UNIVERSITÀ DEGLI STUDI DI SIENA

QUADERNI DEL DIPARTIMENTO
DI ECONOMIA POLITICA E STATISTICA

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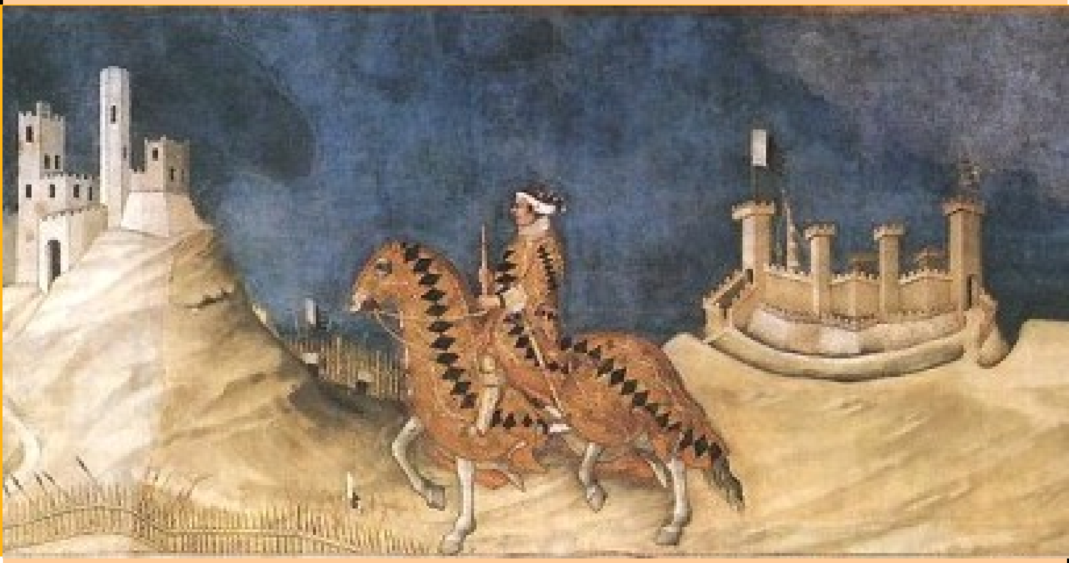
Revealed Bounded rationality:
Testing present bias in a Rational Addiction Equation

n. 666 – Dicembre 2012



ABSTRACT - This paper deals with one of the main theoretical and empirical problems associated with the rational addiction model, namely that the demand equation derived from the rational addiction theory is not empirically distinguishable from models with forward-looking behavior, but with timeinconsistent preferences. The implication is that, even when forward-looking behavior can be convincingly supported, this equation cannot provide evidence in favor of time-consistent preferences against a model with dynamic inconsistency. In fact, we show that the possibility of testing for exponential versus non-exponential time discounting is nested within the rational addiction model. We propose a test of time consistency that uses only the information obtained from the general rational addiction demand equation and the price effects. A pseudo panel of Italian households is used to test for rational addiction in tobacco consumption. GMM estimators are used to deal with errors in variables and unobserved heterogeneity. The results conform to the theoretical predictions. We find evidence that tobacco consumers are forward-looking, but timeinconsistent. The values of the derived present bias and long run discount parameters are statistically significant and in line with the literature.

JEL codes: C23, D03, D12
Keywords: rational addiction, time inconsistency, GMM.

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1. INTRODUCTION

Becker and Murphy (1988) explored the dynamic behavior of the consumption of addictive goods, pointing out that many phenomena previously thought to be irrational are in fact consistent with optimization according to stable preferences. In their model, individuals recognize both the current and the future consequences of consuming addictive goods. This model of rational addiction has subsequently become the standard approach to modeling consumption of goods such as cigarettes. A sizable empirical literature has been developed since then, beginning with Becker, Grossman and Murphy (1994), which has tested and generally supported the empirical predictions of the Becker and Murphy model. These past contributions, however, run into a number of critical drawbacks.

This paper is concerned with one of these problems, namely that forward-looking behavior, implied by the model, does not necessarily mean time consistency. More precisely, the equation derived from the theory is not empirically distinguishable from models with forward-looking behavior, but with time-inconsistent preferences. So, forward-looking behavior does not provide evidence in favor of time-consistent preferences against a model with dynamic inconsistency (Gruber and Köszegi, 2000).

This is a crucial issue, because models with dynamic inconsistency can deliver radically different implications for government policy. In particular, while the rational addiction model implies that the optimal tax on addictive goods should depend only on the externalities that their use imposes on society, the time-inconsistent alternative suggests a much higher tax depending also on the "internalities" that drugs' use imposes on consumers. In modeling and testing for addiction, it is therefore very important to distinguish between time-consistent and time-inconsistent agents.

The early literature on dynamic consumption behavior modeled impatience in decision making by assuming that agents discount future streams of utility or profits exponentially over time. Exponential discounting is pivotal. Without this assumption, inter-temporal marginal rates of substitution will change as time passes, and preferences will be time-inconsistent (Strotz, 1956). Recently, behavioral economics literature has built on the work of Strotz (1956), to explore the consequences of relaxing the standard assumption of exponential discounting. Ainslie (1992) and Loewenstein and Elster (1992) indicate that hyperbolic discounting may explain some basic features of inter-temporal decision-making that are inconsistent with simple models of exponential discounting, namely that hyperbolic discounters value consumption in the present more than any delayed consumption. In the formulation of quasi-hyperbolic discounting adopted by Laibson (1997), the degree of present bias is captured by an extra discount parameter $\beta < 1$, which captures the taste for instant gratification[1]. The consequence of quasi-hyperbolic discounting is that the discount factor between two consecutive future periods (γ) is larger than

[1] The "quasi-hyperbolic" discount function approximates the hyperbolic discount function in discrete time taking β and γ as constants between 0 and 1.

that between today and tomorrow ($\beta\gamma$). O'Donoghue and Rabin (2002) and Gruber and Köszegi (2001) show that present bias can lead individuals to greatly over-consume the addictive good, with the consequence of a substantial welfare loss.

The implications of time-inconsistent preferences, and their associated problems of self-control, have been studied under a variety of economic choices and environments. Laibson (1997), O'Donoghue and Rabin (1999a; b) and Angeletos *et al.* (2001) applied this formulation to consumption and saving behavior; Diamond and Köszegi (1998) explored retirement decisions; Barro (1999) applied it to growth; Gruber and Köszegi (2001), Ciccarelli, Giamboni and Waldmann (2008) and Levy (2010) to smoking behavior; Shapiro (2005) to caloric intake; Fang and Silverman (2009) to welfare program participation and labor supply of single mothers with dependent children; Della Vigna and Paserman (2005) to job search (see Della Vigna 2009 for a review) and Acland and Levy (2010) to gym attendance.

Despite this booming of interest, estimates of the short-run discount factor β and tests of present bias using observational rather than experimental data are still scarce. Few recent works have attempted to use a parametric approach to estimate structural dynamic models with hyperbolic time preferences (Fang and Silverman, 2009; Laibson, Repetto and Tobacman, 2007; Paserman, 2008). Focusing on addictive goods, Levy (2010) derives estimates of the degree of present bias using a model of cigarette addiction based on O'Donoghue and Rabin's (2002) generalization of Becker and Murphy's (1988) rational addiction model. Gruber and Koszegi (2001) develop a new model of addictive behavior that takes as its starting point the standard rational addiction model, but incorporates quasi-hyperbolic discounting preferences. They propose using information extracted from their model to obtain the present bias and long-run discounting parameters and, in a previous version of the same paper, they also propose a test of time consistency *per se*. In practice, however, they were unable to carry out this test and to back out the two discount parameters. Ciccarelli, Giamboni and Waldmann (2008) tested for time preferences by exploring smoking by women before, during and after pregnancy using the European Community Household Panel (ECHP). Their specification does not match the original rational addiction demand equation. Rather, they use a modified specification with several lead consumption terms and make inferences about the time preferences of the underlying actors based on the assumption that, if preferences are time-consistent, smoking at *t+1* is a sufficient statistic for the whole stream of future smoking, i.e., expected smoking more than one period ahead should have no independent effect on smoking. To our best knowledge no research has been developed to date to test the assumption of instant gratification within the structural demand equation derived from the rational addiction model.

This paper makes three distinct contributions to the literature on addiction and time preferences. First, it provides an estimate, using pseudo panel data at the individual level, of the general specification of the rational addiction demand equation that includes past and future prices. As far as we know this formulation has been estimated only twice before, by Becker, Grossman and

Murphy (1994) using aggregated panel data and by Chaloupka (1991) using individual survey data, which cover only two consecutive time periods[2].

Second, a simple test of time consistency is implemented, which exploits only the information revealed by the general rational addiction demand equation and price effects. Third, we identify the present bias and long-run discount parameters separately. Their estimated values are statistically significant and in line with the literature. Our conclusion is that the possibility of distinguishing time-consistent from time-inconsistent preferences is nested within the rational addiction model. The information extracted from a general rational addiction demand equation is sufficient to test for both forward-looking behavior and time consistency. The remainder of the paper is structured as follows. Section 2 reviews the general formulation of the rational addiction model. This review is necessary because this is the formulation of the model that we use to test the assumption of time consistency. Section 3 focuses on the problem of identification of the shape of time discounting in the rational addiction model and introduces our test strategy. The data and the estimation methods are presented in section 4. Results are shown in section 5. Section 6 concludes.

2. THE GENERAL RATIONAL ADDICTION MODEL.

Following Becker, Grossman and Murphy (1994, BGM henceforth), we assume a single addictive good C and a single non-addictive good Y. The individual maximizes the following utility function:

$$\sum_{t=1}^{\infty} \gamma^{t-1} U\,(C_t, Y_t, A_t, e_t) \tag{1}$$

Where γ is the discount factor, e_t represents unmeasured variables that have an impact on utility, and A_t is the stock of the addictive good at time *t*. The utility function has the following properties: $\frac{\partial U}{\partial C} > 0$; $\frac{\partial U}{\partial Y} > 0$; and $\frac{\partial U}{\partial A} < 0$. This simple model also allows for the main properties of addictive substances identified by psychologists: tolerance, reinforcement and withdrawal. The individual maximizes equation (1) subject to a lifetime budget constraint:

$$W_0 = \sum_{t=1}^{\infty} \gamma^{t-1}\,(P_t C_t, +Y_t)$$

Where $\gamma = \frac{1}{1+r}$ and r is the implied interest rate, which is assumed to be equal to the discount rate $r = \sigma$. Considering time as discrete, the evolution of the addictive stock A_t is described by the simple investment function (see Becker and Murphy, 1988, p. 677 and Chaloupka, 1990, p. 9. Becker and Murphy, 1988, and Chaloupka, 1990, use the same formulation; Gruber and Koszegi, 2000, p. 19, use a slight different version):

$$A_t = C_{t-1} + (1-\delta)A_{t-1} \tag{2}$$

[2] In order to approximate consumption in the third period necessary to estimate the rational addiction demand equation, Chaloupka uses maximum reported consumption of individuals who were smoking two years prior to their interview as a proxy for the third period consumption.

δ is the constant, exogenous depreciation rate of the addictive stock over time and represents "*the exogenous rate of disappearance of the effects of the physical and mental effects of past consumption*" (Becker and Murphy, 1988, p. 677). When the stock depreciates completely in one time period, the depreciation rate is $\delta = 1$, the depreciation factor becomes $(1-\delta) = 0$ and equation (2) becomes: $A_t = C_{t-1}$.

Considering a quadratic instantaneous utility function in three arguments: Y_t, C_t and A_t subject to the inter-temporal budget constraint, and assuming a rate of depreciation of the stock of the addictive good of 100% in one time period ($\delta = 1$), the following second-order difference demand equation is obtained from the first order conditions for C_t and A_t in the above maximization:

$$C_t = \theta_0 + \theta C_{t-1} + \gamma\theta C_{t+1} + \theta_1 P_t + \theta_4 e_t + \theta_5 e_{t+1} \tag{3}$$

The general formulation of the model, $\delta < 1$, allowing for more interaction between past and current consumption, results in past and future prices entering equation (3) (see BGM, 1990, p. 22; Chaloupka, 1990, p. 11; Picone, 2005, p. 5):

$$C_t = \theta_0 + \theta C_{t-1} + \gamma\theta C_{t+1} + \theta_1 P_t + \theta_2 P_{t-1} + \gamma\theta_2 P_{t+1} + \theta_4 e_t + \theta_5 e_{t+1} \tag{4}$$

where

$$\theta_0 = \frac{1}{\Omega}\left[\delta\alpha_A - \delta\alpha_C\left[\frac{(1-\delta)}{(1+\sigma)}\right] - 1\right] \tag{5}$$

and the α's are parameters of the quadratic instantaneous utility function, Ω is defined in Chaloupka (1990, pag. 43), σ is the discount rate so that the corresponding discount factor is $1/(1+\sigma) = \gamma$ and μ is the marginal utility of wealth.

$$\theta = \frac{\partial C_t}{\partial C_{t-1}} = \frac{1}{\Omega}\left[\alpha_{CA} - (1-\delta)\alpha_{CC}\right] > 0 \tag{6}$$

$$\theta_1 = \frac{\partial C_t}{\partial P_t} = -\frac{\mu}{\Omega}\left[1 + (1-\delta)^2\gamma\right] < 0 \tag{7}$$

$$\theta_2 = \frac{\partial C_t}{\partial P_{t-1}} = \frac{\mu}{\Omega}(1-\delta) > 0 \tag{8}$$

Using (6) to (8), equation (4) can also be written as:

$$C_t = \phi_0 + \phi C_{t-1} + \gamma\phi C_{t+1} + \phi_1\left[1 + (1-\delta)^2\gamma\right]P_t - \phi_1(1-\delta)P_{t-1} - \phi_1(1-\delta)\gamma P_{t+1} + \phi_4 e_t + \phi_5 e_{t+1} \tag{4.a}$$

where $\theta_0 = \phi_0$, $\theta = \phi$, $\phi_1 = -\mu/\Omega$. Equation (4) or (4.a) is a generalization of equation (3). The future terms in this formulation are discounted at the rate $\gamma(1-\delta)$ since the future is discounted at the rate γ and the stock depreciates at the rate δ (BGM, 1990, p. 24).

For the general demand equation (4 or 4.a), rational addiction implies positive coefficients on past and future consumption, positive coefficients on past and future prices and a negative coefficient on current price. BGM (1990, p. 25) clearly explain why this is so:

> "*Positive coefficients on past and future prices may seem odd, given that past and future consumption are complementary with current consumption when behaviour is addictive. However, controlling for past consumption eliminates the channel through which past prices affect consumption. But the only way that past consumption stays fixed when past prices are higher would be for another force to offset higher past prices by raising the past stock of consumption capital. Since this higher value of the stock continues into the present period (reduced only by depreciation), current consumption must be higher when past prices are higher. This also explains why past and future prices were not in the estimating equation of the simple model behind equation (3). That model implies a depreciation rate of one, so that any larger past stock is eliminated entirely by depreciation.*"

A serious problem in estimating equation (4) or (4a) is the likely high collinearity between current, past and future price, possibly resulting in low statistical significance of the price effects. One approach to this problem, suggested by BGM (1990), is to impose the restrictions implied by theory. In particular, a restriction can be imposed that the coefficients on future prices and future consumption are equal to the past effects multiplied by the discount factor $1/(1+\sigma)=\gamma$. BGM (1990) and Chaloupka (1990) find that this restriction is valid and improves the statistical significance of the price and consumption coefficients.

The general formulation also allows for deeper insights, due to the condition that both the ratio of future-to-past consumption coefficients and the ratio of future-to-past price coefficients equal the discount factor γ. This can be easily shown using equations (6) to (8). The ratio of future-to-current price effects is:

$$\frac{\partial C_t}{\partial P_{t+1}} \bigg/ \frac{\partial C_t}{\partial P_t} = -\frac{\gamma(1-\delta)}{1+(1-\delta)^2\gamma} \qquad (9)$$

When the exogenous depreciation is 100% ($\delta=1$ and $(1-\delta)=0$), equation (9) reduces to zero.

The ratio of future-to-past price effects is, instead:

$$\frac{\partial C_t}{\partial P_{t+1}} \bigg/ \frac{\partial C_t}{\partial P_{t-1}} = \gamma = \frac{1}{(1+\sigma)} \qquad (10)$$

Finally, the ratio of current to past price effects is:

$$\frac{\partial C_t}{\partial P_t} \bigg/ \frac{\partial C_t}{\partial P_{t-1}} = -\frac{1+(1-\delta)^2\gamma}{(1-\delta)} \qquad (11)$$

When the exogenous depreciation is 100% ($\delta=1$ and $(1-\delta)=0$), the denominator of this ratio goes to zero. If the ratio of future to past consumption effects is considered instead we have:

$$\frac{\partial C_t}{\partial C_{t+1}} \Big/ \frac{\partial C_t}{\partial C_{t-1}} = \gamma = \frac{1}{(1+\sigma)} \tag{12}$$

2.1 Dynamics of Consumption

The demand equations derived above are second-order difference equations in current consumption. The roots of these difference equations are useful for describing the dynamics of consumption and are positive if and only if consumption is addictive. For equation (3) and (4) these roots are (BGM, 1994 p. 413 or BGM, 1990, p. 9):

$$\lambda_1 = \frac{1-(1-4\theta^2\gamma)^{1/2}}{2\theta} \tag{13}$$

$$\lambda_2 = \frac{1+(1-4\theta^2\gamma)^{1/2}}{2\theta} \tag{14}$$

with $4\theta^2\gamma < 1$ by concavity. BGM note that both roots are real and depend on the sign of θ. Both roots are positive if and only if consumption is addictive ($\theta > 0$); otherwise both roots will be zero or negative. The smaller root, λ_1, gives the change in current consumption resulting from a shock to future consumption. The inverse of the larger root, λ_2, indicates the impact of a shock to past consumption on current consumption. These shocks may be the result of a change in any of the factors which affect the demand for cigarettes. Besides the restrictions on the values of the two roots, the conditions necessary for stability include that the sum of the coefficients on past and future consumption is less than unity and that the sum of the coefficients on prices is negative (see Chaloupka, 1990, p. 22).

The long-run price elasticity of demand gives the long-run effect on consumption of a permanent change in price and is obtained from equation (4), assuming that, in the long run, some steady-state level of consumption will be reached. Chaloupka (1990, p. 23) derive the formula for the long-run price elasticity of demand from equation (4):

$$\frac{dC_\infty}{dP_t} = \frac{\theta_1 + \theta_2 + \gamma\theta_2}{1-\theta-\gamma\theta} \tag{15}$$

The high collinearity among prices is probably the reason why most empirical work on rational addiction has focused on the estimation of equation (3), neglecting the more general formulation.[3] However, it turns out that the more general formulationsuggests an interesting way of testing the assumption of time consistency underlying the rational addiction model.

3. TESTING PRESENT BIAS IN THE RATIONAL ADDICTION EQUATION

The rational addiction model assumes not only that individuals are rational (maximizers) and forward-looking, but also that they are time-consistent, given that future consumption is discounted exponentially. As mentioned in the introduction, exponential discounting is crucial,

[3] The most notable exceptions are BGM (1990) and Chalopuka (1990).

because it implies that utilities in any two adjacent future time periods are discounted at the same rate or, stated differently, that individuals' short-run and long-run discount rates are the same. However, experimental evidence suggests that individuals may suffer from a present-bias implying a short-run discount rate larger than the long-run one. As a consequence of this short-run impatience, present-bias generates time inconsistency. In the formulation of Laibson (1997) present-bias is captured by an extra discount parameter, $\beta < 1$, applied uniformly to all future periods. As a result, consumption at time *t+1* evaluated at time t will be discounted at $\beta\gamma$, whereas consumption at time *t+2* evaluated at time *t+1*, for example, will be discounted at γ. Since both β and γ are less than one, consumption at time *t+1* evaluated at *t* is discounted more than consumption at any other future consecutive time period.

Starting with the work of Laibson (1997), the literature on hyperbolic discounting has grown dramatically. Nonetheless, attempts at estimating discount functions using observational data are still very scarce (exceptions are Laibson *et al.,* 2007, Levy, 2010 and Paserman, 2008). The only two empirical studies trying to find evidence against exponential discounting within the rational addiction framework using observational data are Gruber and Köszegi (2001) and Ciccarelli *et al.* (2008). Gruber and Köszegi proposed two ways of testing for time consistency, but could not implement them due to data inadequacy. On the other hand, Ciccarelli *et al.* (2008) proposed a test based on a specification that does not conform to the one derived from theory. Moreover, their estimates conflict with theoretical predictions.

Following Laibson (1997), an individual with quasi-hyperbolic time preferences maximizes the following utility function, where the instant gratification parameter β is between 0 and 1:

$$U(C_t, Y_t, A_t, e_t) + \beta \sum_{t=1}^{\infty} \gamma^t U\,(C_{t+1}, Y_{t+1}, A_{t+1}, e_{t+1}) \tag{16}$$

The discount factor between future consecutive periods is γ, but the discount factor between the current and next period is $\beta\gamma$. Therefore, this type of individual prefers instant gratification over delayed rewards.

Considering only naïve agents[4], maximization of equation (16) subject to an inter-temporal budget constraint leads to the following second-order difference demand equations:

$$C_t = \theta^*{}_0 + \theta^* C_{t-1} + \gamma\beta\theta^* C_{t+1} + \theta_1^* P_t + \theta_4^* e_t + \theta_5^* e_{t+1} \tag{17}$$

Equation (17) is identical to equation (3) except that $\gamma\beta$ is used instead of γ. Similarly, when $\delta < 1$ we obtain equation (18) instead of equation (4.a):

$$C_t = \phi_0^* + \phi^* C_{t-1} + \gamma\beta\phi^* C_{t+1} + \phi_1^*\left[1 + (1-\delta)^2\gamma\beta\right]P_t - \phi_1^*(1-\delta)P_{t-1} - \phi_1^*(1-\delta)\gamma\beta P_{t+1} + \phi_1^* e_t + \phi_1^* e_{t+1} \tag{18}$$

Empirical estimates of equations (17) or (18) cannot identify γ and β separately. They will instead estimate $\gamma\beta$. Therefore, the standard equations used to estimate rational addiction models cannot empirically distinguish between time-inconsistent versus time-consistent rational addicts. These two types of time preferences have radically different policy implications, however (Gruber and

[4] See Laibson (2007) for a distinction between naïve and sophisticated quasi-hyperbolic consumers.

Köszegi, 2001). Because time-inconsistent individuals tend to over-consume the addictive good, the optimal value of a Pigouvian tax on addictive goods' consumption, for example, increases drastically when present biased (instead of time-consistent) consumers are considered. This is because the internal costs of impatience have to be added to the external costs caused by consumption of the addictive goods when calculating the optimal level of the Pigouvian tax. For this reason, testing the assumption of time consistency is of crucial importance to assess the ability of the rational addiction model to give useful policy indications.

Our main goal is to develop a test of time consistency. Our strategy is to stick to the general specification of a rational addiction demand function, arguing that information produced by the estimation of this equation is sufficient. More precisely, to test whether data support exponential discounting, we exploit price effects from equation (4) and compare the discount factor obtained from equation (11):

$$\gamma = -\left(\frac{1+\frac{\theta_1}{\theta_2}(1-\delta)}{(1-\delta)^2} \right) \tag{19}$$

and the discount factor obtained from equation (9):

$$\gamma = -\frac{1}{(1-\delta)^2 + \frac{(1-\delta)}{\left(\frac{\gamma\theta_2}{\theta_1}\right)}} \tag{20}$$

In (19) the discount factor is derived by comparing price effects at time *t* and *t-1* and in equation (20) by comparing price effects at time *t+1* and *t*. Under the null hypothesis of time consistency, and conditional to a given depreciation rate, δ, the two ratios should imply the same value of γ. So a test of time consistency would be to test the null hypothesis that γ from the two ratios is statistically the same.

4. DATA AND ESTIMATION

We estimate a variant of the general rational addiction equation, as developed by BGM (1990 and 1994) and by Chaloupka (1990 and 1991) for tobacco consumption as the dependent variable:

$$C_{it} = \theta_i + \theta C_{it-1} + \gamma\theta C_{it+1} + \theta_1 P_{it} + \theta_2 P_{it-1} + \gamma\theta_2 P_{it+1} + \theta_4^{'} X_{it} + \theta_5 u_{it} + \theta_6 u_{it+1} \tag{21}$$

where *i* is the individual, *t* is time, *X* includes relevant time varying and time invariant socio-demographic variables that may affect consumption as well as interactions between price and demographic dummies and θ_i is an unobservable effect intended to encompass idiosyncratic characteristics that can be expected to be correlated with lead and lagged consumption and probably with other determinants of consumption. The restricted version of equation (21) is straightforward to estimate using standard econometric methods, which has contributed to its popularity. In the context of household survey data, $C_{it}, C_{it-1}, C_{it+1}$ could each be subject to censoring. In this case measures of actual consumption *C* would be replaced by latent variables (C^*). Under abstention and corner solution, all three variables would be latent. Under infrequency of purchase (i.e., when the survey period is too short to allow the consumers to report any purchase of a specific product), none of the variables are censored but they are measured with errors[5]. In this paper we assume that zeroes are attributable to infrequency of purchase only and that the purchase policy is time-invariant[6]. In this case we only need to deal with the problem of errors-in-variables during estimation.

The most appropriate form of data to capture the key features of these dynamic models with unobserved heterogeneity is individual level panel data. We can use monthly cross sections from January 1999 to December 2006 of individual Italian household current expenditures on tobacco products (cigarettes, cigars, snuff tobacco and cut tobacco) collected by Istituto Nazionale di Statistica (ISTAT) through a specific and routinely repeated survey called "Indagine sui Consumi delle Famiglie"[7]. ISTAT uses a weekly diary to collect data on frequently purchased items and a face-to-face interview to collect data on large and durable expenditure. Two weeks in each month are randomly selected and households sampled in each month are divided in two groups of equal number and assigned to one of the two randomly selected weeks. Current expenditures are classified in about 200 elementary goods and services with the exact number changing from year to year due to minor adjustments in the items' list. The survey also includes detailed information on the household structure, so that relevant data on demographic characteristics (such as regional location, number, gender, age, education and employment condition of each household member) are available. All annual samples are independently drawn according to a two stage design[8]. Monthly and regional consumer price indices (1998=100) for tobacco matching expenditures reported in the "Indagine sui Consumi delle Famiglie" are also available from ISTAT.

Given the availability of a series of independent cross-sections, it is impossible to track individual households over time and, therefore, to estimate a dynamic model. To overcome this problem, we start from the series of independent cross-sections of micro-data for the period 1999(1)-2006(12) and we construct a pseudo panel using cell averages to identify household. Households in each cell are selected on the basis of 12 combinations of available demographic characteristics plus one residual category, and sample averages for each type in each month and in each region have been

[5] See Jones and Labeaga (2003) for a discussion of this issue.

[6] In the survey on households' expenditures, data on current consumption purchases are collected for each sampled household during one week only (within a month). These weekly expenditures are then aggregated to the month by ISTAT using a statistical model accounting for the frequency of purchase of each item, i.e. for the proportion of households purchasing that specific item during the surveyed week. Thus it may well be that a specific household does not purchase tobacco during the surveyed week and its monthly expenditure on that good is set to zero, but this does not imply that her expenditure has been zero in the other three weeks too. Consistent with the hypothesis of infrequency of purchase and time invariant purchase policy, it can be that the frequency of the survey does not coincide with the frequency of purchase.

[7] A different sample of households is interviewed each month; the items list also includes semi-durable expenditures, with a total number of about 280 goods and services.

[8] Details on the sampling procedure used to collect these data can be found in ISTAT, Indagine sui Consumi delle Famiglie, File Standard, Manuale d'uso, anni 1999-2006.

computed. Since the survey does not provide information on the number of tobacco consumers in the household, households with one member only have been selected to avoid any ambiguity between the recorded expenditure and the individual in the household. Table 1 contains a description of each average household.

Table 1 – Single household types

Household Type	Male	Female	Young	Adult	Senior	Low-Edu	High-Edu	Emp	Unemp
HT1	X			X		X		X	
HT2	X			X		X			X
HT3	X			X			X	X	
HT4	X			X			X		X
HT5		X		X		X		X	
HT6		X		X		X			X
HT7		X		X			X	X	
HT8		X		X			X		X
HT9		X			X				
HT10	X				X				
HT11	X		X						
HT12		X	X						

If *r* is the geographical location, *f* is the household type, *m* is the month and *t* the year considered, the final data have been organized as a pseudo panel Φ(r, f, m, t) by stacking up monthly data (*m* =1, …, 12) for each year (*t* = 1, …, 8) and for each geographical region (*r* = 1, …, 20) on each household type (*f* = 1, …,13) in vectors whose length varies each period, thus giving rise to an unbalanced panel data set of 12,446 mean single households observations. We further collapsed the regional data into four macro-areas of Italy: northwest (NW); northeast (NE); central (CE); south and the islands (SI), obtaining a final unbalanced panel of 4,259 individual observations.

Our dependent variable, the quantity of tobacco consumed, has been obtained implicitly as the ratio between monthly tobacco expenditure (in Euros) and the tobacco price index. In order to introduce some individual variation, the price of tobacco is constructed by deflating the retail price index for tobacco by a weighted average of nine broad categories of the retail price index, as in Labeaga (1999), where the weights are the shares of expenditure devoted to each good in each household. A set of dummy variables is included to account for socio-demographic and geographic factors: location ; gender; employment status (employed, unemployed); education level (higher education, lower education); income level (rich, poor, middle); age (less than 24 years; between 25 and 65 years and more than 65 years); household type (1 to 13) based on gender, age, employment condition and education level of the single member of the household according to combinations displayed in table 1. We also add total current monthly expenditure as a proxy of disposable income. Summary statistics of the data are shown in table 2. Almost 22% of the single households report zero tobacco expenditures during the survey period. On average, tobacco consuming singles have slightly higher total expenditures than non-consuming ones. Non-consuming females are more numerous than non-consuming males. When looking at age, young consumers are less represented than older ones in our data, but among non-consuming households the young are more numerous than the old. There are also more highly educated non-consumers than less educated non-consumers and more unemployed non-consumers than employed non-consumers.

Table 2 - The Data

Variable	Full Sample	Consuming Households	Non-consuming Households
Sample size	4,259	3,304	955
Tobacco expenditures[a]	14.044 (16.390)[b]	18.104 (6.516)	0
Price of Tobacco	113.161 (9.911)	113.115 (9.857)	113.319 (10.096)
Retail price index	110.527 (5.905)	110.635 (5.856)	110.153 (6.060)
Total household expenditures	1414.426 (544.657)	1420.022 (504.472)	1395.066 (665.167)
Dummy variables (yes = 1, no = 0)			
Northwest	0.255 (0.436)	0.268 (0.443)	0.212 (0.409)
Northeast	0.2444 (0.429)	0.241 (0.427)	0.258 (0.437)
Centre	0.241 (0.428)	0.234 (0.423)	0.268 (0.443)
South & Islands	0.259 (0.438)	0.258 (0.438)	0.268 (0.439)
Male	0.449 (0.497)	0.469 (0.499)	0.381 (0.485)
Female	0.469 (0.499)	0.459 (0.498)	0.504 (0.500)
Unemployed	0.312 (0.464)	0.246 (0.431)	0.541 (0.498)
Employed	0.359 (0.479)	0.422 (0.494)	0.139 (0.346)
Young (< 24)	0.067 (0.250)	0.042 (0.201)	0.154 (0.361)
Adult	0.671 (0.469)	0.669 (0.471)	0.681 (0.466)
Senior (>65)	0.180 (0.384)	0.218 (0.413)	0.050 (0.218)
Low Education	0.355 (0.478)	0.366 (0.482)	0.315 (0.465)
High Education	0.317 (0.465)	0.303 (0.459)	0.365 (0.482)
Poor	0.249 (0.433)	0.231 (0.421)	0.315 (0.465)

Rich	0.249	0.249	0.252
	(0.433)	(0.432)	(0.435)
Middle	0.500	0.519	0.432
	(0.500)	(0.499)	(0.496)

Notes:
1. Monthly expenditures in Euros
2. Standard deviations in parentheses.
Source: ISTAT, "I Consumi delle Famiglie", years 1999-2006.

4.1 Estimation Method

OLS is both biased and inconsistent when used to estimate dynamic panel data models. There is an omitted variable bias due to unaccounted demand shifters that may also be serially correlated (BGM, 1994). Moreover, infrequency of purchase accounts for errors-in-variables since, even considering heterogeneity, lag and lead consumption are measured with errors and are correlated with the mixed error terms. Measurement errors lead to the classical error-in-variables model (CEV). CEV causes an attenuation bias in the estimated coefficients and this problem is worsened using panel data[9]. To correct for this endogeneity bias we follow Arellano and Bond (1991) in using a GMM procedure to obtain the vector of parameters:

$$\hat{\beta}_{GMM} = \left[\left(\sum_{i=1}^{N} V_i^{'} K^{'} W_i\right)\hat{A}\left(\sum_{i=1}^{N} W_i^{'} K V_i\right)\right]^{-1}\left(\sum_{i=1}^{N} V_i^{'} K^{'} W_i\right)\hat{A}\left(\sum_{i=1}^{N} W_i^{'} K C_i\right) \tag{22}$$

where $V_i = [C_{it-1}, C_{it+1}, P_{it}, X_{it}]$, K is an upper triangular transformation matrix such that the elements in its rows sum to zero, so that unobservable permanent effects are eliminated[10], W_i is the matrix of instruments and the weighting matrix $\hat{A}$ is a consistent estimate of the inverse of the covariance matrix of the empirical moments given by $\hat{A} = \left[W_i^{'} K \hat{u}_i \hat{u}_i^{'} K' W_i\right]^{-1}$, where $\hat{u}_i = C_i - \hat{\beta}^{'} V_i$ is a consistent estimate of the disturbance. Since the weighting matrix is a function of $\hat{\beta}$, we need a two-step procedure. In the first step, we obtain a preliminary estimate of the parameters vector using an arbitrary positive definite and symmetric weighting matrix which does not depend on $\hat{\beta}$. In the second step, the preliminary estimate of β is used to form $\hat{A}$ and obtain $\hat{\beta}_{GMM}$.

GMM estimators exploit a set of moment conditions between instruments and u, $E\left[W_i^{'} K u_i\right] = 0$ for $i = 1, ..., N$, where the matrix of instruments W_i is block diagonal, with the block structure at each time period depending on the assumptions of strict or weak exogeneity of available instruments (Picone, 2005).

[9] There are two consequences of this measurement error. First, future prices may be correlated with the disturbance term. This will invalidate future prices and other future variables which are not fully anticipated as instruments for C_{it+1}. Second, $E(P_{it}\, u_{is}) \neq 0$ for $s < t$ and P_{it} cannot be strictly exogenous. However it is plausible to assume that $E(P_{it}\, u_{is}) = 0$ for $s \geq t$ which implies that P_{it} is a predetermined random variable in our model.
[10] The typical examples are the first difference and the forward orthogonal deviations. In fact we also report the within transformation.

An augmented version of the above estimator with better finite sample properties can be obtained incorporating extra orthogonality conditions for the equations in levels. This is the system-GMM (Blundell and Bond, 1998), which allows for orthogonality conditions of both transformed $(K \neq I)$ and in level $(K = I)$ equations.

Whether we actually need all these moment conditions is debatable, since in finite samples there is a bias/efficiency trade-off. For example, Ziliak (1997) showed that GMM may perform better with suboptimal instruments and argued against using all available moments, especially when *T* is large relative to N. Since in our case *N* = 52 and *T* = 96 (hence a large number of orthogonality conditions), we use only a subset of them, testing their validity with the Sargan over-identification test (Baltagi and Griffin, 2001).

Finally, we have to choose a set of instruments. Ever since the work of BGM (1994) on US cigarette consumption, past and future prices have been considered natural instruments for lagged and lead consumption. In fact, their empirical support of the rational addiction theory relies heavily on future prices. Exclusion of them from the instrument set yields puzzling results, such as negative interest rates and wrong sings on lagged consumption and own price. So, despite future prices failing a Hausman test, BGM (1994) consider them as valid instruments on several grounds. Specifically, they argue that smokers may have sufficient information on taxation policy to anticipate any cigarette price upswing in advance. Whether their conjecture is legitimate in general or depends on data makes a difference in terms of the stacked matrix W_i. For example, it is unlikely that Italian consumers may have relevant information to forecast tobacco price changes. This invalidates future prices as well as other variables which are not fully anticipated at time *t* as instruments for future consumption of tobacco. At the same time, over our study period the real price series does not show so much time variation that individuals can possibly forecast tobacco prices a month or more from the date of the survey, thus partly reviving BGM's (1994) conjecture.

The use of prices alone to instrument consumption can induce problems of weak instruments and problems of estimators that can be biased towards ordinary least squares (see Jones and Labeaga, 2003, for a discussion of this issue). Time invariant demographic variables can also be used as instruments in any transformation of the model that rules out time invariant explanatory variables. After some experimentation with the matrix of instruments W_i, we use lag and lead prices, the proxy of disposable income as well as a number of demographic variables. One way to decide about the set of instruments is to perform a Hausman test of the null hypothesis that future prices are legitimate instruments.[11]

5. RESULTS

The empirical specification of model (21) uses the quantity of tobacco consumed per month as the dependent variable. The right-hand side variables are the lead and lag consumption, the current

[11] Estimation of the model employs a modified TSP program written by Yoshitsugu Kitazawa (2003). The set of TSP scripts can be obtained from http://www.ip.kyusan-u.ac.jp/J/kitazawa/SOFT/TSP_DPD1/index.htm.

lead and lag real price of tobacco, the proxy of disposable income and the following socio-demographic characteristics: gender, age, high education, high income and the interactions between price and demographic characteristics. We use a subset of all available instruments of prices. Our chosen estimator is the system–GMM (Blundell and Bond, 1998). This unifying GMM framework incorporates orthogonality conditions of both types of equations, transformed and in levels and performs significantly better in terms of efficiency as compared to other IV estimators of dynamic panel data models. We estimate both one-step and two-step system-GMM estimators, but we only report two-step estimates with a robust covariance matrix[12].

In terms of empirical studies and finite sample properties of the GMM estimator, the choice of transformation to be used to remove individual effects is of great concern. First differencing (FD) is just one of the many ways. Arellano and Bover (1995) present an alternative transformation for models with predetermined instruments, forward orthogonal deviations (FOD). This transformation involves subtracting the mean of all future observations for each individual. The key difference between FD and FOD is that the latter does not introduce a moving average process in the disturbance, i.e., it preserves orthogonality among errors. Hayakawa (2009) compares the performances of the GMM estimators of dynamic panel data model wherein different transformations are used. His simulation results show that overall the FOD model outperforms the FD model in many cases. Since we have an unbalanced panel, another practical difference is that the FOD transformation preserves the sample size in panels with gaps, where FD would reduce the number of observations.

Results under the infrequency of purchase interpretation of zeros and three alternative transformation methods are reported in table 3. The fixed-effects transformation or within transformation (WT) is reported for the sake of comparison and completeness. For the reasons discussed above, our preferred specification is the system GMM with FOD (column 2). On the whole, our estimates are consistent with the rational addiction framework. First, past consumption has a significant positive effect. Second, future consumption has a significant positive effect, supporting the idea that behavior is forward-looking. Third, the coefficient of lag consumption is always greater than the coefficient of lead consumption, giving rise to a positive discount rate. Fourth, we obtain a negative coefficient on current price and a positive coefficient on both past and future prices. So, the signs on the two consumption variables and the three price variables conform to theoretical predictions. This finding is further explored in table 5, showing the estimated roots of the second-order difference equation implied by the standard specification. The reciprocal of the larger root measures the impact of an exogenous shock to past consumption on current consumption and can be interpreted as the strength of the addiction effect. The smaller root gives the impact on current consumption of an exogenous shock to future consumption, and can be interpreted as the forward-looking effect. Both roots are always

[12] We report two-step estimates even though we are aware that in finite samples a downward bias of the estimated standard error of the two-step GMM estimator may arise (Davidson and MacKinnon, 2004; Baltagi, 2005).

significantly positive. Our results fulfill the stability condition[13] as both roots are positive and $4\theta^2\gamma < 1$ (BGM, 1994). Finally, the sum of coefficients on past and future consumption is less than unity and the sum of price coefficients is negative, as required by theory.

Table 3 – Estimation of General Rational Addiction Models (infrequency or misreporting)

Parameter	Gmm_Sys WT	Gmm_Sys FOD	Gmm_Sys FD
C_{t-1}	0.506	0.483	0.055
	(0.007)	(0.009)	(0.021)
C_{t+1}	0.486	0.461	0.045
	(0.006)	(0.008)	(0.020)
P_t	-0.474	-0.385	-0.515
	(0.090)	(0.093)	(0.092)
P_{t-1}	0.243	0.225	0.314
	(0.042)	(0.055)	(0.052)
P_{t+1}	0.229	0.150	0.194
	(0.050)	(0.057)	(0.078)
Northwest	1.926	-3.837	
	(5.020)	(3.311)	
Northeast	15.290	-14.043	
	(4.979)	(3.390)	
Centre	3.373	-11.337	
	(4.945)	(3.126)	
Male	-6.457	0.952	6.494
	(7.303)	(4.261)	(1.266)
Employed	-9.418	-2.483	1.801
	(10.427)	(6.435)	(2.295)
Adult	-14.524	11.834	2.790
	(6.427)	(4.006)	(1.858)
College	12.253	1.081	-4.993
	(12.746)	(6.507)	(1.872)
Rich	3.349	2.587	
	(0.589)	(1.160)	
Price*Male	0.014	0.041	
	(0.018)	(0.010)	
Price*Employed	-0.010	-0.038	
	(0.022)	(0.013)	
Price*Adult	-0.019	-0.014	
	(0.023)	(0.011)	
Price*College	0.008	0.028	
	(0.068)	(0.010)	
Male*Employed	9.987	5.046	
	(20.374)	(11.400)	
Male*Adult	0.677	-8.497	
	(18.451)	(10.227)	
Male*College	4.688	-5.644	
	(16.956)	(9.516)	
p-value Sargan test	0.427	0.519	0.322

1. Instrument set: lagged and lead prices, expenditure and demographic dummies for lagged and lead consumption.
2. Consistent standard errors robust to heteroscedasticity are in parentheses.

The proxy of disposable income has a small and positive effect on current consumption of tobacco. As to the demographic variables in our specification, being an adult has a positive and significant

[13] Baltagi (2007) stresses that, in fact, this is somehow improperly known as a stability condition, because the solution to a rational addiction model is generally assumed to be a saddle point and its roots could therefore not pass a stability test.

effect as well as being a high-income household. A price increase has a positive and significant effect on consumption for single males and for singles with higher education, whereas it has a negative and significant effect for employed singles.

Table 4 shows the long run price elasticities of demand for the twelve household types and for four geographic areas of Italy. Chaloupka (1990) estimated long-run price elasticities of demand for cigarettes for the sample of current smokers in the range - 0.46 to - 0.30. BGM 1990 obtain long-run price elasticities of demand in the range -0.74 to -0.80. We obtain a comparable range of elasticities from our sample. Elasticities are higher for females and seniors. Among young households, male are more price-elastic than females.

Table 4 - Long Run Price Elasticities of Demand

Household Type	Northwest	Northeast	Centre	South and Islands
HT1	-0.712	-0.717	-0.722	-0.661
	(0.786)	(0.792)	(0.798)	(0.730)
HT2	-1.168	-0.823	-0.832	-0.755
	(1.291)	(0.909)	(0.919)	(0.834)
HT3	-1.088	-1.420	-1.161	-1.015
	(1.202)	(1.569)	(1.283)	(1.122)
HT4	-1.539	-0.891	-1.584	-0.946
	(1.702)	(0.985)	(1.750)	(1.045)
HT5	-0.996	-1.047	-1.134	-1.791
	(1.101)	(1.157)	(1.253)	(1.979)
HT6	-3.756	-2.548	-2.247	-3.328
	(4.151)	(2.816)	(2.483)	(3.678)
HT7	-1.152	-1.584	-1.107	-1.065
	(1.273)	(1.751)	(1.223)	(1.177)
HT8	-1.002	-1.929	-2.201	-1.480
	(1.107)	(2.131)	(2.432)	(1.636)
HT9	-6.961	-7.484	-5.149	-14.241
	(7.694)	(8.272)	(5.692)	(15.740)
HT10	-1.815	-2.942	-2.401	-1.921
	(2.006)	(3.252)	(2.653)	(2.123)
HT11	-7.946	-2.941	-1.621	-4.541
	(8.783)	(3.250)	(1.791)	(5.019)
HT12	-0.697	-4.253	-0.236	-0.568
	(0.770)	(4.701)	(0.261)	(0.627)

Consistent standard errors robust to heteroscedasticity are in parentheses.

In Table 5 we present the parameters derived from the estimated equation. The implied discount factor, $\frac{\theta\beta\gamma}{\theta}$, is the weight given to future utility, from which one can derive the discount rate, $\frac{\theta}{\theta\beta\gamma} - 1$. When the discount factor is computed as the ratio between the future-to-past consumption coefficients, we obtain a value of 96% corresponding to a monthly discount rate of around 5%.

Table 5 – Strength of Addiction, Discount Rate and Time Consistency

Derived parameter	Model 1 δ=0.20	Model 2 δ=0.25	Model 3 δ=0.30	Model 4 δ=0.35
(Larger root)$^{-1}$	3.115 (0.052)			
Smaller root	0.162 (0.000)			
Monthly discount factor	0.966 (0.029)			
Monthly discount rate	0.047 (0.031)			
$[\beta\gamma]_1$	0.689 (0.253)	0.711 (0.254)	0.769 (0.260)	0.806 (0.265)
$[\beta\gamma]_2$	0.624 (0.270)	0.571 (0.287)	0.398 (0.328)	0.259 (0.353)
$[\beta\gamma]_1 - [\beta\gamma]_2$	0.065 (0.059)	0.140 (0.066)	0.371 (0.092)	0.547 (0.110)
β	0.905 (0.097)	0.803 (0.137)	0.517 (0.258)	0.321 (0.335)
γ	0.689 (0.253)	0.711 (0.254)	0.769 (0.260)	0.806 (0.265)

Consistent standard errors robust to heteroscedasticity are in parentheses.

The next rows of Table 5 contain the results of our proposed test of time consistency. We perform the test for four different values of the depreciation rate, δ, corresponding to the four columns of results in Table 5. The null hypothesis of time consistency is that the difference between the discount factor implied by ratio of the future to current price coefficients and the discount factor implied by the ratio of the current to past price coefficients is statistically not different from zero. For all models we reject the null hypothesis of time consistency. Therefore, consumers behind our data do not discount exponentially. Given this result, under the assumption of hyperbolic discounting, we can recover the present-bias factor β as the ratio of equation (20) and equation (21). This is shown in table 5 for each value of δ.

The present bias parameter is significantly different from 1 and matches estimates obtained in very different contexts. Levy (2010), using a model of addiction based on O'Donoghue and Rabin's (2002) adaptation of Becker and Murphy (1988), obtains estimates of β for cigarette smokers in the United States between 0.71 and 0.89 and a long run discount factor of 0.90. Laibson, Repetto and Tobacman (2007) estimate an annual β of 0.7 and a γ of 0.96 in a structural model of consumption and decisions. Paserman (2008) estimates an annual present bias discount factor for high-wage earners of 0.89 and a long run discount factor of 0.99. Given our specification, we observe that the present bias β decreases as the depreciation rate δ increases. Future research will be directed at further investigating the role of the exogenous rate of depreciation δ. A different dataset and a richer specification of the general rational addiction model, including several lags and leads of price and consumption, might produce even better estimates of the discount parameters.

6. CONCLUDING REMARKS

This paper addresses one of the main theoretical and empirical shortcomings of the rational addiction model, namely that forward-looking behavior, implied by theory, does not necessarily imply time consistency. So, even when forward-looking behavior can be convincingly supported, the dynamic consumption equation derived from the rational addiction theory does not provide evidence in favor of time-consistent preferences against a model with dynamic inconsistency (Gruber and Köszegi, 2001).

In fact we show that the possibility of testing for time consistency and of separately identifying a present bias and a long-run discount parameter is nested within the rational addiction demand equation. Rather than relying on additional assumptions or on a different theoretical and/or empirical framework, we use price effects and the rarely estimated general formulation of the rational addiction demand equation to develop a test of time consistency. The test's purpose is to check whether consumers behind our data reveal time-consistent preferences or not.

Our results for the general rational addiction model conform to theory. We also find evidence of time inconsistency in all of our specifications. Conditional on this evidence, under the assumption of quasi-hyperbolic discounting, we propose a simple way of recovering the short and long run discount parameters separately. Our derived estimates of the short and long run discount parameters are plausible, statistically significant and in line with the literature.

Our conclusion is that the possibility of distinguishing time-consistent from time-inconsistent preferences is nested within the rational addiction model. The information extracted from a general rational addiction demand equation is sufficient to test for both forward-looking behavior and time consistency. Future efforts will be directed at further investigating the role of the exogenous rate of depreciation δ.

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