29.1	18.3	25.8	3390	6475
Brantford, Ontario CAN ♣	31.1	16.6	25.0	3260	6090
Cedar Rapids/Marion IA ♣	22.7	20.8	30.1	3890	8376
Davenport IA	24.9	19.8	28.4	3761	7769
Fitchburg/Leominster MA ♣	28.3	20.1	22.3	3830	7753
Lowell MA	26.2	19.4	27.9	3555	7118
Patterson NJ ♣	24.5	16.9	20.6	4798	12138
Trenton NJ	27.6	17.2	21.0	4746	10545
Las Cruces NM	18.7	21.6	32.4	6298	15434
Santa Fe NM ♣	20.3	23.5	33.8	8524	17826
Yonkers NY ♣	23.8	21.2	25.9	4599	10140
New Rochelle NY	23.6	21.2	26.5	5228	11486
Utica NY ♣	25.6	19.5	27.4	4200	8663
Binghamton/Johnson City NY	25.0	19.2	26.7	3921	8424
Greensboro NC	24.7	18.9	28.9	4444	9365
Raleigh NC ♣	21.1	21.6	28.3	4883	11559
Medford/Ashland OR ♣	20.0	19.1	37.5	5168	11154
Albany/Corvallis OR	18.1	20.1	33.5	4768	12161
Bellingham WA ♣	19.8	21.6	34.2	5911	13140
Longview/Kelso WA	24.7	19.0	31.9	3927	7749

♣ - *Community randomised to receive intervention*

Table 3.2:

Estimated and Observed Mortality risk ratio for white Female
(observed ratio from CPS I in parenthesis)

			1-9 cigarettes a day			
			Duration in Years			
Age	**5-9**	**10-14**	**15-19**	**20-24**	**25-29**	**30-34**
40-44	1.24	1.31	1.39	1.48	1.59	1.73
	(1.01)	(0.98)	(1.55)	(1.54)	(1.76)	(3.16)
45-49	1.20	1.26	1.32	1.38	1.46	1.56
	(1.27)	(1.75)	(0.79)	(1.70)	(1.50)	(1.59)
50-54	1.17	1.21	1.25	1.30	1.35	1.43
	(0.46)	(1.43)	(1.51)	(1.15)	(1.22)	(1.51)
55-59	1.14	1.18	1.21	1.24	1.27	1.32
	(0.60)	(1.12)	(1.24)	(0.87)	(1.23)	(1.13)
60-64	1.11	1.14	1.17	1.19	1.21	1.24
	(1.06)	(1.05)	(0.92)	(0.83)	(0.92)	(1.16)

			20 cigarettes a day			
			Duration in Years			
Age	**5-9**	**10-14**	**15-19**	**20-24**	**25-29**	**30-34**
40-44	1.39	1.63	1.89	2.21	2.64	3.25
	(.)	(1.13)	(2.49)	(3.22)	(2.57)	(3.88)
45-49	1.34	1.53	1.72	1.92	2.19	2.56
	(.)	(1.30)	(1.68)	(2.13)	(1.81)	(2.66)
50-54	1.30	1.45	1.59	1.72	1.88	2.09
	(1.85)	(1.14)	(1.54)	(1.68)	(2.04)	(1.96)
55-59	1.28	1.40	1.50	1.58	1.66	1.78
	(2.05)	(1.14)	(1.31)	(1.50)	(1.43)	(1.68)
60-64	1.26	1.37	1.44	1.48	1.52	1.57
	(0.90)	(1.43)	(1.30)	(1.27)	(1.25)	(1.75)

The mortality risk ratio is the ratio of the death rate of a smoker over that of a non-smoker.
The rates are expressed in number of deaths per 100,000 persons.

Table 3.3:

CROSS-SECTIONAL 2SLS REGRESSION INSTRUMENTING FOR $ln(P_t)$
DEPENDENT VARIABLE : $ln(1 + C_t)$

	1989		1991		1993	
VARIABLES	EST.	T RATIO	EST.	T RATIO	EST.	T RATIO
$ln(\hat{P_t})$	-0.062	-0.95	-0.251	-1.56	-0.370	-2.44
I_2	-0.023	-0.73	-0.016	-0.24	-0.035	-0.50
I_3	0.022	0.72	-0.024	-0.36	-0.140	-1.96
I_4	0.039	1.22	-0.043	-0.63	-0.185	-2.52
Age	0.007	8.78	-0.000	-0.17	-0.005	-2.85
Starting Age	-0.029	-15.72	-0.036	-9.15	-0.035	-8.16
Intv.	-0.021	-1.38	-0.092	-2.84	-0.049	-1.40
Female	-0.143	-8.60	-0.080	-2.24	-0.018	-0.46
Clerical	0.015	0.72	0.029	0.64	0.034	0.69
Tradesman	0.041	1.88	0.066	1.40	0.092	1.83
Unclas.	0.099	1.44	0.216	1.46	0.353	2.21
Homemaker	0.071	2.42	0.074	1.17	0.041	0.60
Student	-0.048	-0.89	-0.134	-1.15	-0.093	-0.74
College	-0.059	-3.40	-0.026	-0.71	-0.007	-0.18
Post Grad.	-0.115	-3.57	-0.161	-2.31	-0.137	-1.82
constant	3.221	18.64	2.469	6.05	2.079	5.25
$\bar{R}^2$	0.07		0.02		0.02	

Key : Omitted occupation and education dummy variable is that for professionals and individuals who didn't complete high school respectively. Total number of observations = 6902.

Table 3.4:

CROSS-SECTIONAL PROBIT REGRESSION INSTRUMENTING FOR $ln(P_t)$
DEPENDENT VARIABLE : Q_t

	1990		1993	
VARIABLES	EST.	T RATIO	EST.	T RATIO
$ln(\hat{P_t})$	0.270	1.88	0.350	2.53
I_2	-0.041	-0.56	0.020	0.30
I_2	-0.010	-0.14	0.138	2.08
I_2	0.050	0.67	0.170	2.50
Age	0.001	0.47	0.007	4.55
Starting Age	0.013	3.14	0.019	5.08
Intv.	0.034	0.95	0.035	1.12
Female	-0.066	-1.70	-0.089	-2.53
Clerical	-0.079	-1.59	-0.051	-1.15
Tradesman	-0.073	-1.44	-0.062	-1.36
Unclas.	-0.242	-1.40	-0.348	-2.20
Homemaker	-0.071	-1.03	0.001	0.02
Student	-0.088	-0.68	0.030	0.26
College	0.045	1.09	-0.031	-0.84
Post Grad.	0.101	1.36	0.064	0.95
constant	-0.462	-1.22	-0.327	-0.90
% correctly predicted	81.54		68.91	
% who quits in sample	18.5		31.0	

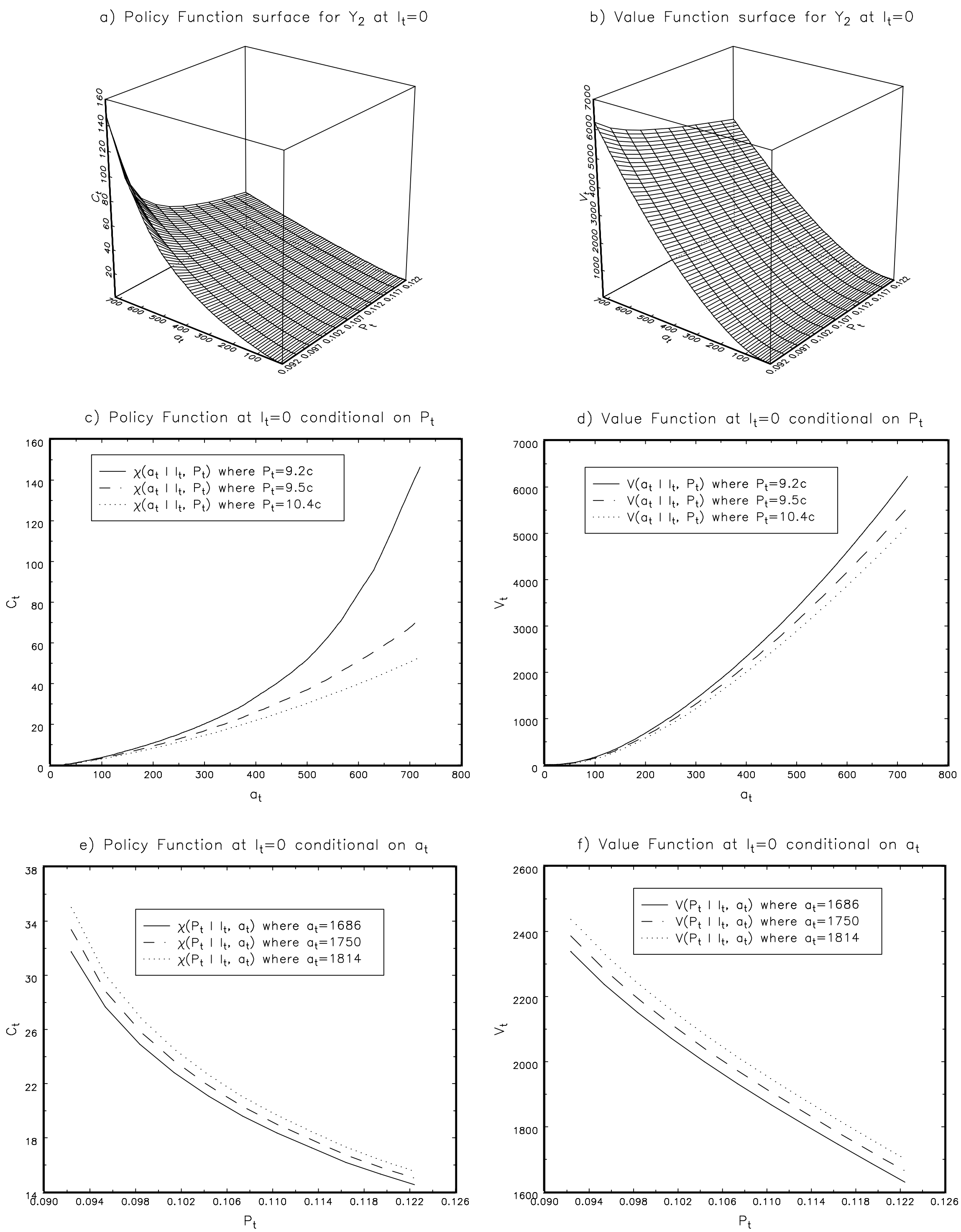
Key : Omitted occupation and education dummy variable is that for professionals and individuals who didn't complete high school respectively. Total number of observations = 6902.

Table 5.1:

PARAMETER VALUES USED IN SIMULATION

		Parameter values
Parameters of the utility function.	γ_0	1.71
	γ_1	0.98
	γ_2	-195.50
	γ_3	0.40
	γ_4	0.30
	γ_5	100.00
Parameters of the addiction process.	δ_0	-0.21
	δ_1	1.10
	σ_ξ	17.8
Parameters of the transition prob. for H_{t+1} *given* $\mathrm{H}_t = \mathrm{h}^{\mathrm{H}}$,*ie.* $\wp_{\mathbf{H}}(\mathrm{H}_{t+1} \mid \mathrm{H}_t = \mathrm{h}^{\mathrm{H}})$	ψ_0	0.80
	ψ_2	-10.00
	ψ_3	-0.01
	ψ_4	0.80
	ψ_5	0.30
Parameters of the transition prob. for H_{t+1} *given* $\mathrm{H}_t = \mathrm{h}^{\mathrm{L}}$,*ie.* $\wp_{\mathbf{H}}(\mathrm{H}_{t+1} \mid \mathrm{H}_t = \mathrm{h}^{\mathrm{L}})$	ω_0	-0.11
	ω_2	2.00
	ω_3	9.90
	ω_4	-0.02
	ω_5	-0.01
	λ	40.00
FIXED PARAMETERS		
	β	0.9
	m_i	0.005

FIGURE 7.1:


a) Policy Function surface for Y_2 at I_t=0
b) Value Function surface for Y_2 at I_t=0
c) Policy Function at I_t=0 conditional on P_t
$\chi(a_t \mid I_t, P_t)$ where P_t=9.2c
$\chi(a_t \mid I_t, P_t)$ where P_t=9.5c
$\chi(a_t \mid I_t, P_t)$ where P_t=10.4c
d) Value Function at I_t=0 conditional on P_t
$V(a_t \mid I_t, P_t)$ where P_t=9.2c
$V(a_t \mid I_t, P_t)$ where P_t=9.5c
$V(a_t \mid I_t, P_t)$ where P_t=10.4c
e) Policy Function at I_t=0 conditional on a_t
$\chi(P_t \mid I_t, a_t)$ where a_t=1686
$\chi(P_t \mid I_t, a_t)$ where a_t=1750
$\chi(P_t \mid I_t, a_t)$ where a_t=1814
f) Value Function at I_t=0 conditional on a_t
$V(P_t \mid I_t, a_t)$ where a_t=1686
$V(P_t \mid I_t, a_t)$ where a_t=1750
$V(P_t \mid I_t, a_t)$ where a_t=1814
C_t
V_t
a_t
P_t