ISSN 2282-6483

Alma Mater Studiorum - Università di Bologna
DEPARTMENT OF ECONOMICS

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Quaderni - Working Paper DSE N°1119

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March 28, 2018

Abstract

The rational addiction model is usually tested by estimating a linear second-order difference Euler equation, which may produce unreliable estimates. We show that a linear first-order difference equation is a better alternative. This empirical specification is appropriate under the reasonable assumption that people are uncertain about the time of their death, it is based on the same structural assumptions used in the literature, and it retains all policy implications of the deterministic rational addiction model. It is also empirically convenient because it is simple, it allows using efficient estimation strategies that do not require instrumental variables, and it is robust to the possible non-stationarity of the data. As an application we estimate the demand for smoking in the US from 1970 to 2016, and we show that it is consistent with the rational addiction model.

Keywords: Euler equation, Saddle-path, Uncertain lifetime, Dynamic panel quasi-maximum likelihood, Smoking

JEL codes: Dll, D12, I12, L66

*We thank Anastasia Arabadzhyan, Maria Elena Bontempi, John Cawley, Irene Mammi, Arsen Palestini, Giulio Zanella, Nicolas Ziebarth and the participants to the 2017 Workshop on Risky Health Behaviors in Hamburg, the Lunch Seminar at the University of Bologna

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"Testing Rational Addiction: When Lifetime is Uncertain, One Lag is Enough"

by Davide Dragone and Davide Raggi

Non-Technical Summary

Becker and Murphy (1988)'s theory of rational addiction is the reference model to study addictive behavior in the economic literature. The model predicts that current and past consumption of addictive goods are positively correlated, and that demand for addiction is sensitive to current and future prices. The latter prediction contradicts the widespread idea that an addict is insensitive to factors affecting the cost of addictive behavior, and it implies that policies changing the monetary price of an addictive good, its legal status or its social approval can significantly affect its consumption.

Since the early empirical contributions of Chaloupka (1991) and Becker et al. (1994), the rational addiction model has been tested using the Euler equation associated to the demand for addictive consumption. This empirical strategy has been used in most tests of the rational addiction hypothesis, with results that are consistent with the theoretical predictions of the model.

Recently, however, some contributions have cast doubts about its reliability and empirical validity. Auld and Grootendorst (2004) show that the rational addiction model may deliver spurious results when tested using aggregate data. Using the Euler equation to estimate the demand for goods such as milk and oranges, they obtain the surprising conclusion that these goods would be more addictive than cigarettes. Baltagi (2007) observe that, although the main predictions of the theory are consistent with the empirical findings obtained in the literature using a variety of addictive goods such as cigarettes, alcohol, and illicit drugs, the empirical results on the estimated interest rate yield implausible estimates. Laporte et al. (2017) suggest that these empirical incongruences are a consequence of the Euler equation describing an intrinsically unstable process. On the basis of this instability, they question the reliability and the testability of the theory of rational addiction.

In this paper we show that these limitations are only apparent, as they can be solved by using a different empirical model. Under the same assumptions used in the previous literature, we show that the theory of rational addiction can be estimated using an AR(1) empirical model that represents the intertemporal demand for an addictive good. This empirical strategy is theoretically justified under the reasonable assumption that lifetime is uncertain. By design, our specification does not suffer of the instability issues that would instead plague the Euler equation. In addition, it is particularly convenient for the empirical test of the model because it is simple, it allows using

efficient estimation strategies that do not require instrumental variables, and it is robust to the possible non-stationarity of the data (Hsiao et al., 2002).

As an illustration, we estimate the demand for smoking in the US, a classic application of the rational addiction model. We consider a relatively long time horizon (from 1970 to 2016), over which the non stationarity assumptions required to apply the methods of Arellano and Bond (1991) and Arellano and Bover (1995) may not hold, and we compare our empirical model with possible competitors such as a model of non-addictive consumption (in which consumption only depends on current price but not on past consumption or on future prices), a model of myopic addictive consumption (in which the good is addictive but the agent does not realize the future consequences of current consumption), and the standard empirical model of rational addiction estimated through the Euler equation. Our results are consistent with the rational addiction theory. Considering our favorite specification –the AR(1) model estimated through Quasi-Maximum Likelihood–, we find that cigarettes are strongly addictive, with a short run price elasticity of cigarettes of about -0.65%, and a long run price elasticity of about -2.61%.

Keywords: Euler equation, Saddle-path, Uncertain lifetime, Dynamic panel quasi-maximum likelihood, Smoking

JEL codes: Dll, D12, I12, L66

1 Introduction

The Becker and Murphy (1988)'s model of rational addiction is the reference model to study addictive behavior in the context of rational choice theory. It predicts that current and past consumption of addictive goods are positively correlated, and that demand for addiction is sensitive to current and future prices. The former prediction, also known as adjacent complementarity (Ryder and Heal, 1973), is due to addiction entailing a form of learning in consumption, so that the current taste for addictive goods depends on past consumption choices. The latter prediction has the appealing policy implication that consumption of an addictive good can be deterred, or stimulated, by affecting the associated costs and benefits through, e.g., taxation, police enforcement or changes in the legal status of the good (Becker and Murphy, 1988; Becker et al., 1991).[1]

Since the early empirical contributions of Chaloupka (1991) and Becker et al. (1994), the rational addiction model has been tested using the Euler equation associated to the demand for addictive consumption. Under a linear-quadratic framework, the Euler equation relates consumption in three adjacent periods. For its empirical convenience this specification has been, and still is, the main reference for the empirical analysis of the theory of rational addiction (see Grossman, 1993; Chaloupka, 1996; Chaloupka and Warner, 2000; Cawley and Ruhm, 2012).[2]

Testing the rational addiction model using the Euler equation, however, is potentially problematic. The reason is that the Euler equation describes a necessary condition that is fulfilled by an infinite number of candidate optimal solutions, and all of them (but one) describe consumption paths that explode as time advances. As illustrated in Laporte et al. (2017), estimating the parameters associated to explosive solutions may lead to noisy and unreliable estimates, in particular when the time window of observation is large.

As a better alternative to the Euler equation, we propose to test the rational addiction model using a linear first-order difference equation in which current consumption depends on past consumption. This AR(1) empirical model is simple, it is theoretically justified as the solution of a stochastic rational addiction model where individuals have finite lives, but they do not know when death will occur,[3] and it provides a theoretically-founded bridge between the different modeling

[1] This view is in contrast with the alternative perspectives which posit the addicts' behavior is irrational and insensitive to incentives (Rachlin, 1997), or with the myopic models of addiction where agents do not anticipate the future consequences of current consumption choices (Pollak, 1970).

[2] A notable exception is Baltagi and Levin (1986), whose main empirical model is a linear first-order difference equation that is comparable to our proposal. Their empirical approach was not accompanied by a theoretical foundation (the rational addiction model was published two years later), and in the subsequent works it has been dropped in favor of the Euler equation (Baltagi and Griffin, 2001; Baltagi and Geishecker, 2006; Baltagi, 2007).

[3] Consideration of a stochastic scenario where people have uncertain lifetime has been used by, e.g., Yaari (1965) in

strategies used in the empirical and theoretical approach to rational addiction. On one hand, the empirical literature typically focuses on the Euler equation and a finite time-horizon, and then it lets the data speak (Chaloupka, 1991; Becker et al., 1994; Baltagi and Griffin, 2001; Baltagi, 2007). This approach is flexible because a single equation can parsimoniously describe an infinite number of different consumption trajectories. The drawback is that most of them are intrinsically explosive. When this is the case, shocks cumulate and amplify over time and the empirical estimates of the Euler equation become unreliable, an outcome that is more likely, the larger the time window of observation (Laporte et al., 2017). On the other hand, the theoretical literature on rational addiction typically focuses on an infinite time-horizon (Becker and Murphy, 1988; Becker et al., 1991). This approach is analytically convenient and it allows restricting the attention to a specific consumption path (the saddle path), although infinity is not a realistic time-span.[4]

Our stochastic rational addiction model reconciles the apparent dichotomy between these modeling strategies because it provides a theoretical justification to select the saddle path as the demand function to be empirically estimated. The theoretical advantage is that this demand function does not feature explosive dynamics. This implies that temporary shocks will be dampened over time and that consumption will tend toward a stationary level, a prediction that is consistent with the empirical observation that consumers of addictive goods typically converge to stable consumption levels (Hser et al., 2008; Teesson et al., 2017). The empirical advantage is that, under assumptions typically used in the literature, the demand for an addictive good can be represented by a linear first-order difference equation. This solution nests the rational addiction model in Becker et al. (1994) as a special case, and it produces the same policy implications described by Becker and Murphy (1988) and popularized by the subsequent literature (see, e.g., Cawley and Ruhm, 2012). Moreover, it allows using standard panel data estimation strategies which are efficient, do not need instruments, and are able to deal with the possible non-stationarity of the data.

Our AR(1) empirical model allows to address and improve on three tests that have been commonly performed in the empirical literature on rational addiction. The first one is the test of

the context of consumption choice and life insurance, Blanchard (1985) in a macroeconomic overlapping generations model, Levy (2002) and Dragone (2009) for rational eating, Dragone and Strulik (2017) in the context of aging and health behavior.

[4]On the different modeling strategies, Laporte et al. (2017) observe that "it is not uncommon for theoretical exercises to assume an infinite horizon, for expositional simplicity. In empirical rational addiction research, however, it clearly makes no sense to assume that our individual is fully rational in every way with the minor exception that she fully believes that she will live forever. If she is going to be a rational addict, she has to face up to the finiteness of her life."

adjacent complementarity in consumption. In the empirical literature this test has been based on the sign of the lead and lag coefficients of the Euler equation. The specification we propose can perform the same exercise, but it is more reliable because the possibility of explosive dynamics cannot arise by design. In particular, differently from the Euler equation, the reliability of the empirical estimates neither depends on the length of the time window of observation, nor on the level of experience with the addictive good.

The second test concerns the forward-looking property that current consumption is related to announced future prices. Our formulation allows to perform the same test, with the empirical advantages just mentioned. Moreover we can show that the response to a temporary, non-contemporaneous price increase is positive if the good is weakly addictive. This surprising result depends on the forward-looking nature of the problem, and it extends the results on temporary price changes presented in Becker et al. (1994), who focus on strongly addictive goods only.

The third test concerns inferring the agent's discount factor using the estimates of the empirical model. We do not rely on the formula used in the empirical literature, which infers the discount factor from the ratio of the estimated lead and lag parameters of an AR(2) empirical model, because this exercise is not valid in general. In fact, an AR(2) specification does not uniquely identify the Euler equation of the model. It could, instead, represent a second-order linear formulation of the saddle path solution. This alternative formulation does not allow computing the steady state, nor the discount factor, nor the response to permanent price changes. In particular, we show that with such formulation the lead and lag coefficients sum to one, which may explain the difficulties in the empirical literature in finding reasonable and significant estimates of the discount rate, and their large variability, when using an AR(2) empirical model (see Baltagi and Griffin, 2001, and Baltagi, 2007, for a discussion). Fortunately, these difficulties can be circumvented by using the estimated parameters of the AR(1) model we propose.

The paper is structured as follows. In the next Section we present the stochastic rational model. In Section 3 we propose the demand function in AR(1) form to be used for the empirical exercise, in Section 4 we discuss possible alternative specifications and competitor models. In Section 5 we apply our model to estimate the demand for smoking in the US from 1970 to 2016. Section 6 concludes.

2 The stochastic rational addiction model

As a starting point, consider the deterministic rational addiction model presented by Chaloupka (1991) and Becker et al. (1994). Denote the per-period utility function as $U\left(c\left(t\right),q\left(t\right),A\left(t\right)\right)$, where $c(t)$ is consumption of an addictive good at time t, $q(t)$ is a composite non-addictive commodity, which is taken as the numeraire, and $A(t)$ is the stock of addiction, which evolves over time as follows,

$$A(t+1) = c(t) + (1-\delta) A(t). \tag{1}$$

The parameter $\delta \in [0,1]$ measures the degree of persistence of addiction.[5]

In a rational addiction model preferences feature reinforcement, which implies that the consumer learns to appreciate a good the more she has consumed it in the past ($U_{cA} > 0$). When the addictive good is harmful, past consumption reduces utility ($U_A < 0$), everything else equal. This it typically the case of smoking, narcotics and alcohol. The model, however, is flexible enough to allow for beneficial addiction and good habits, such as physical exercise or taste for good music (Stigler and Becker, 1977), in which case $U_A > 0$.[6] The per-period utility function is increasing in the consumption of the addictive good and of the non-addictive commodity $(U_c, U_q > 0)$, and it is concave.

Starting from the seminal works of Becker and Murphy (1988), Becker et al. (1991), Chaloupka (1991) and Becker et al. (1994), the literature has mostly focused on a linear-quadratic utility function. This specification is convenient because it produces linear first order conditions, and it can be justified as a local second-order approximation of the individual utility function. In the proceeding we will consider the following specification,

$$U(t) = \mathfrak{u}_c c(t) + \mathfrak{u}_A A(t) + \frac{\mathfrak{u}_{cc}}{2} c^2(t) + \frac{\mathfrak{u}_{AA}}{2} A^2(t) + \frac{\mathfrak{u}_{cA}}{2} c(t) A(t) + \mathfrak{u}_q q(t), \tag{2}$$

with $\mathfrak{u}_c, \mathfrak{u}_q > 0$, $\mathfrak{u}_{cc}, \mathfrak{u}_{AA} < 0$ and $\mathfrak{u}_{cA} > 0$.

For later reference, let $\bar{\mathfrak{u}} = \frac{(1-\delta)\beta \mathfrak{u}_{AA}}{(1-\delta)^2 \beta - 1}$ and denote as *strong addiction* the case $\mathfrak{u}_{cA} > \bar{\mathfrak{u}}$, and as *weak addiction* the case $0 < \mathfrak{u}_{cA} < \bar{\mathfrak{u}}$.

In each period t the agent faces the budget constraint

$$M(t) = p(t) c(t) + q(t), \tag{3}$$

where $M(t)$ is income and $p(t)$ is the price of the addictive good at time t.[7] Expectations about future prices are assumed to be rational.

[5] In Becker et al. (1994) today's addiction only depends on yesterday's consumption, but not on consumption in the previous periods, i.e. $\delta = 1$.

[6] Past consumption of the addictive good might also affect productivity on the job and earnings. For simplicity we ignore this possibility. The case where $U_A = U_{cA} = 0$ corresponds to the case in which past consumption has no effect on current utility, and the problem is essentially static.

[7] These assumptions are made for expositional simplicity because they imply that price changes will affect demand through substitution effects only, and that income and wealth effects are nil. This property does not alter the essence of the results, and it is commonly exploited in the literature focusing on Frisch demand functions, i.e. functions

The relevant time-horizon of the agent is her lifetime. We depart from the deterministic model of Chaloupka (1991) and Becker et al. (1994) by considering a stochastic environment in which lifetime is uncertain. Accordingly, the agent's objective is to choose the path of consumption that maximizes the following expected intertemporal utility function,

$$\mathbb{E}_T\left[\sum_{t=1}^{T} U\left(c\left(t\right), q\left(t\right), A\left(t\right)\right)\right], \tag{4}$$

subject to (1) to (3), and $c(0) = c_0$. We assume that the time of death T is a random event, and that there is no predetermined "expiration date" in which a person will die with certainty. We will refer to the above problem as the stochastic rational addiction model.

3 The demand for addiction

To solve the stochastic rational addiction model presented in the previous Section, we exploit a well-known property of uncertain lifetime models (see e.g., Yaari, 1965; Blanchard, 1985; Dragone and Strulik, 2017), which allows to rewrite the expected intertemporal utility function (4) as the following intertemporal expected utility function (details are in the Appendix):

$$\sum_{t=1}^{\bar{T}} S\left(t\right) U\left(c\left(t\right), q\left(t\right), A\left(t\right)\right). \tag{5}$$

The term $S(t) = \Pr(T \geq t)$ is the probability of being alive until time t, and $\bar{T}$ corresponds to the upper bound of the distribution of the time of death T. By definition, the survival probability is decreasing in t. Survival functions commonly used in demography and epidemiology are the exponential distribution, the Weibull distribution, the logistic distribution and the Gompertz-Makeham law. They assume that there is no finite time-horizon beyond which the probability of survival is zero; this "no expiration date" hypothesis is formally described by survival functions defined over an infinite time-horizon (i.e. $\bar{T} \to \infty$), and where the probability to observe large T quickly converges to zero (see Dragone and Strulik, 2017, for a discussion).

As in Yaari (1965), Blanchard (1985) and Mas-Colell et al. (1995), in the proceeding we assume that the survival function is exponential. Under this assumption, the future is discounted at a constant rate and the stochastic rational addiction model becomes isomorphic to the deterministic

in which the marginal utility of wealth is compensated to remain constant after a price shock (see, e.g. Becker and Murphy, 1988; Chaloupka, 1991; Becker et al., 1994). Our choice of using a fixed budget constraint and a quasi-linear specification produces the same result, without introducing Frisch compensation mechanisms.

version presented in Chaloupka (1991) and Becker et al. (1994).[8] Since the two problems are equivalent, the solution is the same. Note that, due to exponential discounting, the solution is time consistent, which means that the individual will stick to the original plan, in absence of new information, if she were allowed to re-optimize in some future period. This property is explicitly required by Becker and Murphy (1988) as the mark of rationality in the theory of rational addiction.[9]

As shown in the Appendix, the solution of the stochastic rational addiction model is a demand function that corresponds to the saddle path toward the steady state. In the following Proposition we present such demand function using an AR(1) formulation that is particularly convenient for the panel data analysis:

Proposition 1 (Saddle path - AR(1)) *The demand for an addictive good can be represented as*

$$c(t) = \lambda c(t-1) + \varphi_0 + \varphi_1 p(t-1) + \varphi_2 p(t) + \varphi_3 p(t+1) + \sum_{s=2}^{\infty} \varphi_4(s)\, p(t+s) \quad (6)$$

Proposition 1 shows that the demand for an addictive good can be represented as a function of yesterday's consumption, and of all prices starting from yesterday onwards. This linear AR(1) formulation can be used to test four main properties of the rational addiction model.

First, if the good is addictive ($U_{cA} > 0$), then $\lambda > 0$ and the good displays adjacent complementarity. Note that the demand function is asymptotically stable when λ is smaller than one (Chaloupka, 1991; Becker et al., 1994). When empirically satisfied, this property has desirable theoretical and empirical implications. On one hand, it ensures that the demand function does not suffer of the instability issues highlighted by Laporte et al. (2017), and of the associated concerns related to the testability of the rational addiction model. On the other hand, it ensures that the unit root test for panel data estimation is satisfied.

The second property is sensitivity to current price. If the good is addictive, today's consumption is negatively related to its contemporaneous price ($\varphi_2 < 0$), which essentially means that the law of demand is expected to hold even if the good is addictive.

The third property, forward looking behavior, is assessed by estimating whether the response of current demand to future prices is different from zero. A so far overlooked result is that the

[8]Note that, although the individual objective function (4) does not explicitly include a discount function representing the consumer's rate of impatience, the future weights less than the present, as if discounting were assumed from the onset. The reason is that uncertainty introduces the probability that future payoffs will not be enjoyed because of death.

[9]The requirement appears in the first line of the abstract of Becker and Murphy (1988), that states "We develop a theory of rational addiction in which rationality means a consistent plan to maximize utility over time".

sign of such response is ambiguous, as the response of time-t consumption to a price increase in a period $\tau \neq t$ depends on the degree of addictiveness of the good. If the good is strongly addictive, the sign of φ_3 and $\varphi_4(s)$ is negative. If instead the good is weakly addictive, then φ_3 and $\varphi_4(s)$ are *positive*.[10]

Based on the above observations, in the following Proposition we consider the effect on consumption of an unanticipated permanent change in price (see the Appendix for details).

Proposition 2 (Permanent price change) *Consider the demand for addiction described in model (6).*

- *The short and long-run responses of consumption to an unanticipated permanent price change are, respectively,*

$$C_p^S = \varphi_2 + \varphi_3 + \sum_{s=2}^{\infty} \varphi_4(s) < 0, \tag{7}$$

$$C_p^L = \frac{1}{1-\lambda}\left(\varphi_1 + C_p^S\right) < 0; \tag{8}$$

- *Demand is more sensitive in the long than in the short run if addiction is strong, and it is less sensitive in the long than in the short run if addiction is weak.*

The above Proposition (and the subsequent one) confirms one of the main policy implications of the rational addiction model: policies affecting the costs and benefits of consumption will affect its demand, even if the good features addiction. An additional result concerns the magnitude of the price elasticity: with weak addiction the elasticity of demand to a permanent price increase is *smaller* in the long than in the short run. With strong addiction, instead, the standard result of demand being more elastic in the long run than in the short run holds.

Consider now the effect of a temporary change in the price of the addictive good in period τ on consumption in period t:

[10] Strong and weak addiction can be equivalently described in terms of persistence of the addiction stock. Accordingly, the former case corresponds to a quickly vanishing stock of addiction ($1-\delta < \lambda$), and the latter one corresponds the stock of addiction being sufficiently persistent ($1-\delta > \lambda$). Becker et al. (1994), who consider the special case $\delta = 1$, provide results that fall into the strong addiction case. Due to this restriction, in their model future price changes are predicted to have a negative impact on current consumption. Note also that the term φ_1 is positive. This apparently counterintuitive result was already noted in Becker et al. (1990), Chaloupka (1991) and Becker et al. (1994), and it is an artifact of keeping yesterday's consumption fixed. In fact, when taking into account that yesterday's consumption recursively depends on $p(t-1)$, for given consumption at $t-2$, one can show that the effect of a transitory change announced and implemented at $t-1$ is $\varphi_1 + \lambda\varphi_2$, which is negative if addiction is not very persistent (or, equivalently, if addiction is strong), and positive otherwise, as shown in Proposition 3.

Proposition 3 (Temporary price change) *Consider a temporary price change at time τ.*

- *The response of demand at time $t = \tau$ is negative;*
- *The response of demand at time $t \neq \tau$ is negative when addiction is strong, and positive when addiction is weak.*
- *The response of demand is dampened over time.*

As expected, at the time in which the price increase occurs, consumption drops. An unexpected, and so far overlooked property, is that the elasticity of consumption to non-contemporaneous prices can be positive. This result is not due to income effects (which are ruled out by assumption), but to the forward-looking nature of the optimal consumption plan and to the degree of addictiveness of the good. For a graphical illustration of Proposition 3, consider Figure 1. At time

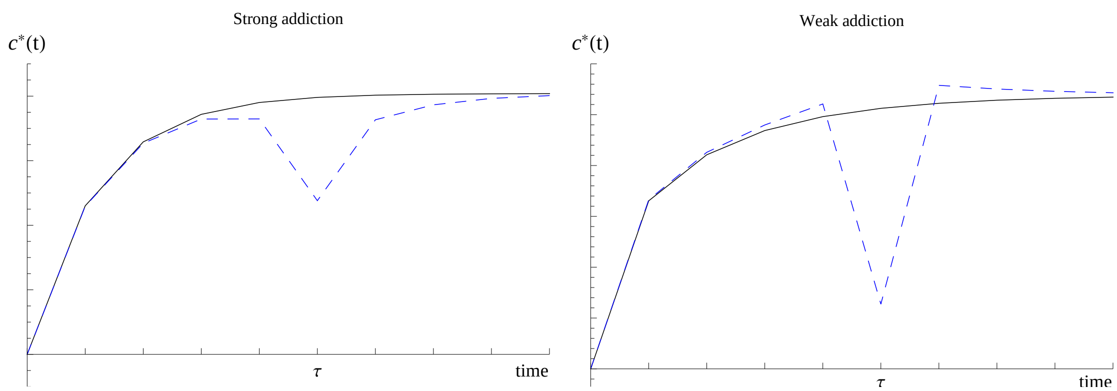

Figure 1: Effect of a temporary price increase announced at time 0 and occurring at time τ. Left panel, strong addiction: consumption decreases in all periods. Right panel, weak addiction: consumption increases in all periods, except in the period in which the price increases. In both cases the effects of the temporary shock are dampened over time.

0, a temporary price increase is announced to take place at time τ. The consumption path before the announcement is represented by the solid line, the revised consumption plan is the dashed line. In either case, consumption decreases in the period in which it becomes more expensive, i.e. at $t = \tau$. Depending on the degree of addictiveness of the good, two different consumption responses are possible before and after time τ. The left panel describes the case in which addiction is strong: the agent reduces consumption before and after τ, with a response that is larger in magnitude for periods closer to τ. Hence, although the price change is transitory, it produces lower consumption over the whole path, with the reduction being larger at time τ. This result extends Becker et al. (1994) to cases in which addiction is strong. The right panel describes the case in which addiction is weak: the individual increases consumption before and after τ, with a response that is larger in magnitude the closer the time of the price shock (dashed line). The revised consumption pattern is aimed at "stockpiling" addiction before the reduction in consumption occurring at time τ, and at recovering the addiction stock after the price shock has occurred. Overall, the optimal response to the announcement will be higher consumption (and higher addiction) before time τ, a drop in consumption (and in the addiction stock) at τ, and higher consumption (but lower addiction stock) after τ. Note that, due to the asymptotic stability of the saddle-path solution, the temporary price shock is absorbed and dampened as time advances.

A fourth property concerns the estimation of the discount factor β. Provided $\varphi_1 + \lambda\varphi_2 \neq 0$, the following holds:

Proposition 4 (Discount factor) *Using model (6), the discount factor can be estimated as follows:*

$$\beta = \frac{\varphi_3}{\varphi_1 + \lambda\varphi_2}. \tag{9}$$

The formula proposed in Proposition 4 is different from the one typically used in the empirical literature, which is instead based on the parameters of the Euler equation. On a theoretical ground, computing the discount factor β using equation (9) or using the Euler equation should yield the same value. Unfortunately, in the latter case the computation of β can be troublesome, as discussed in detail in the following Section.

4 Comparison with alternative empirical specifications

In this section we discuss three alternative empirical models. We first consider an AR(2) model and show that, although it could be used to test for adjacent complementarity and reinforcement, the interpretation of the coefficients and the estimation of the discount factor can be problematic and unreliable. Then we consider the competitor models of myopic addiction and of non-addictive consumption, with which the model of rational addiction is often compared to in the literature (Cawley and Ruhm, 2012).

4.1 AR(2) models: saddle path and Euler equation

In the empirical literature, the rational addiction model is usually tested by estimating the following Euler equation (Chaloupka, 1991; Becker et al., 1994):

$$c(t) = \theta c(t-1) + \theta_1 c(t+1) + \alpha_0 + \alpha_1 p(t-1) + \alpha_2 p(t) + \alpha_3 p(t+1). \tag{10}$$

As discussed in the introduction, and formally shown in the Appendix, this empirical approach can be problematic because the Euler equation features an unstable root which produces consumption trajectories that are intrinsically explosive. As a consequence, transitory shocks persist and amplify as time advances, making the empirical estimation of the structural parameters of the Euler equation potentially unreliable.[11]

As an illustration, consider Figure 2, which depicts some candidate solutions of the Euler equation. They are initially close to each other and they all diverge to $+\infty$ or $-\infty$ as time advances.

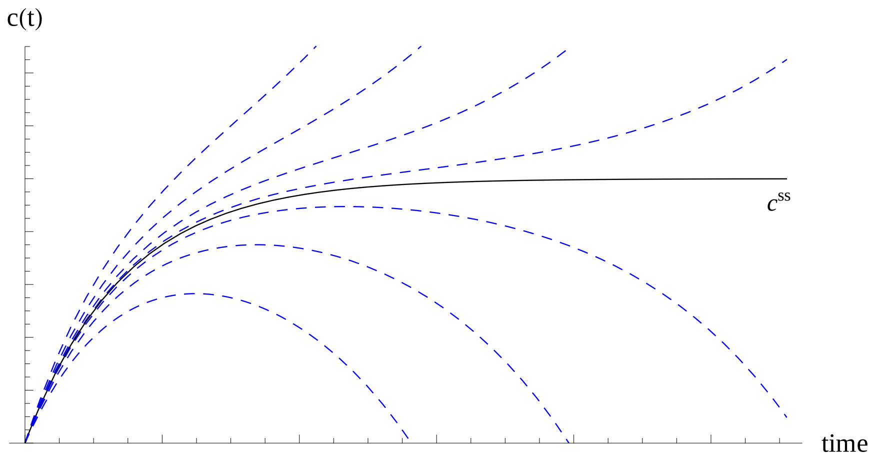

Figure 2: Candidate solutions of the Euler equation, given $c(0) = 0$, constant prices and different terminal conditions. The saddle path (solid line) ensures feasible consumption over any time-horizon. All other paths (dashed lines) are explosive and become unfeasible after some time.

The exception is the saddle path (solid line), which is the only trajectory ensuring that positive consumption levels are feasible over an arbitrarily-long time-horizon. Its asymptotic stability derives from the elimination of the unstable root of the Euler equation (see equations 28 and 33 in the Appendix), and it implies that transitory shocks will be dampened over time (as shown in Figure 1). Accordingly, the demand for addiction can be reliably estimated. For all other trajectories (dashed lines) the empirically observed consumption path and the theoretical demand function will get farther apart the longer the time-horizon of observation because transitory shocks persist and will amplify as time advances.

An additional caveat in using a second-order linear difference equation for testing the rational

[11] Laporte et al. (2017) make clear this point by generating Monte Carlo consumption trajectories that satisfy a known Euler equation, and showing that the coefficients estimated from these trajectories can be very different from the true parameters of the Euler equation that had generated those very trajectories. This outcome is more likely the longer the time window of observation.

addiction model concerns the interpretation of the estimated coefficients. The reason is that the saddle path solution of the model not only satisfies the Euler equation (10), but it also admits the following AR(2) representation:

$$c(t) = \xi c(t-1) + \xi_1 c(t+1) + \varepsilon_1 p(t-1) + \varepsilon_2 p(t) + \varepsilon_3 p(t+1) + \sum_{\tau=2}^{\infty} \varepsilon_4(\tau) p(t+\tau). \quad (11)$$

Both equations (10) and (11) have an AR(2) structure and, as shown in the Appendix, in principle they can both be used to test the rational addiction model by examining the signs of the coefficients of lead and lag consumption. In particular, (i) if the effect of past on current consumption is positive ($\xi, \theta > 0$), then the good is addictive and features adjacent complementarity, (ii) if the effect of future prices on current consumption is positive ($\xi_1, \theta_1 > 0$) the agent is forward-looking.

There are some notable differences between the two equations, though.[12] The main one concerns the relation between the lead and lag coefficients of consumption. When using the Euler equation, the ratio between the lead and lag coefficient can be used to compute the discount factor: $\theta_1/\theta = \beta$.[13] When using the saddle-path solution, instead, the ratio ξ_1/ξ can be any positive number because the coefficients of lead and lag consumption sum to one, $\xi + \xi_1 = 1$ (see equation 48). Accordingly, no obvious information about the discount factor can be obtained from the lead/lag ratio.

We can conclude that, without knowing whether one is estimating the Euler equation (10) or the solution of the model (11) in its AR(2) form, one cannot safely use the lead and lag coefficients of consumption of an AR(2) empirical model to estimate β. This holds *a fortiori* when the sum of the lead and lag coefficients is in the ballpark of 1 and when the empirical estimates of future prices are tiny, because in such a case the two empirical models become empirically indistinguishable. This finding may explain why the literature, when testing the theory of rational addiction using an AR(2) empirical model, has struggled to find convincing estimates of the discount factor β (Baltagi and Griffin, 2001; Baltagi and Geishecker, 2006; Baltagi, 2007).[14]

[12]Recall that the two equations have a different theoretical status: while equation (10) is an (intertemporal) necessary condition for optimality that is satisfied by infinitely many candidates, equation (11) is the optimal solution of the rational addiction model, i.e. it corresponds to the one candidate solution with asymptotic stability, as theoretically required by the "no expiration date"assumption discussed in Section 3.

[13]The latter property has been used as a restriction for the estimation of the price coefficients, see e.g. (Olekalns and Bardsley, 1996)). When addiction is not persistent ($\delta = 1$), parameters $\alpha_1 = \alpha_3 = 0$, as in Becker et al. (1994); Grossman and Chaloupka (1998); Liu et al. (1999); Bask and Melkersson (2004).

[14]A second difference between the Euler equation (10) and the solution of the model (11) is that $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \sum_{\tau=2}^{\infty} \varepsilon_4(\tau) = 0$. Hence, when prices are constant equation (11) becomes the identity $c(t) = \xi c(t-1) + (1-\xi) c(t+1)$, with the consequence that, from a theoretical point of view, one cannot compute the steady state

A final caveat when using an AR(2) model for the empirical estimation of rational addiction concerns the fact that, when the lead and lag coefficients sum to one, the underlying consumption process becomes non stationary.[15] This so far overlooked property implies that the non stationarity assumptions required to apply the methods of Arellano and Bond (1991) and Arellano and Bover (1995) may not hold.

4.2 Non-addictive consumption and myopic addiction

The theory of rational addiction can be contrasted with two alternative, competing models. The first one is a model of non-addictive consumption, in which only the contemporaneous price affects current consumption. Accordingly, the model is

$$c(t) = \eta_0 + \eta_1 p\,(t)\,, \tag{12}$$

where $\eta_1 = 1/\mathfrak{u}_{cc} < 0$. Since the non-addictive model is essentially static, the short and long run elasticities trivially coincide and are equal to η_1.

The second one is a model of myopic addiction, in which individual preferences are affected by past consumption choices, but the individual does not take into account the impact of current choices on future utility. It can be shown that in such a case optimal consumption features adjacent complementarity, as shown in the following equation:

$$c(t) = \mu c\,(t-1) + \mu_0 + \mu_1 p\,(t-1) + \mu_2 p\,(t) \tag{13}$$

with $\mu > 0, \mu_0, \mu_1 \geq 0, \mu_2 < 0$ (see Section A.5 for details). Equation (13) describes the myopic solution in backward-looking format, which relates current and *past* consumption and prices (Chaloupka, 1991). Alternatively, but equivalently, one can represent the myopic solution in forward-looking format,

$$c(t) = \tilde{\mu} c\,(t+1) + \tilde{\mu}_0 + \tilde{\mu}_1 p\,(t+1) + \tilde{\mu}_2 p\,(t)\,, \tag{14}$$

where myopic consumption depends on current and *future* consumption and prices.

Equation (14) shows that testing the myopic addiction model by checking the significance of the lead price coefficient cannot be taken as a test between the rational and the myopic addiction models, as instead claimed in Becker et al. (1994) and Chaloupka, 1991. It is however possible

level of consumption (see equation 52), nor study the effect of an unexpected permanent price change on short and long run consumption. See Section A.4 for details.

[15] Using the notation of (11): when $\xi + \xi_1 = 1$, the two roots associated to the consumption paths are 1 and $\xi/(1-\xi)$. The former is clearly on the unit circle, while the latter is larger than one if $\xi > 1/2$.

to discriminate between the two models by observing that in both formulations of myopic addiction, (13) and (14), current consumption does not depend on lag and lead prices *simultaneously*. Accordingly, a model in which consumption depends on both lead and lag variables is consistent with the rational addiction model, but not with myopic addiction.

Finally, note that neither the non-addictive model nor the myopic addiction model depend on the discount rate β. Accordingly, its value cannot be retrieved from the empirical estimation.

5 An application to smoking

To validate our model with real data, in this Section we present an empirical analysis of the consumption of cigarettes in the United States, a typical application of the theory of rational addiction since the seminal papers of Chaloupka (1991) and Becker et al. (1994). With respect to the previous contributions (Baltagi and Griffin, 2001, amongst others), we consider a relatively long time-span, consisting of yearly data for 51 US States from 1970 to 2016.[16]

Data on consumption c and average retail prices of cigarettes p have been obtained from Orzechowski and Walker (2017), whereas disposable income y for each State has been retrieved from the Bureau of Economic Analysis (BEA) of the US Department of Commerce. Prices and income are measured at constant 2010 prices.[17]

For testing rational addiction, we consider the following dynamic panel data model, that closely mimics the theoretical demand function defined in equation (6),

$$c_{it} = \lambda c_{it-1} + \varphi_{0i} + \varphi_1 p_{it-1} + \varphi_2 p_{it} + \varphi_3 p_{it+1} + \sum_{s=2}^{\infty} \varphi_4(s) p_{it+s} + \beta' X + \theta_t + \epsilon_{it}, \qquad (15)$$

where indexes $i \in \{1, \ldots, 51\}$ and $t \in \{1970, \ldots, 2016\}$ refer to the cross sectional and time dimensions, respectively, φ_{0i} is the usual fixed effect term, and θ_t indicates time dummies. The term $\epsilon_{it} = u_i + e_{it}$ is a combination of a time-invariant unit-specific error u_i, and of an idiosyncratic component e_{it}, described by i.i.d. normal disturbances with variance σ_e^2. We refer to the model above as the first-order autoregressive model, namely AR(1).

[16] The empirical literature testing rational addiction has typically focused on aggregate data. This approach has been criticized in Auld and Grootendorst (2004), who show that aggregation may deliver spurious results and lead to the surprising conclusion that goods such as milk and oranges would be more addictive than cigarettes. Laporte et al. (2017) observe, however, that Auld and Grootendorst (2004)'s empirical exercise suffers from non-stationarity in the data (with the exception of cigarettes), which makes the empirical evidence on milk and orange addiction questionable. Our dataset uses aggregate data, but it is not affected by stationarity issues, as shown below.

[17] To deflate data, we used the Consumer Price Index: Total All Items (CPALTT01USA661S) for the United States obtained from the FRED database.

To improve the quality of our estimates, we have also added to the theoretical specification some control variates, contained in the vector X. We consider nonlinear income effects and tobacco taxes. As previously proposed in Baltagi and Levin (1986), Baltagi and Griffin (2001) and, more recently, in Tauras et al. (2016), in order to reduce possible biases due to cross-border sales or bootlegging effects, we also include the minimum price np on neighboring States.[18] Following Baltagi and Griffin (2001), all the variables considered in the model are taken as exogenous.

Our AR(1) specification (eq. 15) differs from the empirical literature on rational addiction, in which a two lags specification is typically adopted. As previously discussed in Section 4.1, an AR(2) specification may allow to test for forward looking behavior by considering the estimated lead consumption term. The main empirical drawback of this choice is related to the endogeneity of c_{t+1}. To take it into account, researchers have typically relied on GMM-based estimators for inference, and in particular on the methods of Arellano and Bond (1991) and Arellano and Bover (1995), that have proved to be effective because of their flexibility and robustness with respect to endogeneity issues. However, in our experience with the dataset, the system-GMM approach of Arellano and Bover (1995) seems to be rather sensitive to the choice of instruments. In addition, these methods are particularly useful in the 'large N – small T' case, that is, when we observe a large number of statistical units (States) over a limited time horizon. This case corresponds to a different setup with respect to our framework, in which the sample includes 46 time periods. Finally, albeit the system-GMM estimation provides robust results even in case of highly persistent data, it still requires stationarity in the data. This condition might be restrictive and hard to realize, in particular on long time-spans of observation.

Here we take advantage of the AR(1) specification to deviate from GMM, by adopting a Quasi-Maximum Likelihood (QML) approach, proposed for dynamic random effect models in Bhargava and Sargan (1983) and subsequently extended to the fixed effects case in Hsiao et al. (2002). Despite the lack of flexibility of QML with respect to GMM, there are three main benefits from this choice. First, QML provides more efficient estimators for the coefficients, as it will be shown later. This allows to derive a more precise inference for the parameters of interest. Second, and most importantly, the method of Hsiao et al. (2002) appears to be more robust with respect to non stationary or highly persistent variables. As it will be stressed later, this is a particularly welcome feature, since both consumption and prices appear to be almost unit root processes. Third, we do not need to face the endogeneity issues that would be present when considering future levels of consumption.

[18]Consistent with the literature, we adopt the convention that the neighboring prices for Alaska and Hawaii are the same internal prices.

The main drawback of our empirical specification is that equation (15) explicitly depends on the whole set of future prices. Even assuming that they are exogenous and that beliefs about future prices are rational, this specification is empirically unfeasible because of the infinite number of regressors needed to describe the forward looking behavior of consumers. To make the empirical model practical, we make an additional hypothesis on the dynamics of prices, and we assume that they are described by a possibly persistent autoregressive process, namely,

$$p_t = \rho p_{t-1} + \tilde{u}_t, \tag{16}$$

where in particular $\tilde{u}_t$ is independent from ϵ_{it} and $|\rho| < 1$ to guarantee stationarity of prices. It is worth noting that assuming stationarity of prices is consistent with our data: once we control for time dummies, we obtain estimates for ρ ranging between .85 and .89, thus showing that the process is strongly persistent, albeit stationary. Moreover, also consumption tends to be highly persistent and stationary, as the autoregressive coefficient, once controlling for time dummies, ranges between .93 and .96. These evidences are consistent with some unit root tests we implemented, such as the Levin-Lin-Chu test (Levin et al., 2002). The stationarity of the variables used in our dataset contrasts with the crucial point raised in Laporte et al. (2017), in which the authors claim it might be questionable to validate rational addiction models through real aggregated data because of the explosive root of the dynamics involved. With our dataset, this turns out not to be the case, thereby allowing for a reliable inference analysis using standard estimation strategies. As a main consequence of hypothesis (16), future prices can be written as follows

$$p_{t+s} = \rho^{s-1} p_{t+1} + \sum_{j=1}^{s-1} \rho^{j-1} \tilde{u}_{t+s+1-j}, \qquad s > 1. \tag{17}$$

Hence, by plugging equation (17) into (15), we obtain

$$c_{it} = \lambda c_{it-1} + \varphi_{0i} + \varphi_1 p_{it-1} + \varphi_2 p_{it} + \tilde{\varphi}_3 p_{it+1} + \beta' X + \theta_t + \tilde{\epsilon}_{it} \tag{18}$$

where $\tilde{\epsilon}_{it}$ is a combination of the error term ϵ_{it} in equation (15) and of the future shocks $\tilde{u}_{t+1+j}$, $j \geq 1$, appearing in equation (17). It is worth noting that future shocks are unpredictable at $t+1$ and are therefore uncorrelated with p_{t+1}. Furthermore, assuming exogeneity of prices in equation (15), as suggested in Baltagi and Griffin (2001), that is, $\text{cov}(p_{t+1}, \epsilon_{it}) = 0$, leads to a null correlation between $\tilde{\epsilon}_{it}$ and p_{t+1}. This result is important, because it evidences that the future price p_{t+1} is still exogenous in equation (18), hence it allows to estimate the model without recurring to instrumental variables.

For the empirical exercise we consider three alternative models: (i) a static model of non-addictive consumption, described in equation (12), (ii) a model of myopic addiction, described

	Non-addictive	Myopic	Saddle path - AR(1)	Saddle path - AR(2)	Euler
$c(t-1)$		$+$	$+$	$+$	$+$
$c(t+1)$				$+$	$+$
$p(t-1)$		$+$	$+$	$+$	$+$
$p(t)$	$-$	$-$	$-$	$-$	$-$
$p(t+1)$			$\neq 0$	$\neq 0$	$+$
$p(t+s),\ s>1$			$\neq 0$	$\neq 0$	
β			$\frac{\varphi_3}{\varphi_1+\lambda\varphi_2}$	$\frac{\epsilon_1+\epsilon_2+\epsilon_3}{\epsilon_1+\xi\epsilon_2}\xi_1$	$\frac{\theta_1}{\theta}$
C_p^S	η_1	μ_2	$\varphi_2+\varphi_3+\sum\varphi_4$		$\alpha_2+\alpha_3$
C_p^L	η_1	$\frac{\mu_1+C_p^S}{1-\mu}$	$\frac{\varphi_1+C_p^S}{1-\lambda}$		$\frac{\alpha_1+C_p^S}{1-\theta-\theta_1}$

Table 1: Expected signs of the coefficients, and formulas for the discount rate β, the short run elasticity C_p^S and the long run elasticity C_p^L to a permanent unanticipated price increase. Models: non-addictive consumption (*eq.* 12), myopic addiction (eq. 13), and rational addiction: saddle path AR(1) (eq. 6), saddle path AR(2) (eq. 11), and Euler eq. (eq. 10).

in equation (13), and (iii) the rational addiction model, for which we consider three alternative specifications. The first one, which relies on the theoretical solution described in equation (6) and empirically implemented using model (18), corresponds to our preferred specification, namely the demand function (saddle path) represented in AR(1) form. The second one corresponds to the same solution, but represented as an AR(2) model, as described by equations (11) and (17). The third one is the Euler equation, described in equation (10), which has been the empirical reference for the literature on rational addiction since Becker et al. (1990) and Chaloupka (1991). Table 1 summarizes, for each model, the theoretical predictions on the sign of the corresponding coefficients, together with the formulas to compute the discount rate β, the short run elasticity C_p^S and the long run elasticity C_p^L to a permanent unanticipated price increase.[19]

For the empirical analysis, data are taken in log scale. All of the calculations in this Section are based on Stata (StataCorp., 2015). In particular QML estimation has been computed through the `xtdpdqml` package of Kripfganz (2016), whereas for the system-GMM procedure the package `xtabond2` of Roodman (2009) has been used. QML estimates are with robust standard errors with respect to cross sectional heteroskedasticity, as in Hayakawa and Pesaran (2015), whereas

[19]Table 1 extends the results presented in Table 3.6 of Cawley and Ruhm (2012) for the general case where $\delta \in [0, 1]$.

the system-GMM estimates are obtained through the Arellano and Bover (1995) method.[20]

The empirical results are reported in Table 2. The first two columns report estimates of the non-addictive and of the myopic models; columns 3 and 4 report the QML and the system-GMM estimates of the saddle path AR(1) specification. Finally, the last two columns display GMM estimates for the AR(2) specification of the demand function and for the Euler equation.

As a general result, all reported estimates are consistent with the predictions summarized in Table 1, thus providing empirical support on the theoretical credibility of all the parameterizations considered.

Estimates for our favorite model, namely, the saddle path AR(1) specification in Table 2, are reported in columns 3 and 4. We made inference through GMM and QML methods, to emphasize the gain in term of efficiency of QML. As a post-estimation diagnostic check, we analyzed the residuals of the estimated model. In both cases we find significant autocorrelation of the residuals at the first lag. It is instead negligible at subsequent lags, thus providing evidence in favor of serial independence of the original errors. In particular, the two methods provide similar point estimates, even though Quasi Maximum Likelihood strongly improves the efficiency, as shown by the smaller standard errors obtained.

The empirical results show that consumption is negatively related to its contemporaneous price, which means that the law of demand holds ($\varphi_2 < 0$). Furthermore, cigarettes represent an addictive good, since the coefficient of lagged consumption is positive ($\lambda > 0$). Consistent with our focus on asymptotically stable demand functions, λ is smaller than 1. This implies that consumption's trajectories are in fact non explosive, and they will converge to a stationary level of consumption. As observed in the introduction, this outcome is consistent even with the observed individual consumption trajectories of goods that are commonly considered strongly addictive such as, e.g., heroin, crack and cocaine (Hser et al., 2008; Teesson et al., 2017). The finding that the coefficient on future price ($\tilde{\varphi}_3$) is different from 0 provides evidence in favor of a forward looking behavior of agents. This evidence suggests that neither the myopic model, nor the non-addictive model (the estimates of which are reported in the first two columns of Table 2), are suitable to study these data. Moreover, since $\tilde{\varphi}_3$ is negative and statistically significant, cigarettes can be classified as a strongly addictive good (see Proposition 3).

As a side result, in Table 2 we also report the estimated discount factor β, that is about 0.78.[21]

[20] In these cases, instruments for the differences equation are the differenced exogenous variables, whereas for the levels equation the instruments are the level exogenous variables. As an additional check, we considered the GMM-style instruments corresponding to the lags 4 to 10 of taxation. This specification has been chosen so that both the Sargan and the Hansen test of over-identification restrictions allow not to reject the null hypothesis.

[21] In the literature, emphasis is often given to the discount rate $r = \frac{1}{\beta} - 1$, that we do not report for conciseness.

Table 2: Estimates of Rational Models of Addiction: Dependent Variable = c_t

	Non-addictive	Myopic	Saddle path - AR(1)	Saddle path - AR(1)	Saddle path - AR(2)	Euler
	Fixed Effect	QML	QML	GMM	GMM	GMM
c_{t-1}		0.938^{***}	0.933^{***}	0.900^{***}	0.453^{***}	0.465^{***}
		(0.0224)	(0.0218)	(0.0425)	(0.0349)	(0.0339)
c_{t+1}					0.489^{***}	0.488^{***}
					(0.0302)	(0.0282)
p_{t-1}		0.502^{***}	0.483^{***}	0.375^{***}	0.146^{**}	0.159^{**}
		(0.0501)	(0.0512)	(0.0967)	(0.0625)	(0.0644)
p_t	-0.958^{***}	-0.654^{***}	-0.597^{***}	-0.581^{***}	-0.514^{***}	-0.526^{***}
	(0.0392)	(0.0532)	(0.0620)	(0.103)	(0.0986)	(0.106)
p_{t+1}			-0.0582^{**}	-0.0982	0.252^{***}	0.234^{***}
			(0.0297)	(0.0768)	(0.0983)	(0.0772)
p_{t+2}					-0.0474	
					(0.0607)	
np_t	0.503^{***}	0.0830^{**}	0.0948^{***}	0.119^{**}	0.0491^{**}	0.0466^{**}
	(0.0402)	(0.0259)	(0.0260)	(0.0596)	(0.0228)	(0.0211)
y_t	21.34^{***}	1.352^{**}	1.483^{**}	0.430	-1.366	-0.220
	(0.997)	(0.701)	(0.690)	(3.120)	(1.990)	(1.633)
y_t^2	-1.013^{***}	-0.0632^{**}	-0.0695^{**}	-0.0206	0.0677	0.0115
	(0.0480)	(0.0338)	(0.0334)	(0.152)	(0.0972)	(0.0795)
tax_{t-1}	-0.206^{***}	0.0340^{***}	0.0347^{**}	0.0364	0.0171	0.0153
	(0.0231)	(0.0131)	(0.0135)	(0.0300)	(0.0183)	(0.0182)
β	–	–	0.7808	0.6648	0.4865^{*}	1.0491^{***}
			(0.6884)	(0.7584)	(0.2875)	(0.1214)
C_p^S	-0.958^{***}	-0.1523^{***}	-0.6554^{***}	-0.6791^{***}	$-.3092^{***}$	$-.2919^{***}$
	(0.0392)	(0.0365)	(0.0553)	(0.0824)	(.0766)	(.0697)
C_p^L	-0.958^{***}	-2.4680^{***}	-2.6118	-2.9372	-2.8155^{***}	-2.8357^{***}
	(0.0392)	(0.5014)	(1.6428)	(1.9497)	(0.9246)	(1.0901)

Column 1: static/non-addictive model, Column 2: myopic addiction, Columns 3 to 6 represent alternative specifications of the rational addiction model. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In terms of magnitude of the coefficient, this result is in line with Baltagi and Griffin (2001) and Becker et al. (1994). However, due to the high nonlinearity of the formula used to compute β (see equation 9 in Proposition 4), the standard errors are extremely large, thus making the point estimate imprecise and non statistically significant.

Because of the dynamic structure of the model, elasticities may vary depending on the time horizon and in correspondence of permanent or transient shocks. Using the formulas presented in Table 1, it is easy to compute short and long run unanticipated elasticities for consumption. Considering our favorite specification (the AR(1) model estimated through QML), the short run elasticity is $C_p^S = -0.6554\%$, and the long run elasticity is about -2.6118%. The long run estimates are remarkably similar for all the models considered, while in the short run the estimates sensibly differ, even though from a qualitative point of view all the evidences reported in Table 2 provide similar results. Note that the estimates are always larger for the long run elasticity than for the short run one (with the obvious exception of the non-addictive model), thereby providing additional evidence of cigarettes being strongly addictive (see Proposition 2). It is worth observing that, if one ignored the dynamic nature of addictive consumption, the static model of consumption would overestimate the short run price elasticity to a permanent price change, and it would underestimate the long run one, as shown in column 1.

For comparison purposes, we have also tested rational addiction using two AR(2) models: column 5 represents the demand function in AR(2) form and column 6 represents the Euler equation. As stated in Section 4.1, we would like to stress that both alternative specifications can be used to test rational addictive behavior, and that they are not in disagreement if the sum of leads and lag coefficients of consumption sum to 1. A standard F test does not reject this hypothesis, thus providing further evidence in favor of the AR(1) saddle path specification. It is worth noting that for the AR(2) specification of the saddle path, it is theoretically not possible to derive an expression to compute elasticities to permanent price changes. However, the econometric model allows to estimate these quantities, as reported in Table 2.

6 Conclusions

In their seminal contribution, Becker and Murphy (1988) describe the demand for an addictive good by considering an infinite time-horizon model. This modeling choice was admittedly made to simplify the discussion and it was essentially neglected in the subsequent empirical literature. In fact, the rational addiction model is usually tested estimating a second-order difference Euler

However our estimates of r are in line with Baltagi and Griffin (2001).

equation. As observed by Laporte et al. (2017), this approach can be problematic and yield unreliable estimates, due to the existence of unstable roots in the optimal consumption path. In addition, testing the rational addiction model based on an AR(2) model generates problems related to the correct interpretation of the estimated coefficients.

These features should not lead to the conclusion that the rational addiction model cannot be tested. Under the assumptions typically used in the literature, and under the reasonable assumption that agents that do not know when they die, we show that the rational addiction model can be tested using a first-order difference equation. With respect to the Euler equation used by the literature, our specification is simpler, it allows using more efficient estimation strategies, which do not require instrumental variables, and it is more robust to the possible non-stationarity of the data.

Our empirical model is theoretically grounded as the saddle-path solution of a stochastic rational addiction model, which has desirable asymptotic stability properties that solve the concerns raised by Laporte et al. (2017). Moreover, it allows for testing the main theoretical predictions of the rational addiction model, such as adjacent complementarity and forward looking behavior, and to show a so far overlooked result in which the effect of non-contemporaneous price increases can be either positive or negative, depending on the degree of addictiveness of the good.

In principle, one can still use an AR(2) empirical to test some features of the rational addiction model. The interpretation of the estimated parameters, however, is ambiguous, because an AR(2) specification can alternatively describe the Euler equation of the model or just be a second-order difference version of the demand for addiction. In the former case the empirical estimates are intrinsically unstable and potentially unreliable, while in the latter one the steady state (and the corresponding price elasticity) cannot be computed. In addition, we have shown that an exercise commonly performed in the literature, the estimation of the individual discount factor based on the ratio between lag and lead coefficients of an AR(2) empirical model, is not theoretically valid, which may explain why the empirical literature has struggled in finding convincing estimates of the discount factor. Since the empirical model used in the literature to test rational addiction is structural, there is no reason to use a specification that does not allow for a unique interpretation of the coefficients and that can yield unreliable empirical estimates. Fortunately, estimating the demand for addiction using a first-order difference equation solves all above difficulties.

Appendices

A Supplementary material: Theory

A.1 Demand for addiction: Proof of Proposition 1

Applying the definition of expected lifetime over an uncertain time of death T yields

$$\begin{aligned}\mathbb{E}\left[\sum_{t=1}^{T} U(t)\right] &= \sum_{\tau=1}^{\infty} \Pr(T=\tau) \sum_{t=1}^{\tau} U(t) = \sum_{t=1}^{\infty}\sum_{\tau=1}^{\infty} \Pr(T=\tau) U(t) \\ &= \sum_{t=1}^{\infty} \Pr(T \geq t) U(t) = \sum_{t=1}^{\infty} S(t) U(t). \end{aligned} \tag{19}$$

Hence expected intertemporal utility can be transformed into intertemporal expected utility.

To simplify the notation, let $\mathfrak{u}_q = 1$. If the survival function is exponential, $S(t) = \beta^{t-1}$, the objective function to maximize becomes $\sum_{t=1}^{\infty} \beta^{t-1} U(t)$ and the stochastic rational addiction problem becomes equivalent to the deterministic one. Hence the stochastic and deterministic rational addiction model feature the same Euler equation. As shown in Becker et al. (1990); Chaloupka (1991); Becker et al. (1994), the Euler equation is

$$c(t) = \theta c(t-1) + \theta_1 c(t+1) + \alpha_0 + \alpha_1 p(t-1) + \alpha_2 p(t) + \alpha_3 p(t+1) \tag{20}$$

where

$$\theta = \frac{\mathfrak{u}_{cA} - (1-\delta)\mathfrak{u}_{cc}}{\omega} > 0 \quad \text{if } \mathfrak{u}_{cA} > 0; \qquad \theta_1 = \beta\theta; \tag{21}$$

$$\alpha_0 = \delta \frac{\mathfrak{u}_c + \beta[\mathfrak{u}_A - (1-\delta)\mathfrak{u}_c]}{\omega}; \qquad \alpha_1 = \frac{1-\delta}{\omega} \geq 0; \tag{22}$$

$$\alpha_2 = -\frac{1 + (1-\delta)^2 \beta}{\omega} < 0; \qquad \alpha_3 = \beta\alpha_1 \geq 0; \tag{23}$$

$$\omega = \beta(1-\delta)[2\mathfrak{u}_{cA} - (1-\delta)\mathfrak{u}_{cc}] - \mathfrak{u}_{cc} - \beta\mathfrak{u}_{AA} > 0. \tag{24}$$

Using the Euler equation, the discount factor can be computed as the ratio between the coefficients of the lead and lag terms:

$$\beta = \frac{\theta_1}{\theta} = \frac{\alpha_3}{\alpha_1}. \tag{25}$$

The short and long-run responses to an anticipated permanent price change are (Chaloupka, 1991; Becker et al., 1994):

$$C_p^S = \alpha_2 + \alpha_3; \tag{26}$$

$$C_p^L = \frac{1}{1-\theta-\theta_1}\left(\alpha_1 + C_p^S\right). \tag{27}$$

Solving the Euler equation yields the following family of consumption paths:

$$c^*(t) = [c(0) - \mathcal{P}(0) - K]\lambda^t + K\lambda_1^t + \mathcal{P}(t), \qquad \text{for } t \geq 1, \tag{28}$$

where

$$\mathcal{P}(t) = \gamma_0 + \gamma_1 p(t) + \gamma_2 \sum_{s=1}^{\infty} \lambda^s [p(t-s) + \beta^s p(t+s)] \tag{29}$$

is a price index that depends on past, current and future prices,[22]

$$\lambda = \frac{1 - \sqrt{1 - 4\beta\theta^2}}{2\beta\theta}; \qquad \lambda_1 = \frac{1 + \sqrt{1 - 4\beta\theta^2}}{2\beta\theta}; \tag{30}$$

$$\gamma_0 = \frac{\alpha_0}{1 - (1+\beta)\theta} > 0; \qquad \gamma_1 = \frac{\alpha_1 + 2\beta\lambda\alpha_2}{1 - 2\beta\lambda\theta} < 0; \tag{31}$$

$$\gamma_2 = \gamma_1 + \frac{\alpha_2}{\theta} < 0 \quad \Leftrightarrow \quad 1 - \delta < \lambda \text{ and } \theta > 0; \tag{32}$$

and K is to be defined using the transversality condition. The roots λ and λ_1 of the Euler equation are positive if the good displays reinforcement. Saddle point stability requires both roots to be real and the smaller root λ to be smaller than one. The latter condition is more binding and requires $0 < \theta < \frac{1}{1+\beta}$, i.e. that reinforcement is not too strong. In the proceeding we assume this condition holds. Note that $\lambda_1 = 1/(\beta\lambda)$ and that the condition for strong addiction, which formally requires $\mathfrak{u}_{cA} > \frac{(1-\delta)\beta\mathfrak{u}_{AA}}{(1-\delta)^2\beta - 1}$, can be equivalently described as $1 - \delta < \lambda$. Analogously, weak addiction can be equivalently described by $1 - \delta > \lambda$.

The general solution (28) nests the solution presented in Becker et al. (1994), who consider the special case $\delta = 1$, and it satisfies the necessary conditions for optimality (including the Euler equation). The selection of the particular solution depends on the transversality condition, which determines the value of the constant K (see Fig. 2).

Selecting $K = 0$ eliminates the impact of the explosive root λ_1 and yields the demand function of the stochastic rational addiction model,

$$c^*(t) = [c(0) - \mathcal{P}(0)]\lambda^t + \mathcal{P}(t), \tag{33}$$

as a function of initial consumption, time and prices in all periods. This demand function corresponds to the saddle path to the steady state c^{ss} and is asymptotically stable, and it essentially represents the discrete-time equivalent of the theoretical solution of the deterministic rational addiction model presented in Becker and Murphy (1988). In contrast with the general solution (28) of the Euler equation, it does not contain explosive roots, hence it cannot be explosive as time advances.

[22] We assume that $\sum_{s=1}^{\infty} \lambda^s [p(t-s) + \beta^s p(t+s)]$ exists and is finite for all t. This property turns out to be satisfied in our empirical exercise.

To obtain the AR(1) version of the demand for addiction described in Proposition 1, shift equation (28) one period backward and solve for $c(0)$. Replacing back it into (28) and rearranging yields the empirical model:

$$c^*(t) = \lambda c^*(t-1) + \varphi_0 + \varphi_1 p(t-1) + \varphi_2 p(t) + \varphi_3 p(t+1) + \sum_{s=2}^{\infty} \varphi_4(s)\, p(t+s), \tag{34}$$

where

$$\varphi_0 = (1-\lambda)\gamma_0; \qquad \varphi_1 = (\gamma_2 - \gamma_1)\lambda \geq 0; \qquad \varphi_2 = \gamma_1 - \lambda^2 \beta \gamma_2 < 0; \tag{35}$$

$$\varphi_3 = \beta(\varphi_1 + \lambda\varphi_2); \qquad \varphi_4(s) = \varphi_3 (\beta\lambda)^{s-t-1}. \tag{36}$$

Note that φ_3 and $\varphi_4(s)$ are negative if and only if $1-\delta < \lambda$ (strong addiction). This is indeed the case considered in Becker et al. (1994).

The value of β presented in equation (9) is obtained using the definition of φ_3. Using φ_1, φ_2 and φ_3 and replacing the values of $\gamma_1, \gamma_2, \alpha_1$ and α_2 (equations 22, 31 and 30), one can also estimate the value of the depreciation parameter δ:

$$\delta = 1 - \Delta \tag{37}$$

where

$$\Delta = \frac{1}{2\varphi_1\varphi_3}\left(\Omega \pm \sqrt{\Omega^2 - 4(\varphi_1 + \lambda\varphi_2)\varphi_3\varphi_1^2}\right); \tag{38}$$

$$\Omega = \varphi_2(\varphi_1 + \lambda\varphi_2) - \lambda\varphi_1\varphi_3. \tag{39}$$

A.2 Permanent price change: Proof of Proposition 2

When prices are constant, consumption reaches the stationary level

$$c^{ss} = \frac{\varphi_0}{1-\lambda} + \frac{\varphi_1 + \varphi_2 + \varphi_3 + \sum_{s=2}^{\infty}\varphi_4(s)}{1-\lambda} p. \tag{40}$$

To prove Proposition 2, suppose that the price level is permanently and unexpectedly increased by x at time t, i.e. the new price vector is $(p(t)+x, p(t+1)+x, ...)$. The response of consumption to a completely unanticipated permanent change in price is:[23]

$$C_p^S = \varphi_2 + \varphi_3 + \sum_{s=2}^{\infty}\varphi_4(s) < 0. \tag{41}$$

The long run effect is

$$C_p^L \equiv \frac{\partial c^{ss}}{\partial x} = \frac{1}{1-\lambda}\left(\varphi_1 + C_p^S\right) < 0. \tag{42}$$

[23]The response of consumption at time t to a permanent price increase is $\frac{\partial c(t)}{\partial x} = \varphi_2 + \varphi_3 + \sum_{s=2}^{\infty}\varphi_4(s) = \varphi_2 + \frac{\lambda}{1-\lambda^2\beta}\varphi_3 + \frac{1-\lambda^{2t-1}\beta^{t-1}}{(1-\lambda^2\beta)(1-\lambda\beta)}\varphi_3$. At $t=1$, such response can be interpreted as the short-run effect, i.e. $C_p^S \equiv \frac{\partial c(1)}{\partial x}$ (see Becker et al., 1994), which results in equation 41.

A.3 Temporary price change: Proof of Proposition 3

Consider an announced, transitory change in price taking place at some τ and write the demand function (33) as follows:

$$c^*(t) = \gamma_0+\gamma_1 p(t)+\gamma_2\left(\sum_{z=0}^{t-1}\lambda^{t-z}p(z)+\sum_{z=t+1}^{\infty}\lambda_1^{t-z}p(z)\right)+\lambda^t\left(c(0)-\gamma_0-\gamma_1 p(0)-\gamma_2\sum_{z=1}^{\infty}\lambda_1^{-z}p(z)\right). \tag{43}$$

Hence:

$$\text{if } \tau = t: \qquad \frac{\partial c^*(t)}{\partial p(\tau)} = \gamma_1 - \left(\frac{\lambda}{\lambda_1}\right)^t \gamma_2 < 0 \tag{44}$$

$$\text{if } \tau > t: \qquad \frac{\partial c^*(t)}{\partial p(\tau)} = \left[1-\left(\frac{\lambda}{\lambda_1}\right)^t\right]\lambda_1^{t-\tau}\gamma_2 < 0 \quad \Leftrightarrow \quad \gamma_2 < 0 \tag{45}$$

$$\text{if } \tau < t: \qquad \frac{\partial c^*(t)}{\partial p(\tau)} = \left[1-\left(\frac{\lambda}{\lambda_1}\right)^\tau\right]\lambda^{t-\tau}\gamma_2 < 0 \quad \Leftrightarrow \quad \gamma_2 < 0 \tag{46}$$

A.4 AR(2) models: saddle path and Euler equation

The solution of the model solves the Euler equation by construction. To prove it formally, shift equation (34) one period forward and solve for $\sum_{s=2}^{\infty}\varphi_4(s)\,p(t+s)$. Replacing it back into (34) and rearranging yields the Euler equation reported in (20).

Importantly, the solution of the model can also be written as a second-order linear equation that does not represent the Euler equation. To see it, shift equation (34) one period forward and solve for φ_0. Replace into (34) and obtain the following second-order difference equation:

$$c(t) = \xi c(t-1) + \xi_1 c(t+1) + \varepsilon_1 p(t-1) + \varepsilon_2 p(t) + \varepsilon_3 p(t+1) + \sum_{\tau=2}^{\infty}\varepsilon_4(\tau)\,p(t+\tau) \tag{47}$$

where

$$\xi = \frac{\lambda}{1+\lambda}; \qquad \xi_1 = \frac{1}{1+\lambda} = 1-\xi \tag{48}$$

$$\varepsilon_1 = \frac{\lambda}{1+\lambda}(\gamma_2-\gamma_1) \geq 0; \qquad \varepsilon_2 = \gamma_1 - \frac{(1+\lambda_1)\lambda}{(1+\lambda)\lambda_1}\gamma_2; \tag{49}$$

$$\varepsilon_3 = \frac{\lambda}{1+\lambda}\left[\left(\frac{1}{\lambda_2}+\beta-\frac{1}{\lambda_1^2}\right)\gamma_2 - \frac{\gamma_1}{\lambda}\right]; \qquad \varepsilon_4(\tau) = \left(1+\lambda-\lambda_1-\frac{\lambda}{\lambda_1}\right)(\beta\lambda)^\tau\gamma_2. \tag{50}$$

If the good features reinforcement, the lead and lag coefficients of consumption are positive and ε_1 is non negative. Note that $\xi+\xi_1 = 1$ and $\varepsilon_1+\varepsilon_2+\varepsilon_3+\sum_{\tau=2}^{\infty}\varepsilon_4(\tau) = 0$.

By rearranging the above expressions, one can estimate β as follows:

$$\beta = \xi_1\frac{\varepsilon_1+\varepsilon_2+\varepsilon_3}{\varepsilon_1+(1-\xi_1)\varepsilon_2}. \tag{51}$$

To compute the response to an unanticipated permanent price increase, let $p(t)$ be constant over the whole time-horizon. In such a case, the price terms clear out, and (47) simplifies to

$$c(t) = \xi c(t-1) + \xi_1 (t+1). \tag{52}$$

Accordingly, the AR(2) version of the solution described (47) does not allow to unambiguously assess the short and long-run response to an anticipated permanent price change.

A.5 Myopic consumption

The agent maximizes her instantaneous utility by considering the stock of addiction as given and without considering the future consequences of current behavior. From the first order condition,

$$U_c(t) - p(t) = \mathfrak{u}_c + \mathfrak{u}_{cA} A(t) + \mathfrak{u}_{cc} c(t) - p(t) = 0, \tag{53}$$

one obtains optimal consumption at time t as a function of the current stock of addiction and price. Replacing

$$A(t) = -\frac{1}{\mathfrak{u}_{cA}} \left(\mathfrak{u}_{cc} c(t) + \mathfrak{u}_c - p(t)\right) \tag{54}$$

into the law of motion (1) yields

$$c(t) = \mu c(t-1) + \mu_0 + \mu_1 p(t-1) + \mu_2 p(t) \tag{55}$$

where

$$\mu = 1 - \delta - \frac{\mathfrak{u}_{cA}}{\mathfrak{u}_{cc}} > 0; \qquad \mu_0 = -\frac{\delta \mathfrak{u}_c}{\mathfrak{u}_{cc}} \geq 0; \tag{56}$$

$$\mu_1 = -\frac{1-\delta}{\mathfrak{u}_{cc}} \geq 0; \qquad \mu_2 = \frac{1}{\mathfrak{u}_{cc}} \leq 0; \tag{57}$$

or, equivalently,

$$c(t) = \tilde{\mu} c(t+1) + \tilde{\mu}_0 + \tilde{\mu}_1 p(t+1) + \tilde{\mu}_2 p(t) \tag{58}$$

where

$$\tilde{\mu} = \frac{1}{\mu}; \qquad \tilde{\mu}_0 = -\frac{\mu_0}{\mu}; \tag{59}$$

$$\tilde{\mu}_2 = -\frac{\mu_2}{\mu}; \qquad \tilde{\mu}_2 = -\frac{\mu_1}{\mu}. \tag{60}$$

The open-loop solution of (55) is

$$c(t) = \mu^t c(0) + \sum_{s=0}^{t-1} \mu^{t-s-1} \left[\mu_1 p(s+1) + \mu_2 p(s) + \mu_3\right]. \tag{61}$$

If $\mu < 1$, consumption converges to the stationary level

$$c^{**} = \frac{(\mu_1 + \mu_2)\, p + \mu_3}{1 - \mu}. \tag{62}$$

Suppose that the price level is permanently and unexpectedly increased by x at time t, i.e. the new price vector is $(p\,(t) + x, p\,(t+1) + x, ...)$. Note that it does not depend on β, which cannot be retrieved in this model. Using (55), the short and long-run effects of an anticipated permanent price change are, respectively,

$$C_p^S = \mu_2 < 0; \tag{63}$$

$$C_p^L = \frac{1}{1-\mu}\left(\mu_1 + C_p^S\right) < 0. \tag{64}$$

Hence the response is larger long-run than in the short-run: $\left|C_p^L\right| > \left|C_p^S\right|$.

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