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ABSTRACT

Rational Addiction and Time Consistency: An Empirical Test*

This paper deals with one of the main empirical problems associated with the rational addiction theory, namely that its derived demand equation is not empirically distinguishable from models with forward looking behavior, but with time inconsistent preferences. The implication is that, even when forward looking behavior is supported by data, the standard rational addiction equation cannot distinguish between time consistency and inconsistency in preferences. We show that an encompassing general specification of the rational addiction model embeds the possibility of testing for time consistent versus time inconsistent naïve agents. We use a panel of Russian individuals to estimate a rational addiction equation for tobacco with time inconsistent preferences, where GMM estimators deal with errors in variables and unobserved heterogeneity. The results conform to the theoretical predictions and the proposed test for time consistency does not reject the hypothesis that Russian cigarettes consumers discount future utility exponentially. We further show that the proposed empirical specification of the Euler equation, whilst being indistinguishable from the general empirical specification of the rational addiction model, it allows to identify more structural parameters, such as an upper-bound for the parameter capturing present bias in time preferences.

JEL Classification: C23, D03, D12

Keywords: rational addiction, general versus standard specification, time consistency, naïveté, GMM

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1 Introduction

Becker & Murphy (1988) explored the dynamic behavior of consumption of addictive goods, showing how many phenomena previously thought to be irrational can be consistent with utility optimization according to stable preferences. In their model, individuals recognize both the current and future consequences of consuming addictive goods. This model has subsequently become the standard approach to modeling consumption of goods such as cigarettes. A sizable empirical literature has emerged since then, beginning with Becker et al. (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 imply time consistent preferences. Indeed even when evidence of forward looking behavior is found, the standard rational addiction demand equation does not allow to separately identify the short-run and long-run discount factor applied to future consumption periods (Picone, 2005). This is a crucial issue, because dynamic inconsistency can deliver radically different implications for government policy. In particular, while time consistency implies that the optimal tax on addictive goods should depend only on the externalities imposed on society, time inconsistency suggests a much higher tax depending also on the "internalities" that drugs' use imposes on consumers future selves (Gruber & Köszegi, 2001; O'Donoghue & Rabin, 2006).

This paper offers the following contributions to the literature on addiction and time preferences. First, it provides the solution to a generalization of the rational addiction model that embeds time inconsistency through quasi-hyperbolic discounting, similar to Gruber & Köszegi (2001). We show that while the empirical specification is indistinguishable from the general specification of the rational addiction model (Becker et al., 1994)[1], the testable implications are richer.

Second, it provides an estimate, using panel data at the individual level, of the general specification of the rational addiction demand equation that includes current, past and future prices. As far as we know this general specification has been estimated before only by Becker

[1]We use the expression "general specification" of the demand equation as opposed to the most popular "standard specification" which is usually estimated in the empirical literature on rational addiction. While the general specification includes current, past and future prices of the addictive good as explanatory variables, the standard version only includes current prices. We shall return on this.

et al. (1994); Chaloupka (1991); Waters & Sloan (1995).

Third, we implement a simple test of time consistency based on the additional structural information that can be extracted from the empirical general specification of the rational addiction demand equation. The purpose of the proposed test is to disentangle time consistent versus naïve agents, and it is possible because the proposed theoretical framework encompasses the rational addiction theory with time consistency as a special case involving no present bias in time preferences. Fourth, we compare our results with a time consistency test proposed by Gruber & Köszegi (2000), the working paper version of Gruber & Köszegi (2001).

Fifth, we show that while point estimates of the present bias parameter cannot be obtained under the proposed theoretical framework, it is still possible to recover an upper-bound, which provides further insights on the degree of time inconsistency.

In our framework we can only discriminate between time consistent and naïve agents. This is because the equilibrium of both naïve and time consistent individuals can be solved as an optimization problem and leads to the same empirical demand equation. We recognize, however, that time inconsistent agents could also be sophisticated. However, the equilibrium of sophisticated agents can only be analyzed as the equilibrium of a dynamic game (see O'Donoghue & Rabin, 1999b, 2002, for more details).

The implications of our findings are the following. First, the rational addiction model and its derived general demand equation (Becker & Murphy, 1988; Becker et al., 1994) can be easily extended to discriminate between time consistent and naïve time inconsistent consumers, with the advantage of producing exactly the same empirical specification. Second, the possibility of distinguishing time consistent from naïve agents is nestled within the same general specification. Stated differently, the information extracted from the general rational addiction demand equation is sufficient to test for both forward looking behavior and time consistency. The possibility of testing for time consistency using field data opens up the opportunity of using the rational addiction demand equation to predict the impact of price measures on consumption of addictive goods in a more general way. This has relevant policy implications as time inconsistent preferences generally imply larger optimal taxes on the addictive goods.

The paper proceeds as follows. Section 2 summarizes the literature on time consistency and addiction. Section 3 reviews the general formulation of the rational addiction model while

Section 4 introduces time inconsistent preferences and our test strategy. Section 5 discusses the data. Section 6 details the estimation methods and instruments choice. Section 7 presents and discusses the results and Section 8 concludes.

2 Prior Research

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). Behavioral economics has built on the work of Strotz (1956) to explore the consequences of relaxing the standard assumption of exponential discounting. Ainslie (1992) and Loewenstein & Elster (1992) indicate that some basic features of inter-temporal decision-making that are inconsistent with simple models of exponential discounting, namely that many individuals value consumption in the present more than any delayed consumption, may be explained by a particular type of time inconsistency: hyperbolic discounting. In the formulation of quasi-hyperbolic discounting adopted by Laibson (1997) the degree of present bias is captured by an extra discount parameter $\beta \in (0, 1)$ which accounts for instant gratification. Accordingly, the consumption path planned at each time period for the future time periods may never be realized, because the inter-temporal trade-off changes over time. The implications of such self-control problems depend on individuals' awareness of their future preferences (O'Donoghue & Rabin, 1999a, 2002). Extreme assumptions about such awareness, e.g. full awareness and full unawareness, identify two types of individuals usually considered in the literature (Strotz, 1956; Pollak, 1968; O'Donoghue & Rabin, 1999a): naïve and sophisticated. A sophisticated person is fully aware of what her future selves preferences will be. A naïve person believes her future selves' preferences will be identical to her current self's, not realizing that as she gets closer to executing decisions her tastes will have changed. To analyze equilibrium behavior of individuals with different time preferences, researchers have formally modeled a consumer as a sequence of temporal selves making choices in a dynamic game (Laibson, 1997; O'Donoghue & Rabin, 1999a, 1999b, 2002). Hence, a $T-$period consumption problem translates into a $T-$period game, with T players or selves, indexed by their respective periods of consumption decision. In their analysis of consumption behavior of time consistent (TC henceforth), sophisticated and naïve agents, O'Donoghue & Rabin (1999a, 1999b, 2002) assume individual behavior to be described by *perception-perfect strategies*, i.e. solution concepts describing the individual's optimal action in all periods given her current preferences and her perception of future behavior. Naïfs have present biased preferences, but believe that they are time consistent. Therefore, the decision process for naïfs is identical to that for TCs even though naïfs have different time preferences. For naïfs and TCs this amounts to just choosing an optimal future consumption path. Thus, both naïfs and TCs equilibrium can be solved as an optimization problem.

Since naïfs' optimization problem is encompassing the TC case, its solution and the resulting demand equation offer the opportunity to develop an empirical test of time consistency. Such distinction is very important from a policy perspective. Because quasi-hyperbolic 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 add to the external costs caused by consumption of the addictive goods when calculating the optimal level of the Pigouvian tax.[2]

The implications of present biased preferences, and their associated problems of self-control, have been studied under a variety of economic choices and environments: Laibson (1997), O'Donoghue & Rabin (1999a, 1999b, 2002), and Angeletos et al. (2001) applied this formulation to consumption and saving behavior; Diamond & Köszegi (2003) explored retirement decisions; Barro (1999) applied it to growth; Gruber & Köszegi (2001) and Levy (2010) to smoking behavior; Shapiro (2005) to caloric intake; Fang & Silverman (2009) to welfare program participation and labor supply of single mothers with dependent children; Della Vigna & Paserman (2005) to job search (see Della Vigna, 2009, for a review); Acland & Levy (2015) to gym attendance.

Few works have attempted to use a parametric approach to estimate structural dynamic

[2] Since the equilibrium of sophisticated cannot be solved as an optimization problem, our empirical analysis and our test of time consistency do not apply to sophisticated agents. O'Donoghue & Rabin (1999a) stress that even though sophistication is closer to standard economic assumptions than naïveté, it may have departures from conventional predictions that are even more extreme than those implied by naïveté. Focusing on naïfs only produces results which arise from present biased preferences only, rather than from present biased preferences in conjunction with sophistication. In addition, naïveté is more empirically relevant than sophistication as some studies demonstrate (Ariely & Wertenbroch, 2002; Della Vigna & Malmendier, 2003).

models with hyperbolic time preferences (Fang & Silverman, 2009; Laibson et al., 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 & Rabin (2002) generalization of Becker & Murphy (1988) rational addiction model. Gruber & Köszegi (2001) develop a model incorporating present biased preferences into the Becker and Murphy theory. Under this theory, the individuals would always change their plan and regret their earlier decisions. The authors propose using their model to obtain the present bias and long-run discounting parameters and, in the year 2000 version of the same paper, they propose a test of time consistency per se.

To our best knowledge no research has to date tested the assumption of time consistency within the structural demand equation derived from the rational addiction model of Becker & Murphy (1988). As pointed out by Picone (2005), the standard version of the rational addiction demand equation does not allow identification of the short and long run discount factor thus making it impossible to empirically test for time consistency of the agents. However, as we shall explain in the next section, the less popular general formulation of the rational addiction demand equation opens the possibility of testing for time consistency.

3 The General Rational Addiction Demand Equation

Following Boyer (1978, 1983) and Becker et al. (1994) (BGM henceforth), considering time as discrete, the individual is assumed to maximize over time the following concave instantaneous utility function

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

where C_t is the quantity of a single addictive good consumed in period t, A_t is the stock of past consumption in period t, Y_t is the consumption of a composite commodity in period t and e_t reflects the impact of unmeasured life-cycle variables on utility. $\delta = \frac{1}{(1+r)}$ is the long run discount factor and r is the individual rate of time preference. Preferences are stationary the sense that the instantaneous utility function in (1) does not change over time. This means that a person's instantaneous utility function depends on his current consumption level but not on the specific period t. This utility function has the following properties $\frac{\partial U_t}{\partial C_t} > 0$; $\frac{\partial U_t}{\partial Y_t} > 0$; and $\frac{\partial U_t}{\partial A_t} < 0$. Utility maximization is subject to the lifetime budget constraint $W_0 = \sum_{t=1}^{\infty} \delta^{t-1}(Y_t + P_t C_t)$, where W_0 is the present value of wealth and P_t is the relative price of the addictive good at time t. The evolution of the addictive stock A_t is described by the simple investment function $A_t = (1-\gamma)A_{t-1} + C_{t-1}$ where γ measures the depreciation rate of the stock over time and represents the exogenous rate of disappearance of the effects of the physical and mental effects of past consumption (Becker & Murphy, 1988). When the stock depreciates completely in one time period, the depreciation rate is $\gamma = 1$, the depreciation factor becomes 0 and $A_t = C_{t-1}$. Assuming this restriction holds, considering a quadratic instantaneous utility function in the three arguments[3] subject to the inter-temporal budget constraint, and solving the first-order conditions for C_t and A_t BGM obtain the following second-order difference demand equation:

$$C_t = \theta_0 + \theta C_{t-1} + \theta\delta C_{t+1} + \theta_1 P_t + \theta_2 e_t + \theta_3 e_{t+1} \tag{2}$$

Equation (2) gives current consumption as a function of past and future consumption, the current price P_t and the unobservable shift variables e_t and e_{t+1}. This is the restricted or standard formulation of the rational addiction demand equation usually estimated in the empirical literature (Baltagi & Griffin, 2001, 2002; Baltagi & Geishecker, 2006; Grossman & Chaloupka, 1998; Grossman et al., 1998; Gruber & Köszegi, 2001; Jones & Labeaga, 2003; Labeaga, 1993, 1999; Liu et al., 1999; Olekalns & Bardsley, 1996; Saffer & Chaloupka, 1999; Ziliak, 1997).

In the more general case, i.e. with $\delta < 1$, we have past and future prices entering equation (2) (Becker et al., 1990; Chaloupka, 1990; Picone, 2005):

$$C_t = \theta_0 + \theta C_{t-1} + \theta\delta C_{t+1} - \theta_1[1+(1-\gamma)^2\delta]P_t + \theta_1(1-\gamma)P_{t-1} + \theta_1(1-\gamma)\delta P_{t+1} + \theta_2 e_t + \theta_3 e_{t+1} \tag{3}$$

Equation (3) is a generalization of equation (2). A serious problem in estimating this general specification is the likely high collinearity between prices, possibly resulting in low statistical significance of the relevant effects. To overcome this problem Becker et al. (1990)

[3] This is a standard assumption in the rational addiction literature. The quadratic specification delivers linear first-order conditions that allow for empirical estimation.

impose the restrictions implied by theory. In particular, since the ratio of future-to-past price effects is equal to the ratio of future-to-past consumption effects, i.e.

$$\frac{\frac{\partial C_t}{\partial P_{t+1}}}{\frac{\partial C_t}{\partial P_{t-1}}} = \frac{\frac{\partial C_t}{\partial C_{t+1}}}{\frac{\partial C_t}{\partial C_{t-1}}} = \delta,$$

the coefficients of P_{t+1} and C_{t+1} are equal to the respective past effects multiplied by the discount factor. Becker et al. (1994) and Chaloupka (1990) find that this restriction is valid and improves the statistical significance of the price and consumption coefficients. The difficult identification of price effects in the general specification explains why the vast empirical literature on rational addiction has focused on estimating the restricted equation (2). However, its great advantage is that it provides deeper insights into inter-temporal preferences, since we can estimate consumption responses to price changes at three different time periods.

Gruber & Köszegi (2000) proposed an alternative model which is also consistent with forward looking behavior, but embeds quasi-hyperbolic preferences (Laibson, 1997) and showed that tests of forward looking behavior *only* cannot distinguish the rational addiction model from their own. They also proposed a test of time consistency based on the idea that the responses to changes in prices at three different time periods could be used to distinguish time consistent from present biased consumers. The ratio of the responses to a two-periods-ahead price change and to a one-period-ahead price change should be the same if the individual is time consistent, but the response to a one-period-ahead price change should be smaller than the response to a two-periods-ahead price change if the individual is present biased. Unfortunately, Gruber & Köszegi (2000) could not implement this test with their data and the test disappeared from the published version of the paper (Gruber & Köszegi, 2001).

Building on this previous contribution, we show that, by introducing quasi-hyperbolic discounting into the general version of the rational addiction model, it is possible to develop an easy test allowing to distinguish TCs from naïfs consumers. In addition, we borrow the idea behind the test proposed by Gruber & Köszegi (2000) and adapt it to our theoretical framework, giving it a slightly different interpretation.

4 Quasi-Hyperbolic Discounting and the Test of Time Consistency

In what follows we embed quasi-hyperbolic discounting (Laibson, 1997) in the previous model. We solve the maximization problem step by step reproducing passages from Chaloupka (1990) mathematical appendix.

O'Donoghue & Rabin (1999b, 2002) show that, under stationarity of preferences, for both TCs and naïfs the infinite-horizon perception-perfect strategy is unique and corresponds to the unique finite-horizon perception-perfect strategy as the horizon, T, becomes long. Therefore, in what follows we will keep assuming an infinite time-horizon $T = \infty$ in part for expositional ease and in part because an infinite time horizon is the typical assumption in rational addiction models. Individuals are assumed to maximize the sum of lifetime discounted utility

$$Max\ U_t + \beta \sum_{i=1}^{\infty} \delta^i U_{t+i} = U_t + \beta\delta U_{t+1} + \beta\delta^2 U_{t+2} + ... \tag{4}$$

where $\delta = \frac{1}{(1+r)}$ is the long-run discount factor, r is the discount rate, and the extra discount parameter $\beta \in (0, 1]$ is intended to capture the essence of hyperbolic discounting, namely, that the discount factor between consecutive future periods (δ) is larger than between the current period and the next one ($\beta\delta$). If $\beta \neq 1$ preferences in equation (4) are dynamically inconsistent, in the sense that preferences at date t are inconsistent with preferences at date $t+1$.[4] To analyze equilibrium behavior when preferences are dynamically inconsistent researchers usually model a consumer as a sequence of temporal selves making choices in a dynamic game (Laibson, 1997; O'Donoghue & Rabin, 1999a, 1999b, 2002), as explained in Section 2. However, O'Donoghue & Rabin (2002) show that the equilibrium of both naïfs and TCs solves the same optimization problem. Therefore, the demand equation that solves (4) applies to both TCs and naïfs consumers. As before, interaction between past and future consumption is modeled by the investment function $A_t = (1 - \gamma)A_{t-1} + C_{t-1}$, with$\gamma < 1$. The consumer solves the maximization problem such that $C_0 = C^0$ and $(Y_t + P_t C_t) + \beta \sum_{i=1}^{\infty} \delta^i (Y_{t+i} + P_{t+i} C_{t+i}) = W_0$,

[4] Halevy (2015) shows that a decision maker is time consistent if and only if her preferences are both stationary and time invariant. Since preferences in our model are assumed to be stationary, our test of time consistency reduces to a test of time invariance. Time invariance requires preferences over future consumption streams to be the same in each evaluation period. See Halevy (2015) page 341 for a formal definition of time invariance.

where C^0 measures the level of addictive consumption in the period prior to that under consideration. The consumer's problem becomes:

$$\begin{aligned} &Max\ U_t(Y_t, C_t, A_t, e_t) + \beta \sum_{i=1}^{\infty} \delta^i U_{t+i}(Y_{t+i}, C_{t+i}, A_{t+i}, e_{t+i}) \\ &\quad s.t.\ \ (Y_t + P_t C_t) + \beta \sum_{i=1}^{\infty} \delta^i (Y_{t+i} + P_{t+i} C_{t+i}) = W_0 \end{aligned} \tag{5}$$

Taking a quadratic function in the three arguments, the resulting instantaneous utility is:

$$U_t = b_Y Y_t + b_C C_t + b_A A_t + \frac{1}{2} U_{YY} Y_t^2 + \frac{1}{2} U_{CC} C_t^2 + \frac{1}{2} U_{AA} A_t^2 + U_{YA} Y_t A_t + U_{CA} C_t A_t + U_{YC} Y_t C_t \tag{6}$$

The maximized value of utility becomes:

$$\begin{aligned} V^*(\cdot) = \max_{C_t, Y_t, A_t} &\Bigg\{ U_t(Y_t, C_t, A_t) + \beta \sum_{i=1}^{\infty} \delta^i U_{t+i}(Y_{t+i}, C_{t+i}, A_{t+i}) - \\ &\lambda \Bigg[(Y_t + P_t C_t) + \beta \sum_{i=1}^{\infty} \delta^i (Y_{t+i} + P_{t+i} C_{t+i}) - W_0 \Bigg] \Bigg\} \end{aligned} \tag{7}$$

which can be re-written as:

$$\begin{aligned} V^*(\cdot) = \lambda W_0 + \max_{C_t, Y_t, A_t} &\Bigg\{ U_t(Y_t, C_t, A_t) + \beta \sum_{i=1}^{\infty} \delta^i U_{t+i}(Y_{t+i}, C_{t+i}, A_{t+i}) - \\ &\lambda \Bigg[(Y_t + P_t C_t) + \beta \sum_{i=1}^{\infty} \delta^i (Y_{t+i} + P_{t+i} C_{t+i}) \Bigg] \Bigg\} \end{aligned}$$

where λ is the marginal utility of wealth. Maximizing (5) with respect to Y_t and subject to the budget constraint results in the following first order condition for Y_t:

$$Y_t = \frac{1}{U_{YY}} [\lambda - U_{YA} A_t - U_{YC} C_t - b_Y] \tag{8}$$

Plugging this result into (6) results in the maximization problem being a function of only consumption of the addictive good and the stock of the addictive good:

$$V^*(\cdot) = \lambda W_0 + \max_{C_t, A_t} \Bigg\{ F_t(C_t, A_t) + \beta \sum_{i=1}^{\infty} \delta^i F_{t+i}(C_{t+i}, A_{t+i}) \Bigg\} \tag{9}$$

where

$$F_t(C_t, A_t) = \alpha_k + \alpha_A A_t + \alpha_C C_t + \frac{1}{2}\alpha_{AA} A_t^2 + \frac{1}{2}\alpha_{CC} C_t^2 + \alpha_{CA} A_t C_t - \lambda P_t C_t \tag{10}$$

and

$$\begin{aligned}
\alpha_k &= -\frac{(\lambda - b_Y)^2}{2U_{YY}} \\
\alpha_A &= b_A - \frac{U_{YA}}{U_{YY}}(b_Y - \lambda) \\
\alpha_C &= b_C - \frac{U_{YC}}{U_{YY}}(b_Y - \lambda) \\
\alpha_{AA} &= U_{AA} - \frac{(U_{YA})^2}{U_{YY}} \\
\alpha_{CC} &= U_{CC} - \frac{(U_{YC})^2}{U_{YY}} \\
\alpha_{CA} &= U_{CA} - \frac{U_{YC}U_{YA}}{U_{YY}}
\end{aligned}$$

Considering $A_t = (1-\gamma)A_{t-1} + C_{t-1}$ and maximizing (9) with respect to C_t implies the following first-order condition:

$$\frac{\partial V(\cdot)}{\partial C_t} = \frac{\partial F_t(\cdot)}{\partial C_t} + \beta\delta \frac{\partial F_{t+1}(\cdot)}{\partial A_{t+1}} \frac{\partial A_{t+1}}{\partial C_t} + \beta\delta^2 \frac{\partial F_{t+2}(\cdot)}{\partial A_{t+2}} \frac{\partial A_{t+2}}{\partial A_{t+1}} \frac{\partial A_{t+1}}{\partial C_t} + ... = 0 \tag{11}$$

Noting that:

$$\frac{\partial F(C_t, A_t)}{\partial C_t} = [\alpha_C + \alpha_{CC} C_t + \alpha_{CA} A_t] - \lambda P_t \tag{12}$$

and

$$\frac{\partial F(C_t, A_t)}{\partial A_t} = \alpha_A + \alpha_{AA} A_t + \alpha_{CA} C_t \tag{13}$$

define the first term on the right hand side of (12) as $U_{C,t} = [\alpha_C + \alpha_{CC} C_t + \alpha_{CA} A_t]$ and the right hand side of (13) as $V_{A,t} = \alpha_A + \alpha_{AA} A_t + \alpha_{CA} C_t$. Substituting these definitions in equation (11) the first order condition can be rewritten as:

$$U_{C,t} = \lambda P_t - \beta\delta V_{A,t+1} - \beta\delta^2 V_{A,t+2}(1-\gamma) - ..... = \lambda P_t - \beta \sum_{i=1}^{\infty} V_{A,t+i}\delta^i(1-\gamma)^{i-1} \quad (14)$$

The consumption demand equation can be obtained starting from equation (14), as similar equations can be derived for each time period. Consider the differences $\delta(1-\gamma)U_{C,t} - U_{C,t-1}$ and $\delta(1-\gamma)U_{C,t+1} - U_{C,t}$. Using equation (14) they can be written as

$$\delta(1-\gamma)U_{C,t} - U_{C,t-1} = \lambda\delta(1-\gamma)P_t - \lambda P_{t-1} + \beta\delta V_{A,t} \quad (15)$$

$$\delta(1-\gamma)U_{C,t+1} - U_{C,t} = \lambda\delta(1-\gamma)P_{t+1} - \lambda P_t + \beta\delta V_{A,t+1}. \quad (16)$$

Now multiply both sides of equation (15) by $(1-\gamma)$ and subtract it from equation (16):

$$\delta(1-\gamma)U_{C,t+1} - U_{C,t} - \delta(1-\gamma)^2 U_{C,t} + (1-\gamma)U_{C,t-1} = \lambda\delta(1-\gamma)P_{t+1} - \lambda P_t + \beta\delta V_{A,t+1} - \Big[\lambda\delta(1-\gamma)^2 P_t - \lambda(1-\gamma)P_{t-1} + \beta\delta(1-\gamma)V_{A,t}\Big]. \quad (17)$$

Substituting $U_{C,i}$ and $V_{A,i}$ with their definitions, using $A_t = (1-\gamma)A_{t-1} + C_{t-1}$ to eliminate the stock of habits, and solving for C_t produces the demand equation:

$$C_t = \theta_0 + \theta^- C_{t-1} + \theta^+ \delta C_{t+1} - \theta_1\left[1 + (1-\gamma)^2\delta\right] P_t + \theta_1(1-\gamma)P_{t-1} + \theta_1\delta(1-\gamma)P_{t+1} \quad (18)$$

where:

$$\Omega = \alpha_{CA}(1+\beta)\delta(1-\gamma) - \alpha_{AA}\beta\delta - \alpha_{CC}\left[1 + \delta(1-\gamma)^2\right] > 0 \quad (19)$$

$$\theta_0 = \frac{\gamma}{\Omega}\Big[\alpha_C\big(\delta(1-\gamma) - 1\big) - \alpha_A\beta\delta\Big] \quad (20)$$

$$\theta^- = \frac{1}{\Omega}\Big[\alpha_{CA} - \alpha_{CC}(1-\gamma)\Big] > 0 \quad (21)$$

$$\theta^+ = \frac{1}{\Omega}\Big[\beta\alpha_{CA} - \alpha_{CC}(1-\gamma)\Big] > 0 \quad (22)$$

$$\theta_1 = \frac{\lambda}{\Omega} > 0 \quad (23)$$

Equation (18) is very similar to equation (3) except that the coefficient θ that multiplies

C_{t+1} and C_{t-1} is not exactly the same. The difference between θ^- and θ^+ is that the α_{CA} parameter in equation (22) is multiplied by β.

5 Testing Time Consistency

Noting that $\beta = 1$ implies time consistency and the model reduces to the standard BGM rational addition model, equation (18) can thus be used to test whether consumers are time consistent or not by testing the equality $\theta^- = \theta^+$.

Recalling that the empirical reduced form of the demand equation (18) is identical to the general formulation of the rational addiction demand equation, i.e.[5]

$$C_{it} = \phi_0 + \phi_1 C_{it-1} + \phi_2 \; C_{it+1} + \phi_3 P_{it} + \phi_4 P_{it-1} + \phi_5 P_{it+1} + \phi_6 e_t + \phi_7 e_{t+1} \tag{24}$$

it is possible to identify all needed coefficients.

$$\begin{aligned}
\delta &= \frac{\phi_5}{\phi_4} \\
\theta^- &= \phi_1 \\
\theta^+ &= \frac{\phi_2}{\delta} = \frac{\phi_2 \phi_4}{\phi_5}
\end{aligned}$$

and the test of time consistency reduces to a non linear hypothesis test on the estimated parameters, i.e. that $\phi_1\phi_5 = \phi_2\phi_4$. If the test rejects the null, then $\beta \neq 1$ and the data do not support time consistent preferences –as implied by the BGM rational addiction model– in favor of quasi-hyperbolic discounting for naïve agents.

Given the parametric specification of equation (18) and the corresponding reduced form equation (24), it is not possible to directly identify the value of present bias parameter β. It is however possible to extract further information about it, and in particular an upper limit compatible with the estimated coefficients. From equations (21) and (22), the ratio of consumption coefficients can be written as

$$\frac{\theta^+}{\theta^-} = \frac{\beta\alpha_{CA} - \alpha_{CC}(1-\gamma)}{\alpha_{CA} - \alpha_{CC}(1-\gamma)}, \tag{25}$$

[5]For simplicity of exposition, we omit from the equation further covariates, which will be introduced later in the empirical section.

from which an expression for β can be obtained, i.e.

$$\beta = \frac{\theta^+}{\theta^-} + \left(1 - \frac{\theta^+}{\theta^-}\right)(1-\gamma)\frac{\alpha_{CC}}{\alpha_{CA}} \tag{26}$$

Thus, β is a linear function of the unknown ratio α_{CC}/α_{CA}. If, as suggested by the theory, α_{CA} is positive, α_{CC} is negative, and $\beta \leq 1$, then by equations (21) and (22) the function is increasing in the α_{CC}/α_{CA} ratio, and a natural upper bound for equation (26) is hit when $\alpha_{CC} = 0$, i.e.

$$\beta^{max} = \frac{\widehat{\theta}^+}{\widehat{\theta}^-} = \frac{\phi_2\phi_4}{\phi_1\phi_5} \tag{27}$$

In the unpublished version of their paper, Gruber & Köszegi (2000) also developed a model that embeds the hyperbolic discounting preferences by Laibson (1997) and proposed a test of time consistency. Their test is based on the idea that the responses to changes in prices at three different time periods could be used to distinguish time consistent from hyperbolic discounters. We implement this test using model (24). This general specification allows calculation of the effects on consumption at time t of price changes at three different time periods (t-1, t and t+1). The consumption responses to price changes at different points in the future can be used to assess whether consumers discount exponentially or not. According to the authors, the ratio of the response to a current price change over a lagged price change should be the same as the ratio of the response to a one-period-ahead price change over the response to a current price change if consumers discount exponentially. The first ratio will be smaller than the second if in reality the underlying consumer is a hyperbolic discounter. The ratio of future-to-current and current-to-past price effects from equation (24) are

$$\frac{\frac{\partial C_t}{\partial P_{t+1}}}{\frac{\partial C_t}{\partial P_t}} = -\frac{\delta(1-\gamma)}{1+\delta(1-\gamma)^2} \tag{28}$$

$$\frac{\frac{\partial C_t}{\partial P_t}}{\frac{\partial C_t}{\partial P_{t-1}}} = -\frac{1+\delta(1-\gamma)^2}{(1-\gamma)} \tag{29}$$

Under the null hypothesis of time consistency, and conditional on an exogenous depreciation rate, the two ratios (28) and (29) are equal at a given significance level. In the results section we report the results of both tests.

6 Data and Empirical Strategy

6.1 Data preparation

The empirical analysis of cigarette addiction for Russia is based on 13 waves (from 2006 to 2018) of the Russia Longitudinal Monitoring Survey (RLMS-HSE). The survey is conducted by the Higher School of Economics and ZAO Demoscop together with the Carolina Population Center and follows individuals and their families from childhood to adulthood.[6] Households participating in the survey were selected trough a multi-stage probability sampling procedure in order to guarantee cross-sectional national representativeness. Within each of the 38 primary sample unit (PSU), the population was stratified into urban and rural substrata in order to guarantee representativeness of the sample in both areas. The survey covers approx 5,000 hh; 12,000 adults and 2,000 children (aged up to 15 years) per wave.

To each individual aged 13 and above, the survey asks whether she/he smokes and if so the number of cigarettes smoked per day. This is the main consumption measure used in our study. The household questionnaire also asks about family tobacco expenditure and quantity, but that is at the household level and is not suitable for individual consumption analysis. The price variable is computed from the community questionnaire, where interviewers go to local stores in the community and check minimum and maximum prices of a large sample of commodities, including domestic and foreign branded cigarettes. Because several missing values are recorded at community level (if, for instance, no store had a particular item or if the store was closed), the price was averaged across communities within the same primary sample units to reduce the impact of measurement errors. Because the prices are at current level, and the survey does not provide consumer price indices do deflate prices, we compute a consumer price index at PSU level following the Törnqvist procedure (Törnqvist, 1936). The reference price is that of the Moscow PSU in 1998, and the index is computed on a wide set of food commodities, excluding tobacco and alcohol items. Cigarettes prices –together with other monetary variables described below– are then deflated using this consumer price index.

The original sample for years 2006 to 2018 is composed of 43,247 individuals and 237,579 observations, of which 9,179 individuals and 40,335 observations are in the child questionnaire, assigned to children up to 12, which does not record information on smoking. Retaining only

[6] More information can be found in the RLMS-HSE site: http://www.cpc.unc.edu/projects/rlms-hse.

Table 1: Evolution of consumption and price of cigarettes

	Nr. of cigarettes		Price of cigarettes	
Year	Mean	Std. Dev.	Mean	Std. Dev.
2006	15.4	8.0	10.8	3.5
2007	15.7	8.2	12.5	7.2
2008	15.5	8.2	12.3	5.4
2009	15.5	8.2	13.4	6.5
2010	15.7	8.6	16.9	7.8
2011	15.8	8.5	18.1	6.0
2012	16.1	8.5	19.4	5.3
2013	15.8	8.4	23.3	7.5
2014	15.1	8.1	23.6	6.1
2015	15.2	8.1	26.4	6.8
2016	14.9	7.7	28.0	6.2
2017	14.7	7.5	30.6	6.8
2018	14.3	7.3	32.2	12.4

smokers reduces the sample to 14,423 individuals and 60,754 observations, while selecting individuals in the age range 22-74 and keeping only singles or families with at most 2 children further restricts the sample to 11,415 individuals and 45,238 observations. Given that the estimation of the structural model requires the observation of at least three consecutive time periods for each individual, the actual estimation sample is composed of 5,924 individuals and 24,006 observations. When adding covariates –some of which are measured with a small number of missing values– the estimation sample is composed of 5,789 individuals and 22,346 observations.

The evolution of consumption and price of cigarettes in the estimation sample is presented in Table 1. Among smokers, the number of cigarettes per day is fairly stable, with a slight decrease only after 2012. The real price of a package of cigarettes instead shows a substantial increase over time, with a faster growth since 2010. This is in part due to a stronger anti-tobacco policies that resulted in increasing excise taxes starting in 2010, when nominal excises were about 6.6 rubles, to 2018 when excises were about 85.9 rubles.

This information would be sufficient to estimate the model presented in equation (24), but the introduction of control variables can improve the precision of estimates.[7] The list of

[7]In addition, as for most panel data surveys, also the RLMS suffers a certain level of attrition. According to Gerry & Papadopoulos (2015), who analyze years 2001-2010, the average yearly attrition rate is below 10%, but attrition is significantly correlated with some individual characteristics that makes a missing completely at

Table 2: Descriptive statistics of the control variables

Variable	Mean	Std. Dev.	Min	Max
Female	0.28	0.45	1	2
Age	42.70	12.60	22	74
BMI	25.66	4.68	12.17	61.14
Work hours in a typical working day	7.25	5.81	0	24
Chronic disease	0.51	0.50	0	1
Share of children and teens by PSU	0.23	0.04	0.12	0.32
Share of non-working population by PSU	0.43	0.07	0.27	0.89

control variables include: age, gender, labor market status (work hours in a typical working day) and characteristics (population share of non working individuals and share of children and teenagers), health variables (body mass index and having any chronic disease[8]), and the day of the week in which the individual was interviewed.

The descriptive statistics of the control variables for the estimation sample are reported on Table 2. The estimation sample is clearly male dominated (more than 70%), has an average age of about 43 and has an average body mass index of about 25.7, indicating that this sample of smokers tend to be overweight. The typical working day is only slightly above 7 hours, an average that includes non-working individuals and a small share of people that work 24 hours per day (in the days they work). Half of the sample is affected by at least one chronic disease, an expected figure as the list of included diseases is very large and some of them are relatively widespread in the population (eyes disease, diabetes, hypertension, allergies, and so on). The average PSU population is composed by 23% of children and teens, while on average about 43% of the PSU population does not work.[9] Finally, not shown in Table 2, interviews were carried on slightly more frequently on the weekend (18.3%) rather than on a working day (12.7%).

random assumption implausible. Given that several studies show relatively small attrition biases, in the current work instead of applying more rigorous and complex correction techniques, we opted to include in the list of control variables also those characteristics that proved to be relevant for attrition in Gerry & Papadopoulos (2015). Our working hypothesis is that if the parameters of interest do not vary substantially with the inclusion of these controls, then attrition should generate small biases.

[8]The questionnaire asks whether a doctor have ever diagnosed the following chronic diseases: hearth, lung, liver, kidney, stomach, spinal, diabetes, endocrine system, hypertension, joint, upper respiratory tract, neurological, eyes, gynecological, allergies, varicose veins, skin, cancer, urological and other. The indicator is equal to one if any of the listed diseases has been ever diagnosed.

[9]This indicator is not to be confused with the unemployment rate, it is computed summing all non-working individuals (including children, retired, unemployed and inactive) over the total PSU population.

6.2 Estimating the General Rational Addiction Model

Our empirical demand equation is a variant of equation (24):

$$C_{it} = \phi_0 + \phi_1 C_{it-1} + \phi_2 C_{it+1} + \phi_3 P_{it} + \phi_4 P_{it-1} + \phi_5 P_{it+1} + \phi_6 X_{it} + v_i + d_t + u_{it} \quad (30)$$

where C_{it} is the number of smoked cigarettes by individual i in period t, P_{it} is cigarettes real price, X_{it} is a vector of exogenous economic and socio-demographic variables that affect cigarettes consumption, v_i are individual fixed effects capturing time invariant preferences that are correlated with lead and lagged consumption and probably with other determinants of consumption, d_t are time fixed effects, and $u_{it} = \phi_7 e_t + \phi_8 e_{t+1}$ is the idiosyncratic error term. OLS estimates of the dynamic panel data equation (30) can suffer from an omitted variable bias due to unaccounted demand shifters that may also be serially correlated (Becker et al., 1994). To correct for the endogeneity bias we follow Arellano & Bond (1991) in using a GMM procedure to obtain the vector of parameters. The GMM estimators exploit a set of moment conditions between instrumental variables and time-varying disturbances. The basic idea is to take first-differences to deal with the unobserved fixed effects and then use the suitably lagged levels of the endogenous and predetermined variables as instruments for the first-differenced series, under the assumption that the error term in levels is spherical and taking into account the serial correlation induced by the first-difference transformation. This idea extends to the case of lags and leads of the dependent variable and to the case where serial correlation already exists in the error term of the original model, as in equation (30). After first differencing equation (30) becomes:

$$\Delta C_{it} = \phi_1 \Delta C_{it-1} + \phi_2 \Delta C_{it+1} + \phi_3 \Delta P_{it} + \phi_4 \Delta P_{it-1} + \phi_5 \Delta P_{it+1} + \phi_6 \Delta X_{it} + \phi_7 \Delta d_t + \Delta u_{it} \quad (31)$$

the strategy is to find a set of instruments Z_{it} that are uncorrelated with the first-differenced error term Δu_{it} and correlated with the regressors. By definition

$$\Delta u_{it} = \phi_7 \Delta e_t + \phi_8 \Delta e_{t+1} \quad (32)$$

for $i = 1, ..., N$ and $t = 3, ..., T-1$. Given the error term u_{it} in (32), the following moment conditions are available: $E(C_{it-s}\Delta u_{it}) = 0$ for $t = 4, ..., T-1$ and $s \geq 3$. This allows the use of lagged levels of observed consumption series dated $t-3$ and earlier as instruments for the first-differenced equation (31). The moment restrictions can be written in matrix form as $E(Z_i'\Delta u_i) = 0$ for $t = 4, ..., T-1$, where Δu_i is the $(T-4)$ vector $(\Delta u_{i4}, \Delta u_{i5}, ..., \Delta u_{iT-1})'$. $\Delta u_i = u_{it} - u_{it-1}$ and Z_i is a $(T-4) \times g$ block diagonal matrix, whose i^{th} block is given as

$$Z_i = \begin{pmatrix} C_{it} & 0 & 0 & \dots & 0 & \dots & 0 & \Delta W_{i4}' \\ 0 & C_{i1} & C_{i2} & \dots & 0 & \dots & 0 & \Delta W_{i5}' \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & C_{i1} & \dots & C_{iT-4} & \Delta W_{iT-1}' \end{pmatrix}.$$

where the block diagonal structure at each time period exploits all of the instruments available, concatenated to one-column first differenced exogenous regressors $\Delta W_{it}' = (\Delta P_{it}, \Delta P_{it-1}, \Delta P_{it+1}, \Delta X_{it})$ that act as instruments for themselves (Arellano & Bond, 1991).

Ever since the work of BGM on US cigarette consumption, past and future prices have been considered as natural instruments for lagged and lead consumption, as well. We maintain this pivotal option here.

The first-differenced GMM estimator is poorly behaved in terms of finite sample properties (bias and imprecision) when instruments are weak. This can occur here given that the lagged levels of consumption are usually only weakly correlated with subsequent first-differences. More plausible results and better finite sample properties can be obtained using a system-GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998). This augmented version exploits additional moment conditions, which are valid under mean stationarity of the initial condition. This assumption yields $(T-4)$ further linear moment conditions which allow the use of equations in levels with suitably lagged first-differences of the series as instruments

$$E(\Delta C_{it-2}u_{it}) = 0 \text{ for } t = 4, ..., T-1 \tag{33}$$

The complete system of moment conditions available can be expressed as $E(Z_i^{+'} u_i^+) = 0$, where $u_i^+ = (\Delta u_{i4}, ..., \Delta u_{iT-1}, u_{i4}, ..., u_{iT-1})'$. The instrument matrix for this system is

$$Z_i^+ = \begin{pmatrix} Z_i & 0 & 0 & \dots & 0 \\ 0 & \Delta C_{i2} & 0 & \dots & 0 \\ 0 & 0 & \Delta C_{i3} & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & \dots & \Delta C_{iT-3} \end{pmatrix}$$

Whether we actually need all these moment conditions is debatable, since in finite samples there is a bias/efficiency trade-off (Biørn & Klette, 1998). A large instruments collection, like that generated by the system GMM, over-fits the endogenous explanatory variables and weakens the power of the over-identification tests (Roodman, 2009b). Ziliak (1997) showed that GMM may perform better with suboptimal instruments and argued against using all available moments. We use only a subset of them and, after some experimentation, we report in the next section estimates using the following parsimonious matrix of instruments Z_i, which represents a compromise between theory, previous applied work and the characteristics of the data.

$$Z_i = \begin{pmatrix} C_{i1}, P_{i3}, P_{i5}, X_{i4} & 0 & \dots & 0 & \Delta W'_{i4} \\ 0 & C_{i2}, P_{i4}, P_{i6}, X_{i5} & \dots & 0 & \Delta W'_{i5} \\ \vdots & \vdots & \dots & \vdots & \vdots \\ 0 & 0 & \dots & C_{iT-4}, P_{iT-2}, P_{iT}, X_{iT-1} & \Delta W'_{iT-1} \end{pmatrix}$$

where the least informative lagged levels of consumption have been dropped[10].

The performance of system GMM in finite samples has been under scrutiny in the recent literature (Bun & Sarafidis, 2013; Bun & Kleibergen, 2013). One issue that has attracted attention is the credibility of the assumption described as "constant correlated effects" (cce) by Bun & Sarafidis (2013) and employed for deriving the additional moment conditions made available by system GMM[11]. This assumption requires the correlation between the variables and the unobserved time-invariant heterogeneity to be constant over time, $E(y_{it}\eta_i) = c_y$ and $E(x_{it}\eta_i) = c_x$, so that first-differenced variables are uncorrelated with the individual effects, $E(\Delta y_{it}\eta_i) = 0$ and $E(\Delta x_{it}\eta_i) = 0$ (Bun & Sarafidis, 2013, page 13). For this assumption to be

[10] Estimation was carried out using the xtabond2 routine of STATA version 15.

[11] This assumption is often labeled "mean stationarity" assumption. However, Bun & Sarafidis (2013) notice that this is a somewhat imprecise definition because the additional moment conditions in sys GMM do not require mean stationarity.

valid changes in the instrumenting variables must be uncorrelated with the fixed effects. In our context this means that throughout our study period deviations from steady state cigarettes consumption levels are not systematically related to unobserved fixed effects such as family background, genetics or (slowly varying) social norms about smoking, for example. The first of the two conditions, $E(\Delta y_{it}\eta_i) = 0$, is satisfied by theory as our demand equation is a steady state equation and $E(\Delta y_{it}) = 0$. Whether these conditions are satisfied is an empirical question. To test for the validity of the cce assumption we use difference overidentifying restrictions tests. In particular we use the difference between the overidentifying restrictions in system and difference GMM statistics.

7 Results and discussion

The empirical specification (30) uses the number of smoked cigarettes per day as the dependent variable restricting our sample to smokers only. All models are estimated for individuals between 22 and 74 years of age, for a household size not larger than 4 individuals and for thirteen waves: 2006 to 2018. The actual number of observations used in estimation varies depending on the specification, the estimator, and the instruments' choice. In our preferred specification we use 21,187 observations and 5,679 individuals.

The right-hand side variables are the lead and lag consumption, current, lead and lag real price of cigarettes at PSU level from the community questionnaire, and a number of socio-demographic characteristics described in Section 6. In all specifications we use time dummies to make the assumption of no correlation across individuals in the idiosyncratic disturbances more likely to hold (Roodman, 2009a).

To avoid istruments proliferation we limit the lags used in GMM-style instruments. Our chosen estimator is the system-GMM (Blundell & 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 using the Windmeijer (2005) correction.

In terms of empirical studies and finite sample properties of the GMM estimator, the choice of transformation used to remove individual effects is important. First differencing (FD) is one option, but Arellano & Bover (1995) propose 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. orthogonality among errors is preserved. Another practical difference is that the FOD transformation preserves the sample size in panels with gaps, where FD would reduce the number of observations (Roodman, 2009a).[12] Results under the FOD transformation method are reported in Table 3 for model (30) without and with covariates in columns 3 to 6. We report the instruments count and the p-value of the Hansen test for the joint validity of all instruments (Hansen p-value full) for all GMM estimators (columns 3 to 6). For SYS-GMM estimators (columns 4 and 6) we also report the p-value of the Hansen test for the validity of instruments used in the transformed model corresponding to DIFF-GMM (Hansen p-value transformed model), and the p-value of the Hansen test for the additional instruments used in SYS-GMM compared to DIFF-GMM (Difference-in-Hansen p-value). The latter tells us about the mean stationarity condition needed for the validity of the level instruments . Finally, we report the Arellano-Bond test for third-order serial correlations in the residuals.[13] We also estimated model (30) using OLS and Fixed Effects (FE) (columns 1 and 2 in Table 3) and no additional covariates. As Bond (2002) points out, while in the OLS regression the lagged dependent variable is positively correlated with the error, biasing its coefficient estimate upward, the opposite is the case in the FE model. Good estimates of the true parameters should therefore lie near the range between these values. Models in columns 3 and 4 of Table 3 use the DIFF-GMM estimator and the SYS-GMM estimator, respectively, on the specification with no covariates. Models in columns 5 and 6 use DIFF-GMM and SYS-GMM on the full specification.

Estimates reported for our preferred specification, System GMM with FOD and covariates (column 6 in Table 3), are consistent with the rational addiction framework. First, past

[12] Notice that precisely the same instruments set would be used to estimate the model in orthogonal deviations.

[13] As reported by Roodman (2009a), in general we check for serial correlation of order l in levels by looking for correlation of order $l+1$ in differences. Because in our model current consumption depends on both past and future consumption, this is an autoregressive process of order 2 (AR2) and we have second-order serial correlation by construction. So, for the validity of our instrument set, we need to detect no serial correlation of order 3 in the residuals.

consumption has a significant positive effect. Second, future consumption also has a significant positive effect, supporting the idea that smokers' behavior is forward looking. Third, the coefficient of lagged consumption is greater than the coefficient of lead consumption, giving rise to a positive discount rate. Fourth, we obtain a negative coefficient on the 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. Among the socio-demographic variables included, gender, level of education, the number of hours worked per day, monthly wage, the consumer price index, the amount of vodka consumed, and a dummy for whether the household lives in a rural area are all statistically significant and take on the expected sign. The p-values of the Hansen J statistic for over-identifying restrictions for the full model, of the additional instruments used in SYS-GMM compared to DIFF-GMM (i.e. the instruments for the level equation), and of the Difference-in-Hansen test are all consistent with the null hypothesis of no-overidentification. Finally, the Arellano-Bond test for third-order autocorrelation in the residuals does not detect third-order serial correlation.

Table 3: Estimates of the General Rational Addiction Models

Parameter	OLS (1)	Fixed Effects (2)	DIFF-GMM (3)	SYS-GMM (4)	DIFF-GMM (5)	SYS-GMM (6)
C_{t-1}	0.397***	0.071***	0.494***	0.446***	0.472***	0.438***
	(0.006)	(0.008)	(0.089)	(0.039)	(0.077)	(0.046)
C_{t+1}	0.400***	0.066***	0.314***	0.456***	0.246***	0.395***
	(0.009)	(0.009)	(0.072)	(0.045)	(0.075)	(0.051)
P_t	-0.007	0.001	-0.011	-0.022***	-0.006	-0.025***
	(0.005)	(0.005)	(0.009)	(0.008)	(0.009)	(0.009)
P_{t-1}	0.007	-0.023	0.100**	0.014	-0.025	0.038**
	(0.005)	(0.005)	(0.071)	(0.013)	(0.074)	(0.016)
P_{t+1}	-0.004	-0.001	0.131*	0.029**	0.079	0.030**
	(0.004)	(0.005)	(0.068)	(0.011)	(0.067)	(0.014)
Female						-0.539***
						(0.193)
Age					-0.261	0.020
					(0.483)	(0.002)
Age^2					-0.000	-0.000
					(0.001)	(0.000)
BMI					-0.092	-0.080
					(0.149)	(0.062)
BMI^2					0.002	0.002
					(0.002)	(0.001)
Work hours in a typical working day					0.099***	0.054***
					(0.035)	(0.019)
Years of education					0.015	-0.029***
					(0.033)	(0.011)
Monthly wage					0.000***	0.000***
					(0.000)	(0.000)
Dummy for rural area						0.270***
						(0.10)
Dummy for married individual					-0.431*	-0.005
					(0.246)	(0.077)
Consumption of Vodka					0.203**	0.177***
					(0.090)	(0.071)
Consumer Price Index					-0.019	0.332***
					(0.351)	(0.114)
Excise Taxes					0.029	0.019
					(0.084)	(0.017)
Time dummies	yes	yes	yes	yes	yes	yes
Constant	3.154***	11.507***	1.525			
	(0.159)	(0.285)	(1.683)			
Hansen p-value full			0.499	0.840	0.195	0.423
Hansen p-value transformed model				0.463		0.202
Difference-in-Hansen p-value				0.936		0.713
p-value Arellano-Bond test for AR(2) in FD			0.000	0.000	0.000	0.000
p-value Arellano-Bond test for AR(3) in FD			0.548	0.250	0.488	0.854
# Obs	47,058	47,048	18,467	24,006	15,896	21,187
Instruments count			155	303	167	317
Time consistency test $\chi^2(1)$						0.00
p-value						0.868
Gruber-Koszegi time consistency test $\chi^2(1)$						1.18
p-value						0.276

Notes: Robust SE in parentheses. Windmeijer correction used in models (3)-(6). $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

7.1 Time consistency test

We implemented the tests of time consistency on the estimated parameters from our preferred specification (model 4 in Table 3). As explained in section 5 our test boils down to testing the null hypothesis $\phi_1\phi_5 = \phi_2\phi_4$. Our test has a χ^2 distribution with 1 degree of freedom. We obtain a test statistics of $\chi^2(1) = 0.03$ with a $Prob > \chi^2 = 0.861$. Thus we accept the hypothesis of time consistency at the 5% level. Consistently with this result, the estimated upper bound for the present bias parameter β is $\beta^{max} = \frac{\widehat{\theta}^+}{\widehat{\theta}^-} = \frac{\phi_2\phi_4}{\phi_1\phi_5} = 1.124$.

As a further test of time preference we also tested the null hypothesis that the ratio of current-to-past responses to a price change is equal to the ratio of future-to-current responses to a price change, as suggested by Gruber & Köszegi (2000). The test is again distributed as a $\chi^2(1)$. We obtain $\chi^2(1) = 1.18$ with $Prob > \chi^2 = 0.276$, supporting again the hypothesis of time consistency.

The estimated discount factor $\delta = \phi_5/\phi_4 = 0.802$, which corresponds to a long run discount rate of 8.0%. This set of results seems to suggest a pretty standard time preference structure, with no evidence of time inconsistency and with a reasonably small discount rate.

7.2 Dynamics of Consumption

Our demand equation is a second-order difference equation in current consumption. The roots of this difference equation are useful for describing the dynamics of consumption and are positive if and only if consumption is addictive (Chaloupka, 1990). For equation (30) these roots are $\lambda_{1,2} = \frac{1 \pm \sqrt{1-4\phi_1\phi_2}}{2\phi_1}$ with $4\phi_1\phi_2 < 1$ from the assumption of concavity. BGM note that both roots are real and depend on the sign of ϕ_1 and ϕ_2. Both roots are positive if and only if consumption is addictive ($\phi_1 > 0$); both roots will be zero or negative otherwise. 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 affecting demand for cigarettes. In our preferred specification (system GMM with FOD) $\phi_1 = 0.393$ and both roots are positive ($\lambda_2 = 1.773$; $\lambda_1 = 0.508$), so cigarettes consumption is actually addictive.

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 (Chaloupka, 1990). Our results fulfill the first of these stability conditions as the sum of coefficients on past and future consumption is less than unity (0.833), while the sum of price coefficients is close to zero (0.043).[14]

8 Conclusion

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. Then, even when forward looking behavior is supported by data, 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 & Köszegi, 2001).

We show that the possibility of testing for time consistency is nested within the rational addiction demand equation. Rather than relying on additional assumptions or on a different theoretical or empirical framework, we use price effects and the rarely estimated general formulation of the rational addiction demand equation to implement a test of time consistency. The test's purpose is to check whether consumers behind our data reveal time consistent or naïve time inconsistent preferences. Our estimates of the general rational addiction demand equation conform to theory and our test of time consistency does not reject the hypothesis that consumers discount exponentially.

The value added of our contribution is to show that the possibility of distinguishing time consistent from time inconsistent naïve preferences is nestled within a rational addiction model with quasi-hyperbolic discounting. The information extracted from a general rational addiction demand equation is then sufficient to test for both forward looking behavior and time consistency of the underlying consumers.

This has relevant policy implications for the optimal taxation of addictive goods. As Gruber & Köszegi (2002, 2004) point out, when agents are time inconsistent positive taxation is optimal even in the absence of externalities, as time inconsistency will imply self-control

[14] In a recent paper Laporte et al. (2017) investigate whether the unstable root (λ_2) complicates the estimation of the rational addiction model even when the true data generating process possesses the true characteristics of rational addiction. In our case, however, the restrictions implied by theory are satisfied by the data without imposing constraints on the estimated parameters.

problems and the optimal future consumption path planned at time t will not be realized by the agent. Hence, in case of time inconsistent agents taxes on addictive goods are substantially larger than for time consistent consumers. O'Donoghue & Rabin (2006) considering non-addictive unhealthy goods with quasi-hyperbolic time preferences, shows that the optimal tax is proportional to $(1 - \beta)$ times the marginal health cost of consumption and that even very small levels of present bias (β close to 1) produce significantly large optimal taxes.

In this context, having the possibility of testing for time consistency can be of great value to the policy maker. In addition, the possibility of estimating at least an upper bound for the present bias parameter (β_{max}), would enable the policy maker to compute the lower bound of an optimal tax on addictive goods by extending O'Donoghue & Rabin (2006) optimal taxation model to addictive consumption. This would be an interesting avenue for future research.

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