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Resolving the Milk Addiction Paradox*

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Abstract

The milk addiction paradox refers to an empirical finding in which consumption of non-addictive commodities such as milk appears to be consistent with the theory of rational addiction. This paradoxical result seems more likely when consumption is persistent and with aggregate data. Using both simulated and real data, we show that the milk addiction paradox disappears when estimating the data using an AR(1) linear specification that describes the saddle-path solution of the rational addiction model, instead of the canonical AR(2) model. The AR(1) specification is able to correctly discriminate between rational addiction and simple persistence in the data, to test for the main features of rational addiction, and to produce unbiased estimates of the short and long-run elasticity of demand. These results hold both with individual and aggregated data, and they imply that the AR(1) model is a better empirical alternative for testing rational addiction than the canonical AR(2) model.

Keywords: Adjacent complementarity, Forward-looking behavior, Milk addiction, Rational addiction, Spurious correlation

JEL codes: Dll, D12, I12, L66

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1 Introduction

The milk addiction paradox refers to the surprising finding that the consumption of milk appears to be addictive when estimated using the empirical model of rational addiction of Becker et al. (1990, 1994). The spurious evidence on milk addiction seems to be more likely when the data are aggregated and serially correlated, two common features of time series (Auld and Grootendorst, 2004). The milk addiction paradox, and the additional observation that the canonical AR(2) addiction model features an explosive root (Laporte et al., 2017), has had wide resonance in the literature, and it has raised the question of whether the rational addiction model can be estimated altogether.

In this paper we provide a positive answer, and we show that the rational addiction theory can indeed be tested, provided one considers the AR(1) addiction model derived in Dragone and Raggi (2018), instead of the canonical AR(2) specification. Using both simulated and real data, we show that the AR(1) model is able to correctly discriminate rational addiction from simple persistence in the data. Moreover, it produces unbiased estimates of the short and long-run elasticity of demand. These results hold both with individual and aggregated data, and they are robust to the possible endogeneity of prices and of lagged consumption. They are likely due to the fact that the AR(1) model is stationary (while the AR(2) model is explosive) and that it does not suffer of the endogeneity concerns that arise when including lead consumption in the estimating equation.

To introduce the reader to the theoretical background, in section 2 we present the rational addition model and the two specifications used in the empirical literature: the AR(1) equation describing the saddle path solution of the model (Dragone and Raggi, 2018), and the AR(2) equation describing the corresponding Euler equation (Becker et al., 1990, 1994). While the former only includes lagged consumption in the estimating equation, the latter, which is the canonical specification used in the empirical literature, includes both lead and lagged consumption terms (Becker et al., 1990; Chaloupka, 1991; Becker et al., 1994; Chaloupka, 1996; Grossman and Chaloupka, 1998; Chaloupka and Warner, 2000; Cawley and Ruhm, 2012).

In section 3 we test the performance of the AR(1) addiction model through a battery of Monte Carlo experiments. We first generate trajectories that feature no addiction by construction, then we estimate the corresponding parameters using the AR(1) addiction model. The results correctly show that the simulated trajectories are not consistent with rational addiction, that there is no tendency of the AR(1) addiction model to detect addiction when there is just spurious correlation in the data, and that the corresponding estimates of the short and long-run elasticity of demand are unbiased. As a validation exercise, we also check whether the AR(1) is able to correctly detect rational addiction when, in fact, the simulated consumption trajectories do feature rational addiction. As shown in Laporte et al. (2017), an analog exercise can produce unreliable estimates if one generates and estimates addiction trajectories using the canonical AR(2) model. On the contrary, when using the AR(1) model we find that the results are reliable and unbiased.

Notably, all results hold irrespective of whether we consider individual or aggregate consumption data, a reassuring finding that mitigates the concerns raised by Auld and Grootendorst (2004) about testing rational addiction with aggregate data. To further explore the sensitivity of the AR(1) model, and to address some endogeneity concerns that have been raised in the literature, section 4 performs two additional sets of experiments as robustness checks. In the first set, we generate price trajectories that have both an exogenous and an endogenous component. In the second set of experiments, lagged consumption is explicitly considered to be endogenous. In the literature these endogeneity concerns have been addressed using further leads and lags of prices, or taxes, as instruments (see, for example, Chaloupka, 1991; Becker et al., 1994; Gruber and Köszegi, 2001; Baltagi and Geishecker, 2006). We proceed along the same lines and find that the IV estimates are still unbiased (although, as expected, the IV estimates are less efficient). We conclude that the AR(1) correctly discriminates between persistence and rational addiction, and that aggregation, endogeneity of prices and endogeneity of lagged consumption pose no significant threat to testing the theory of rational addiction.

In section 5 we extend the analysis to real data, and we estimate the demand for milk, oranges, eggs and cigarettes using the same Canadian dataset analyzed in Auld and Grootendorst (2004). Instead of using the canonical AR(2) model, however, we estimate the AR(1) addiction equation. This allows to directly address the milk addiction paradox, and to compare the performance of the AR(1) addiction model with the results of Auld and Grootendorst (2004). Our results show no evidence of milk being rationally addictive, and they allow us to conclude that the milk addiction paradox is an artifact of using the Euler equation rather than the AR(1) solution of the model. In fact, in our estimations the consumption of milk, oranges and eggs is not consistent with the theory of rational addiction, while smoking, as expected, is rationally addictive. Section 6 concludes.

2 The rational addiction model

Consider an intertemporal problem in which an agent allocates income between an addictive good c and a numeraire good q. Consumption of the addictive good increases the stock A of addiction according to $A(t) = c(t-1) + (1-\delta)A(t-1)$, where $\delta \in (0,1]$ describes the degree of persistence of the state of addiction and t is time. Becker and Murphy (1988)'s model of rational addiction assumes that the marginal utility of current consumption is higher, the higher the consumption stock $(U_{cA} > 0)$. This property, called reinforcement, represents the effect of a learning-by-consuming process in which the more an agent consumes, the more she appreciates the good (at the margin). The marginal utility of addiction is negative if the addictive commodity is harmful, and positive if it is beneficial. As usual, the per-period utility is increasing in the two consumption goods, and concave.

While reinforcement describes the effect of past choices on current preferences, the second main feature of rational addiction, forward-looking behavior, implies that current choices take into account expectations about future events and how current behavior will affect future preferences. This property is in stark contrast with myopic models, where current behavior only depends on past events and choices, and not on future events and expectations (see, for instance, the habit formation model presented in Pollak, 1970, or in Gilleskie and Strumpf, 2005). Finally, agents are assumed to be time consistent. Accordingly, unless new information arrives, any optimal plan will be faithfully implemented and no self-control failure should be observed. This property is explicitly required by Becker and Murphy (1988) and is formally obtained assuming that the discount factor $\beta \in (0, 1)$ is constant.[1]

Under the above assumptions, the rational addiction model can be formalized as the following intertemporal problem

$$\max_{c,q} \sum_{t=0}^{\infty} \beta^t U\left(c\left(t\right), q\left(t\right), A\left(t\right)\right) \tag{1}$$

$$\text{s.t. } A\left(t\right) = c\left(t-1\right) + \left(1-\delta\right) A\left(t-1\right) \tag{2}$$

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

where $p(t)$ is the price of the addictive good at time t, $M(t)$ is income and $A(0) = A_0$.

When the utility function is quadratic, the solution of problem 1 to 3 satisfies the following second-order difference equation (see Appendix A.1 for details):[2]

$$c\left(t\right) = \alpha_0 + \alpha_1 p\left(t-1\right) + \alpha_2 c\left(t-1\right) + \alpha_3 p\left(t\right) + \alpha_4 c\left(t+1\right) + \alpha_5 p\left(t+1\right) \tag{4}$$

[1] To address self-control in a rational addiction context, Gruber and Köszegi (2001) augment the Becker and Murphy (1988) model and allow for time-inconsistent preferences through quasi-hyperbolic discounting. They show that forward-looking behavior and the effect of announced tax changes can still be tested, but since the time-consistent and the time-inconsistent solutions are isomorphic, it is not possible to derive a sharp empirical test that distinguishes the augmented model from the original one.

[2] The quadratic specification is standard in the rational addiction literature as it allows to obtain a closed-form analytical solution (see, e.g., Becker and Murphy, 1988; Chaloupka, 1991; Becker et al., 1994). Alternatively, one can consider a more general utility function and take a linear approximation of the first-order conditions. Note that Chaloupka (1991) and Becker et al. (1990, 1994) allow for saving and borrowing and consider the case in which the

which, if $\delta = 1$, simplifies to

$$c(t) = \alpha_0 + \alpha_2 c(t-1) + \alpha_3 p(t) + \alpha_4 c(t+1). \tag{5}$$

Equation 4 (or 5) is the Euler equation of the rational addiction problem, and it constitutes the canonical model used in the empirical literature to estimate the demand for addictive goods (see, Cawley and Ruhm, 2012, for an overview). A positive sign of α_2 is consistent with reinforcement. When this is the case, past and current consumption are positively correlated, a property called adjacent complementarity (Ryder and Heal, 1973). Forward-looking behavior is assessed from the coefficient α_4 of lead consumption being positive (Chaloupka, 1990, 1991; Becker et al., 1994).[3]

A so far overlooked observation is that the Euler equation describes an infinity of candidate solutions. Among them, only one is optimal and stationary, while the others are explosive (Laporte et al., 2017). To see it, consider the family of consumption paths that satisfy the Euler equation 4:

$$c(t) = [c(0) - \mathcal{P}(0) - K]\lambda^t + K\lambda_1^t + \mathcal{P}(t) \qquad \text{for } t \geq 1, \tag{6}$$

where

$$\mathcal{P}(t) = g_0 + g_1 p(t) + g_2 \sum_{s=1}^{\infty} \lambda^s [p(t-s) + \beta^s p(t+s)] \tag{7}$$

is a function of prices. It can be shown that root $\lambda \in (0,1)$ if reinforcement is not too strong. The second root λ_1, instead, is always larger than one. Hence, for all $K \neq 0$ the term $K\lambda_1^t$ in 6 quickly diverges to infinity as time advances. When $K = 0$, instead, this explosive dynamics is neutralized and equation 6 describes a saddle path that smoothly converges to a steady state level of consumption.

Given the infinite time-horizon of problem 1 to 3, the saddle path is the appropriate solution of the rational addiction model.[4] Since it is stationary, it can be estimated with standard time series

marginal utility of wealth is constant. This produces the same solution and the same Euler equation of the model presented here.

[3] Saddle-point stability requires $\alpha_2 + \alpha_4 < 1$, which in turn implies the restriction $\alpha_2, \alpha_4 \in (0,1)$. In addition, $\beta = \alpha_4/\alpha_2$, a property that has sometimes been used as a restriction, or to test the validity of the rational addiction model (Auld and Grootendorst, 2004; Baltagi and Geishecker, 2006). As shown in Laporte et al. (2017), however, these theoretical properties cannot be reliably estimated because of the existence of an explosive root in the general solution of the Euler equation (see eq. 6).

[4] See Dragone and Raggi (2018) for a justification of infinity as the appropriate time-horizon in a scenario in which lifetime is uncertain, and of the saddle path as the appropriate solution to consider. Note that the saddle path to the steady state was already the focus of Becker and Murphy (1988)'s analysis. Here we consider a discrete-time analogue, with the major difference that we allow prices to vary over time. More in general, focusing on the steady state is an approach that is typically taken to generate estimable consumption equations derived from

econometrics (provided the time series of prices is also non-explosive). For empirical purposes, however, equation 6 is not ideal. By shifting equation 6 one period forward, and replacing $c(0)$, the saddle path can be equivalently described by the following AR(1) equation (see Appendix A.2 for details),

$$c(t) = \lambda c(t-1) + \varphi_1 p(t-1) + \varphi_2 p(t) + \sum_{s=1}^{\infty} \varphi_3(s) p(t+s) + \varphi_0 \tag{8}$$

or, when $\delta = 1$,

$$c(t) = \lambda c(t-1) + \varphi_2 p(t) + \sum_{s=1}^{\infty} \varphi_3(s) p(t+s) + \varphi_0. \tag{9}$$

Equation 8 (or 9) states that optimal current consumption depends on past consumption and on current and future prices. The significance and sign of the estimated coefficients allow to test the main properties of the rational addiction model. Reinforcement implies that λ is expected to be positive, i.e. adjacent complementarity between past and current consumption, analogously to the role played by $\alpha_2 > 0$ in the Euler equation. Saddle path stability further requires $\lambda < 1$.

Forward-looking behavior implies that $\varphi_3 \neq 0$. A positive value of φ_3 means that a future expected price increase triggers an increase in current consumption, a behavior that is consistent with stockpiling today as a response to the announcement or expectation of a future price increase (see, for instance, Gruber and Köszegi, 2001). A negative value of φ_3, instead, reveals the opposite reaction in which consumption today decreases in expectation of a future price or tax increase. The fact that future prices can either have a positive or negative effect on current consumption contrasts with the Euler equation, in which the sign of future price or consumption on current consumption can only be positive. Finally, current consumption is predicted to negatively depend on its current price (as in the Euler equation), so that the (static) law of demand applies.

Testing the rational addiction model using the AR(2) Euler equation can be problematic (see for example Auld and Grootendorst, 2004; Baltagi and Geishecker, 2006; Laporte et al., 2017). In particular, Auld and Grootendorst (2004) observe that the empirical model based on the AR(2) Euler equation tends to find rational addiction when in fact the commodity under investigation does not feature addiction.[5] For example, when estimating the demand for Canadian milk, they find the puzzling result that milk would be more addictive than smoking. Auld and Grootendorst

the optimization problem of a representative consumer, as in growth models based on the Ramsey-Cass-Koopmans model or the Blanchard (1985)'s model of perpetual youth.

[5] In this paper we denote as "rational addiction", or simply "addiction", the case in which both adjacent complementarity and forward-looking behavior are satisfied. The case where only adjacent complementarity holds (which in the literature is sometimes denoted as myopic habit formation or myopic addiction) is labelled "persistence in consumption".

(2004) suggest that this paradox and, more in general, the tendency of the Euler equation to produce false positives and erroneously classify a non-addictive good as rationally addictive, can be due to the endogeneity arising from the presence of a lead and lag consumption term in the AR(2) model, and to the use of aggregate data. To explore these possible explanations, they generate simulated consumption trajectories that feature persistence, but not rational addiction. Then they estimate the corresponding parameters using the Euler equation to check for possible biases. The results show that the estimates are often unstable and very sensitive to the choice of the instruments, with a tendency to produce false positives that is more likely when the data generating process exhibits high serial correlation. This finding is particularly problematic, since time series typically display high serial correlation, in particular when data are aggregated. Accordingly, Auld and Grootendorst (2004) conclude that "time-series data will often be insufficient to differentiate rational addiction from serial correlation in the consumption series".

In the following sections we show that the above claims do not hold when the empirical model is the AR(1) equation describing the saddle path, instead of the AR(2) equation describing the Euler equation. We claim that the better performance of the AR(1) model over the AR(2) model is likely due to the fact that the Euler equation is not the solution of the model, but an intertemporal necessary condition that the solution of the rational addiction model must satisfy. Moreover, the Euler equation is intrinsically unstable because it has at least one root that is explosive, as shown by Laporte et al. (2017). This violates the basic assumptions needed to perform econometric analysis of time series and it could produce erroneous estimates. On the contrary, the AR(1) specification is stationary. Moreover, since it does not contain the lead of consumption, the endogeneity concerns afflicting the AR(2) model are likely to be less severe.

3 Monte Carlo experiments

In this section we run a set of Monte Carlo experiments to investigate whether rational addiction can be detected and distinguished from non-addictive consumption that features persistence but no forward-looking behavior. Differently from the Monte Carlo experiments of Auld and Grootendorst (2004) and Laporte et al. (2017), who estimate the simulated trajectories using the AR(2) Euler equation, we use the AR(1) addiction model.

We consider consumption trajectories generated using two alternative data generating processes (DGP). The first one corresponds to the process considered in Auld and Grootendorst (2004). It consists of a static demand model where prices and errors are autocorrelated. Specifically, consumption is assumed to depend on current price and errors, $c_t = -\eta p_t + u_t$, where prices and errors are autocorrelated according to $p_t = \rho_p p_{t-1} + \nu_t$ and $u_t = \rho u_{t-1} + \epsilon_t$. Parameters $\rho_p, \rho \in (0, 1)$, while u_t, ν_t and ϵ_t are sequences of i.i.d. Gaussian shocks.

Manipulating the above equations yields

$$c_t = \rho c_{t-1} + \gamma_1 p_{t-1} + \gamma_2 p_t + \gamma_0 + \epsilon_t \tag{10}$$

where $\gamma_1 = \eta\rho$ and $\gamma_2 = -\eta = -\gamma_1/\rho$. Since $\rho \in (0, 1)$, the trajectories generated by 10 are stationary and persistent (in the form of adjacent complementarity in consumption). This model, however, does not allow for forward-looking behavior. In fact, it formally resembles the solution of a myopic habit or taste formation model in which current consumption only depends on current and past variables (see, e.g. Pollak, 1970; Becker et al., 1994; Gilleskie and Strumpf, 2005; Dragone and Raggi, 2018). In the following we refer to 10 as to the non-addiction DGP.

The second DGP features rational addiction. Based on the saddle path solution 8, the consumption trajectories are generated according to the following process

$$c_t = \rho c_{t-1} + \gamma_1 p_{t-1} + \gamma_2 p_t + \gamma_3 p_{t+1} + \gamma_0 + \epsilon_t, \tag{11}$$

while the price and error dynamics follow the same autoregressive processes used for the non-addiction DGP. As emphasized in Becker et al. (1991), testing for the effects of future prices on current consumption distinguishes rational models of addiction from myopic models. Accordingly, the main difference with respect to the non-addiction DGP is that the addiction DGP features forward-looking behavior ($\gamma_3 \neq 0$).[6]

Equation 11 is the AR(1) addiction equation used to generate trajectories compatible with the theory of rational addiction, and it will also be used as the empirical model for testing rational addiction. Given that the only difference between the two DGPs is the presence of the lead of price, we expect the estimated γ_3 to be non statistically significant when the trajectory is generated by the non-addiction process (eq. 10), and to be different from zero when it is generated by the addiction process (eq. 11).

For later reference, the short and long-run response of consumption to a permanent price increase are, respectively,

$$C_S = \gamma_2 + \gamma_3 < 0, \qquad C_L = \frac{\gamma_1 + \gamma_2 + \gamma_3}{1 - \rho} < 0. \tag{12}$$

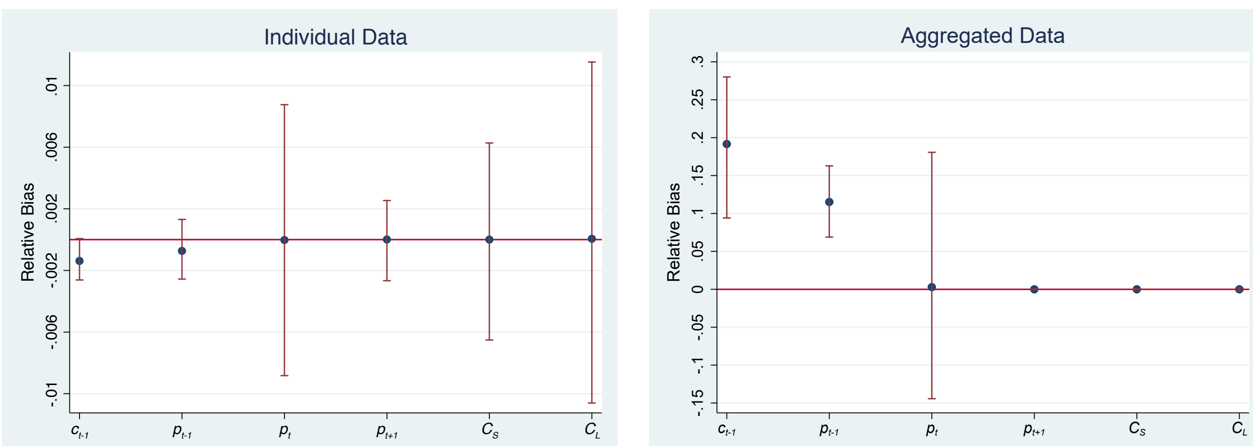
where $\gamma_3 = 0$ when the DGP features non-addiction.

[6] Differently from equation 10, in equation 11 the coefficients ρ, γ_1 and γ_2 are independent. The assumption of exogenous prices is relaxed in the robustness checks in Section 4.

3.1 Experiment 1: Estimating non-addictive consumption

In the first set of experiments we generate individual consumption trajectories using the non-addiction DGP described in equation 10. We randomly select ρ and γ_1 from a uniform distribution $(0,1)$ and compute $\gamma_2 = -\gamma_1/\rho$ to generate $2,000$ different sets of parameters $\alpha_i = (\rho, \gamma_1, \gamma_2)_i$. Each set of parameters represents an individual i and determines the individual short and long-run elasticity according to equations 12. We assume that prices are strictly exogenous and we keep ρ_p fixed. Then, for each set, we generate 1000 different trajectories of length 500 of consumption and prices, which are meant to represent *alternative life courses* of individual i, depending on the sequence of random shocks experienced by i over her lifetime. Using the AR(1) addictive model, we estimate α_i over the 1000 alternative life courses of i, that is, $\hat{\alpha}_{i,j},\ j = 1, \dots, 1000$. Since we know the true values of the DGP, we can compute the (relative) estimation bias $\mathbf{b}_{i,j}$ for each i using the formula $\mathbf{b}_{i,j} = (\hat{\alpha}_{i,j} - \alpha_i)/(1 + \alpha_i)$. Aggregating these individual biases yields a measure of the average bias $\bar{\mathbf{b}}_i = \frac{1}{1000}\sum_j \mathbf{b}_{i,j}$ that results when using individual level data.

Figure 1: Estimation bias when consumption is not addictive



Notes: Left panel: estimation of the relative bias $\bar{\mathbf{b}}_i$ on individual trajectories. Right panel: estimation of the relative bias $\bar{\mathbf{b}}_k$ on aggregate trajectories. Non-addictive consumption trajectories are generated according to 10, and estimated using 11 and OLS. The vertical bars represent the 95% confidence intervals for the estimated bias.

The left panel of Figure 1 reports the average bias $\bar{\mathbf{b}}_i$ obtained using OLS.[7] The results show no notable bias in the estimation of the true parameters of the data generating process. In particular, the AR(1) model correctly finds that the lead price coefficient is not statistically significant, which is indeed the case because the DGP features non-addiction. If anything, there is a slight downward bias in the estimation of the parameter of lag consumption, but its is negligible (less than 1%) with respect to the true value of ρ. In addition, the short and long-run elasticities estimated using the individual trajectories are unbiased. In contrast with the findings of Auld and Grootendorst (2004), these results suggests that the AR(1) empirical addiction model is not prone to wrongly detect rational addiction when the data display persistence but no forward-looking behavior.

To assess whether the results above are robust to using aggregate data, we consider a second set of experiments. We consider 2000 *villages* k, each composed of 100 individuals j. Each individual is characterized by a different set of parameters $\alpha_k^j = (\rho, \gamma_1, \gamma_2)_k^j$, $j = 1, 2, \ldots, 100$, $k = 1, 2, \ldots, 2000$, which are used to generate individual consumption trajectories of length 500. For a given village k, we aggregate the corresponding 100 individual trajectories to obtain a village-specific trajectory with average parameters $\bar{\alpha}_k = \sum \alpha_k^j$ and average short and long-run elasticity $\bar{C}_{S,k}$ and $\bar{C}_{L,k}$. Generating 1000 alternative life courses for each individual, we generate 1000 alternative life courses of village k. We thus estimate 1000 times α_k using the aggregated trajectories, and we compute $\hat{C}_{S,k,i}$ and $\hat{C}_{L,k,i}$, $i = 1, \ldots, 1000$, which we compare to the true values to measure the village-specific relative bias $\mathbf{b}_{k,i} = (\hat{\alpha}_{k,i} - \bar{\alpha}_k)/(1 + \bar{\alpha}_k)$. (The same formula is used to measure the relative bias for elasticity). We define $\bar{\mathbf{b}}_k = \frac{1}{1000} \sum_i \mathbf{b}_{k,i}$ as the average bias over the 1000 trajectories for each village, and we report it with 95% confidence intervals in the right panel of Figure 1.

The results are consistent with those obtained with individual data, and they show that the AR(1) model correctly detects that the aggregated data feature no forward-looking behavior. Hence it does not erroneously detect addiction when there is no addiction in the data. Considering the estimated coefficients, we find an upward bias for the lagged variables, a result that is not surprising because aggregation tends to increase the persistence in time series (Granger and Morris, 1976; Havranek et al., 2017). Importantly, despite the overestimation in the persistence

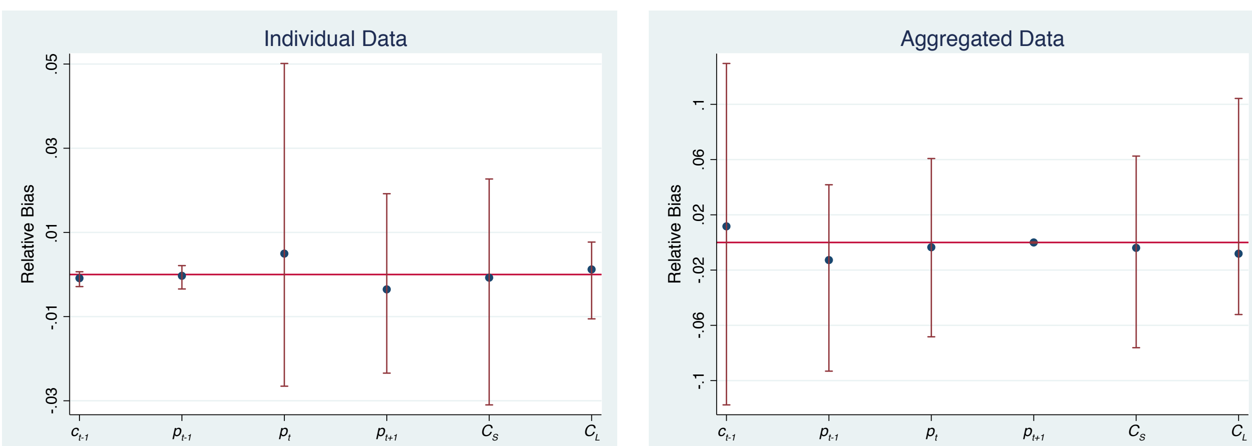
[7] For Figures 1 and 2 we consider $\rho_p = 0.9$, as in Auld and Grootendorst (2004). The results are qualitatively similar in a sensitivity analysis (available upon request) where ρ_p varies between 0.5 and 0.95, a range that is consistent with the empirical finding that prices are persistent but stationary. Note that we refer to (un)biasedness because we use trajectories of 500 steps, which is a rather large number, but not infinite. The results do not change if we consider more iterations, hence one could also claim the results to be consistent. The results obtained with IV estimation are presented in Section 4.

of consumption, the estimated coefficient of future price is unbiased and equal to zero, which is indeed correct because the non-addiction DGP features no forward-looking behavior. Moreover, the estimates of short and long-run elasticity are unbiased. Similar results hold also when we run additional regressions using 2SLS and prices as instruments for lagged consumption (see Section 4.2). We can therefore conclude that, even with aggregated data, the AR(1) model is able to properly distinguish pure autocorrelation from rational addiction, and to correctly detect persistence in consumption and the absence of forward-looking behavior in the data.

3.2 Experiment 2: Estimating addictive consumption

Laporte et al. (2017) show that generating and estimating consumption series using the AR(2) Euler equation can produce unreliable estimates. In this subsection, we show that this is not the case when using the AR(1) model. We run additional Monte Carlo experiments with individual and aggregate trajectories generated and estimated as in the previous subsection. The difference is that we now generate trajectories that display forward-looking behavior (with γ_2 and γ_3 selected from a uniform distribution with support $(-1, 0)$ and $(-1, 1)$, respectively), and that we use the AR(1) model both as the DGP and as the empirical model.

Figure 2: Estimation bias when consumption is addictive



Notes: Left panel: estimation of the relative bias $\bar{\mathbf{b}}_i$ on individual trajectories. Right panel: estimation of the relative bias $\bar{\mathbf{b}}_k$ on aggregate trajectories. Addiction consumption trajectories are generated according to 11, and estimated using 11 and OLS. The vertical bars represent the 95% confidence intervals for the estimated bias.

The estimated biases using individual and aggregate trajectories and OLS are reported in Figure 2 (left and right panel, respectively). The results show that the AR(1) model produces unbiased estimates of the parameters and of the corresponding elasticities, both when using individual and aggregate data. With respect to the previous Monte Carlo experiments, here the coefficient of lead price is estimated to be different from zero, which is correct because the DGP is addictive. The lagged variables are precisely estimated. Given that the estimates of the coefficients are unbiased, the estimation of the short and long-run elasticity is also unbiased. We conclude that the AR(1) model is able to correctly detect rational addiction when the data truly feature rational addiction, and that using aggregated data pose no particular threat for the empirical estimation.

4 Robustness checks

4.1 Endogenous prices

In the previous section we have shown that the AR(1) empirical model can reliably test rational addiction, both with individual and aggregate data. The results were obtained assuming that prices are exogenous. As a robustness check, in this section we investigate the performance of the AR(1) model when prices are endogenous. Specifically, we consider the case in which the observed price can be decomposed as follows

$$p_t = a\tau_t + (1-a)\,\pi_t \tag{13}$$

where $a \in [0,1]$. The term τ_t is exogenous, and it can be interpreted as taxes, or as the effect of a regulation that affects the opportunity cost of consuming the good (e.g. smoking bans). The term π_t is endogenous and is assumed to be negatively correlated with contemporaneous consumption.[8]

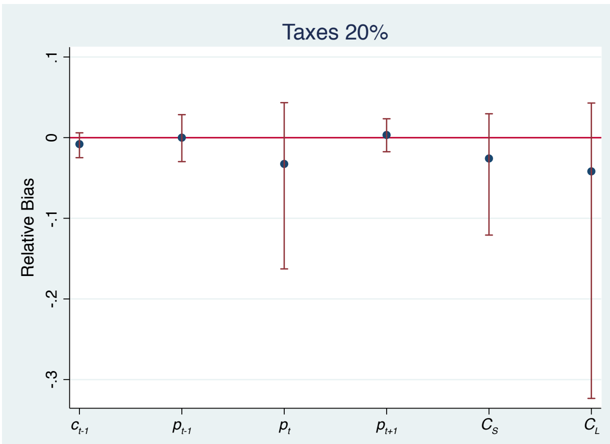
Parameter a describes the relative weight of the exogenous with respect to the endogenous component of price. Accordingly, the limit case $a = 1$ implies that prices are fully exogenous. The case where $a < 1$ seems to be more realistic, with various degrees depending on the specific application. For example, in the US cigarette taxation has changed substantially over time. In the seventies Federal and State taxes per pack were about 50% of the total price. In the following decades the impact of taxation declined over time, down to an average level of 21% at the end of the nineties. Since then, average taxation has increased up to 46% in 2016. Consistently, variation

[8] We assume $\pi_t = \rho_\pi \pi_{t-1} + \xi_t$ and $\tau_t = \rho_\tau \tau_{t-1} + \nu_t$, where ξ_t, ν_t are Gaussian i.i.d. sequences, $\text{corr}(\xi_t, \epsilon_t) = r$, and ϵ_t is the error used in Section 3. Figure 3 displays the results corresponding to $\rho_\pi = \rho_\tau = 0.7$, $r = -0.5$ and either $a = 0.2$ or $a = 0.8$. Similar results are obtained in a sensitivity analysis (available upon request) where r is picked randomly from a uniform distribution with support $(-0.8, -0.2)$ and (ρ_π, ρ_τ) from uniforms with support $(0.5, 0.95)$. Different values of a, ranging between 0.2 and 0.9, deliver equivalent qualitative results. When the exogenous component accounts for less than 1/3 of the price, the estimates are less efficient, likely because the instruments become weak.

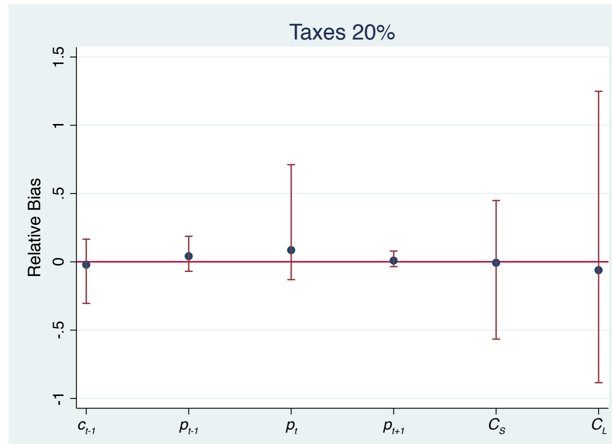
on taxation represents the major cause of variations in prices, raising from an average 55% in the period 1970–2000 to about 85% over the period 2000–2016 (Orzechowski and Walker, 2017).

Figure 3: Estimation bias when prices are endogenous

Scenario 1

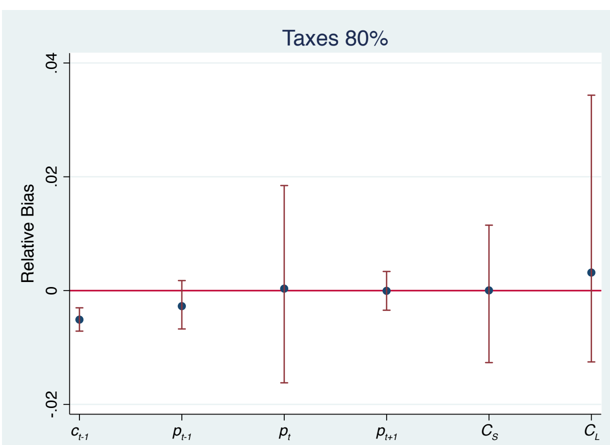


DGP: non-addictive consumption

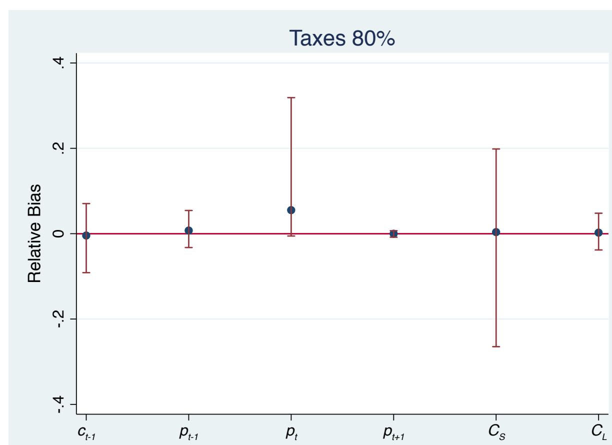


DGP: addictive consumption

Scenario 2



DGP: non-addictive consumption



DGP: addictive consumption

Notes: Scenario 1: prices are mildly exogenous ($a = 0.2$). Scenario 2: prices are almost exogenous ($a = 0.8$). The left panel reports the results obtained with a non-addictive data generating process. The right panel reports results obtained from trajectories featuring addiction. All individual trajectories are estimated using 11 and 2SLS. The vertical bars represent the 95% confidence intervals for the estimated bias.

In the following we consider two different values of a: $a = 0.2$ ('mild exogeneity') and $a = 0.8$ ('almost exogeneity'). For each value of a we generate price trajectories and we perform the same exercise of the previous experiments, both with individual and aggregate data, with the difference that we use 2SLS and instrument for prices using τ_{t-1} up to τ_{t+2} (see, for example, Gruber and Köszegi, 2001; Gruber et al., 2003).

The results using individual data are reported in Figure 3. They show no significant bias, both when estimating the non-addictive and the addictive trajectories. A possible exception is the bias in the coefficient of lagged consumption when prices are almost exogenous and the DGP features non-addiction (bottom-left panel). This bias, however, is negligible (less than 1%) and, importantly, it does not bias the estimation of lead terms, nor the short and long-run elasticity of consumption. When using aggregate data, instead of individual trajectories, the results (not shown and available upon request) are similar to those obtained in the previous simulations with exogenous prices. We can therefore conclude that, even when prices are endogenous, the AR(1) model is able to correctly distinguish between pure persistence and rational addiction, and to produce unbiased estimates of the elasticity of demand.

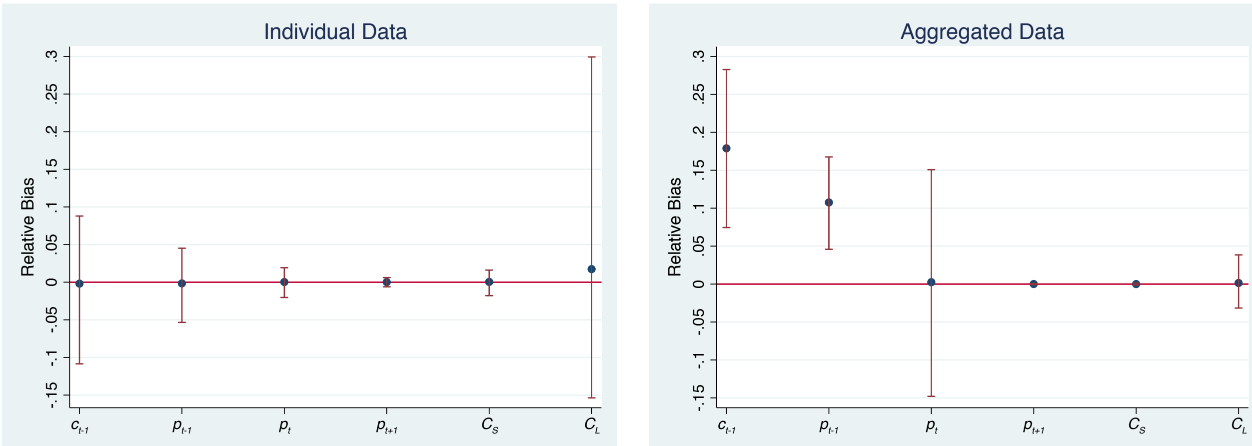
4.2 Endogenous lagged consumption

When estimating rational addiction using the AR(2) model (eq. 5), Becker et al. (1994) observe that past and future consumption can be endogenous, and they suggest using past and future prices as instruments. The AR(1) model does not contain future consumption, but the presence of a past consumption term can still raise legitimate endogeneity concerns. To address them, in this subsection we re-run the analysis presented in Section 3, with the only difference that we use 2SLS, with p_{t-2} and p_{t+2} as instruments (overidentification), rather than OLS.

In Figure 4 we report the estimation bias obtained when the DGP features non-addiction and the estimating model is the AR(1) equation 11. This experiment is analog to the first one reported in Section 3, which uses OLS estimation, and the results are similar. We find (i) no significant bias when considering individual trajectories, (ii) a positive bias on the lag coefficients when using aggregate trajectories, and (iii) unbiased estimates of the short and long-run elasticity, both when using individual and aggregated consumption series. As expected, since IV estimation is less efficient than OLS estimation, the confidence intervals are wider.

As an additional check, we also re-run the experiment when the DGP features rational addiction, as in the second experiment reported in Section 3. The IV estimates (not reported here and available upon request) are similar to those obtained when estimating with OLS and they show non significant bias. We can therefore conclude that the endogeneity concerns due to presence of lag consumption in the estimating equation do not pose a relevant threat for the empirical estimation.

Figure 4: Estimation bias when lagged consumption is endogenous



Notes: Left panel: estimation on individual trajectories. Right panel: estimation on aggregate trajectories. Consumption trajectories are generated according to the non-addiction process 10, and estimated using 11 and 2SLS. The vertical bars represent the 95% confidence intervals for the estimated bias.

5 Is milk really rationally addictive? No.

In this section we use real data to investigate the Auld and Grootendorst (2004)'s result about milk rational addiction. To allow for a direct comparison, we consider the same Canadian dataset containing annual aggregate national data on consumption and prices for milk, oranges, eggs and cigarettes (Auld and Grootendorst, 2004).[9] Instead of the AR(2) equation 5 used by Auld and Grootendorst (2004), here we use the AR(1) empirical model (eq. 11). Accordingly, rational addiction predicts the coefficient of c_{t-1} to be positive and less than one, the coefficient of p_t to be negative, and the coefficient of p_{t+1} to be significantly different from zero. The first prediction reveals adjacent complementarity and is consistent with reinforcement in preferences, the second one shows consistency with the law of demand, and the third one reveals forward-looking behavior and is the main test to distinguish between rational addiction and simple persistence in consumption.

As a preliminary analysis, we test for stationarity, a necessary condition for both the rational addiction theoretical model and for the empirical estimation. A battery of stationarity tests (the

[9] We thank M. Christopher Auld and Paul Grootendorst for kindly sharing the data used in Auld and Grootendorst (2004). Our analysis spans over the same time period they consider. More precisely, oranges are observed starting from 1960, eggs and milk starting from 1961, cigarettes starting from 1968. Prices are expressed in real terms by adjusting by all-items CPI (1992 = 100). All quantities (liters for milk, dozens for eggs, kilos for oranges) are in per-capita terms. As in Auld and Grootendorst (2004), cigarette consumption includes cigars and is computed as the sum of domestic and export sales to account for smuggling between Canada and the USA. Real per-capita outlays on consumer non-durables are used as a proxy for permanent income.

Augmented Dickey-Fuller, the GLS Dickey-Fuller, and the Zivot-Andrews tests) consistently rejects the unit-root hypothesis only for oranges. For milk, eggs and cigarettes, instead, we are unable to reject the null hypothesis of non-stationarity, both for consumption and prices. Additional testing shows that there exists a cointegration relationship between consumption and prices for milk, eggs and cigarettes. Hence, when estimating the parameters for milk, eggs and cigarettes, we follow the two-step Engel-Granger procedure for cointegration modeling. We consider the Error Correction Mechanism (ECM) representation of the AR(1) model 11 and we apply Dynamic OLS for estimation (Stock and Watson, 1993). As shown in Appendix B.2, this is relatively easy to implement using our linear AR(1) model. For oranges, we simply use OLS.[10]

A potential concern for the empirical analysis is that the AR(1) model can suffer of endogeneity, due to the inclusion of a lag consumption term (Gilleskie and Strumpf, 2005). This concern is also present (and actually more pervasive) when using the AR(2) Euler equation, due to the existence of both a lead and a lag term, and it has been addressed in the literature using instrumental variables and GMM (Becker et al., 1990; Chaloupka, 1991; Auld and Grootendorst, 2004; Baltagi and Geishecker, 2006). The post-estimation analysis (available upon request) shows that the model's residuals are uncorrelated, which corroborates the exogeneity assumption of lag consumption. In addiction, the results of the Monte Carlo simulations reported in the previous sections show that endogeneity is a minor concern when testing the rational addiction model using the AR(1) model. According to these preliminary considerations, we consider c_{t-1} to be exogenous and we run OLS when stationarity is satisfied (i.e. for oranges), and the two-step procedure described in Engle and Granger (1987) when the data are non-stationary but cointegrated (cigarettes, milk and eggs).

The empirical results shown in Table 1 suggest that only cigarettes are consistent with the Becker and Murphy (1988)'s theory of rational addiction. As predicted by the theory, the coefficient of lagged consumption is positive and less than one, that of current price is negative, and the coefficient of lead price is different from zero. These results are statistically significant, and they imply that that law of demand holds and that the demand for cigarettes features adjacent complementarity and forward-looking behavior.[11] These results are consistent with those obtained estimating the AR(1) model using US aggregate data (Dragone and Raggi, 2018). On the contrary,

[10] In both models deterministic trends have not been included, because of their irrelevant impact on the results. As in Auld and Grootendorst (2004), we add outlays as a control variate. Additional information on the unit-root and cointegration tests is reported in Table 2 in Appendix B.1. Details on the ECM representation and on the estimation procedure of the AR(1) model are in Appendix B.2.

[11] Although our goal is not to provide new estimates for the elasticity of demand, note that estimated values of the short and long-run elasticity are -0.23 and -0.59, respectively. These values are compatible with those found by Gruber et al. (2003), who report an elasticity of the demand for Canadian cigarettes in the range from -0.45 to

Table 1

Coefficient	Cigarettes		Milk		Eggs		Oranges	
ρ (c_{t-1})	0.879***	(0.100)	0.772***	(0.160)	0.832***	(0.088)	0.751***	(0.134)
γ_2 (p_t)	-0.093**	(0.045)	-0.478**	(0.175)	-0.087	(0.052)	-0.634***	(0.142)
γ_3 (p_{t+1})	-0.140***	(0.015)	0.285	(0.169)	0.021	(0.050)	0.136	(0.120)
Rational Addiction?	Yes		No		No		No	

Notes: Estimation of the demand for cigarettes, milk, eggs and oranges using the AR(1) model 11 and the data considered in Auld and Grootendorst (2004). Dependent Variable = c_t; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors in parentheses. Prices are expressed in real terms by adjusting by all-items CPI (1992 = 100). All quantities are in per-capita terms. Cigarette consumption includes cigars and is the sum of domestic and export sales to account for smuggling between Canada and the USA. Rational addiction predicts the coefficient of c_{t-1} to be positive and less than one, the coefficient of p_t to be negative, and the coefficient of p_{t+1} to be significantly different from zero. Only cigarettes are consistent with rational addiction. Milk, eggs and oranges are consistent with persistence in consumption, but do not display forward-looking behavior.

for milk, eggs and oranges there is not evidence of forward-looking behavior, because the coefficient on future price is not statistically significant. Hence it is consistent with a myopic habit formation (or myopic addiction) model, but not with rational addiction, which requires also forward-looking behavior.

Our result that the consumption of milk, oranges, and eggs does not feature forward-looking behavior is at odds with Auld and Grootendorst (2004)'s finding. We suspect a main reason for this discrepancy is the role played by the lead term of consumption c_{t+1} in the AR(2) equation they use to test rational addiction. Theoretically, the coefficient of c_{t+1} signals the existence of forward-looking behavior. Empirically, however, its estimate is very unstable and sensitive to the choice of the instruments (see, for example, Baltagi and Geishecker, 2006, and Auld and Grootendorst, 2004), which suggests that endogeneity is a serious problem when estimating an AR(2) model, and that it is empirically difficult to handle it by using instrumental variable estimators. Fortunately, the Monte Carlo experiments presented in the previous sections suggest that the AR(1) model does not particularly suffer from endogeneity. This is further corroborated by a robustness check in which we instrument for the lagged consumption of oranges (for which we know that non-

-0.47, as well as with the estimates obtained using US data (Chaloupka and Warner, 2000; Gruber and Köszegi, 2001; Callison and Kaestner, 2014; Zheng et al., 2017).

stationarity can be rejected) and we find that the IV estimates are qualitatively similar to the ones obtained with OLS, although they are more imprecise, as expected.

An additional reason for the discrepancy between our empirical results and Auld and Grootendorst (2004) is that some of the time series under examination are non stationary. This may have produced unreliable estimates, even in absence of endogeneity. To address this concern, before running our analysis we have tested the data for stationarity and cointegration. This has allowed to distinguish between cases in which stationarity holds and OLS can be used (oranges), and cases in which one should follow a different route, such as the two-step procedure of Engle and Granger (1987).

6 Conclusion

The evidence on milk addiction found by Auld and Grootendorst (2004) has raised the question of whether the AR(2) model typically used to test the model of rational addiction is an appropriate empirical specification. The AR(2) model tends to find spurious evidence for rational addiction and it is very sensitive to the choice of the instrumental variable estimators, a result that is more likely when the consumption series display high persistence (Auld and Grootendorst, 2004). In addition, Laporte et al. (2017) show that the AR(2) model is intrinsically explosive, which makes estimating and testing the rational addiction model problematic. In this paper we have shown that the above results do not hold when, instead of the AR(2) equation, a linear AR(1) model is used. This specification describes the saddle path solution of the rational addiction model, it retains the main theoretical predictions that have been investigated in the literature using the canonical AR(2) model, and it is empirically simpler to estimate.

Using Monte Carlo simulations, we first show that the AR(1) model does not produce false positives and is able to correctly detect rational addiction. Moreover, it produces unbiased estimates of the short and long-run elasticity of consumption, and it does not suffer of the endogeneity concerns that may arise when using lag consumption in the estimating equation. These results hold both with individual and aggregate data, a finding that is particularly appealing because consumption series are typically available as aggregate data.

To directly address the milk addiction paradox, we then consider the same Canadian data used by Auld and Grootendorst (2004) and we proceed with the empirical analysis using the AR(1) model, instead of the AR(2) model. This allows to show that the milk addiction paradox is only apparent. In fact, using the AR(1) addiction model, we find that milk is not compatible with the rational addiction model, while cigarettes are, as expected.

These results allow us to conclude that the AR(1) model is a reliable candidate to test the theory of rational addiction. We claim that the better performance of the AR(1) model over the AR(2) is likely due to the fact that the Euler equation is not the solution of the model, but an intertemporal necessary condition that the solution of the rational addiction model must satisfy. Moreover, the Euler equation is intrinsically unstable, because it has at least one root that is explosive (Laporte et al., 2017). This violates the basic assumptions needed to perform econometric analysis of time series and it could produce erroneous estimates. On the contrary, the AR(1) specification we propose is stationary and, since it does not contain the lead of consumption, the endogeneity concerns afflicting the AR(2) model are likely to be less severe.

Our results suggest a word of caution when interpreting past studies that use the canonical AR(2) model, but they do not imply that the corresponding results are necessarily flawed. In fact, as shown in Laporte et al. (2017), over a short time horizon the explosive root of the AR(2) model plays a negligible role. Accordingly, it is possible to obtain reasonable estimates of the associated parameters. Given the tendency to produce false positives, however, we believe that the estimates obtained from the AR(2) canonical model cannot be the basis of a satisfactory test of the theory of rational addiction. Similarly, it is unlikely that a good test of the theory consists in checking whether the discount factor computed from the coefficients of the AR(2) canonical model is economically meaningful. Although this exercise has been sometimes used in the literature as a test for the validity of the rational addiction model, the formula to compute the discount factor is non linear and very sensitive to minor variations in the coefficients of lead and lag consumption. Since the estimates of these coefficients tend to be unstable and unreliable, it is possible that meaningless estimates of the discount factor can result even when the data are truly consistent with rational addiction and, on the contrary, that apparently meaningful estimates result when in fact the data are not consistent with rational addiction.

Our approach to the demand for addiction makes simplifying assumptions about preferences, constraints, and expectations, that could be modeled more explicitly to obtain richer structural models, such as those proposed in the recent literature by Darden (2017) and Hai and Heckman (2019). A limitation of the AR(1) model we propose and, more in general, of the theory of rational addiction, is the assumption that the individual is capable of calculating a lifetime optimal consumption trajectory of an addictive commodity. In particular, all consequences of current actions are known with certainty and individuals have rational expectations about the trajectory of future prices (or, in the empirical specification we test, of the next period's price). In addition, consumers are assumed to be price takers. This partial equilibrium approach ignores the possible strategic interaction between firms and consumers and how pricing strategies may respond to the demand for addictive goods. For example, it does not take into account that a seller can initially set a low price to capture the consumer, and then increase the price once the consumer is sufficiently addicted. Our approach also abstracts from the possible substitutability between multiple addictive goods, which is a mechanism that likely underlies the demand of, e.g. legal, bootleg cigarettes and vaping, or the demand for conventional and synthetic opioids, or for marijuana and opioids. These extensions are interesting and possible (see, e.g. Becker et al., 1990; Orphanides and Zervos, 1995; Driskill and McCafferty, 2001; Bask and Melkersson, 2003, 2004), and they can be dealt within the benchmark framework considered in this paper. Since they are out of the scope of this paper, they are left for future research.

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Appendices

A Theoretical background: Supplementary material

A.1 Deriving the solution

Replacing the budget constraint in the utility function, the Bellman equation associated to the rational addiction problem can be written as

$$V(A(t)) = \max_{c(t)}\{\mathcal{U}(t) + \beta V(A(t+1))\} \tag{14}$$

where $\mathcal{U}(t) \equiv U(c(t), M(t) - p(t)c(t), A(t))$. The associated first order and envelope condition are, respectively,

$$\frac{\partial \mathcal{U}(t)}{\partial c(t)} + \beta \frac{\partial V(A(t+1))}{\partial c(t)} = 0 \tag{15}$$

$$\frac{\partial V(A(t))}{\partial A(t)} = \frac{\partial \mathcal{U}(t)}{\partial A(t)} + \beta(1-\delta)\frac{\partial V(A(t+1))}{A(t)} \tag{16}$$

which yields the Euler equation

$$\frac{\partial \mathcal{U}(t)}{\partial c(t)} = \beta\left[(1-\delta)\frac{\partial \mathcal{U}(t+1)}{\partial c(t+1)} - \frac{\partial \mathcal{U}(t+1)}{\partial A(t+1)}\right] \tag{17}$$

Considering the quadratic utility function,

$$U(c(t), q(t), A(t)) = u_c c(t) + u_A A(t) + \frac{u_{cc}}{2}c^2(t) + \frac{u_{AA}}{2}A^2(t) + u_{cA}c(t)A(t) + q(t) \tag{18}$$

with $u_c > 0$, $u_{cc}, u_{AA} < 0, u_{cc}u_{AA} - u_{cA}^2 > 0$ and $u_{cA} > 0$, and using the law of motion of the addiction stock, the Euler equation becomes

$$c(t) = \theta c(t-1) + \theta_1 c(t+1) + \alpha_0 + \alpha_1 p(t-1) + \alpha_2 p(t) + \alpha_3 p(t+1) \tag{19}$$

where

$$\theta = \frac{u_{cA} - (1-\delta)u_{cc}}{\omega} > 0 \quad \text{if } u_{cA} > 0; \qquad \theta_1 = \beta\theta > 0 \text{ if } u_{cA} > 0; \tag{20}$$

$$\alpha_0 = \delta\frac{u_c + \beta[u_A - (1-\delta)u_c]}{\omega}; \qquad \alpha_1 = \frac{1-\delta}{\omega} \geq 0; \tag{21}$$

$$\alpha_2 = -\frac{1 + (1-\delta)^2\beta}{\omega} < 0; \qquad \alpha_3 = \beta\alpha_1 \geq 0; \tag{22}$$

$$\omega = \beta(1-\delta)[2u_{cA} - (1-\delta)u_{cc}] - u_{cc} - \beta u_{AA} > 0. \tag{23}$$

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

$$c(t) = [c(0) - \mathcal{P}(0) - K]\lambda^t + K\lambda_1^t + \mathcal{P}(t), \qquad \text{for } t \geq 1, \tag{24}$$

where

$$\mathcal{P}(t) = g_0 + g_1 p(t) + g_2 \sum_{s=1}^{\infty} \lambda^s \left[p(t-s) + \beta^s p(t+s) \right] \tag{25}$$

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

$$\lambda = \frac{1-\sqrt{1-4\beta\theta^2}}{2\beta\theta}; \qquad \lambda_1 = \frac{1+\sqrt{1-4\beta\theta^2}}{2\beta\theta}; \tag{26}$$

$$g_0 = \frac{\alpha_0}{1-(1+\beta)\theta} > 0; \qquad g_1 = \frac{\alpha_1 + 2\beta\lambda\alpha_2}{1-2\beta\lambda\theta} < 0; \tag{27}$$

$$g_2 = g_1 + \frac{\alpha_2}{\theta} < 0 \quad \Leftrightarrow \quad 1-\delta < \lambda \text{ and } \theta > 0; \tag{28}$$

and K is to be defined using the transversality condition. The price index $\mathcal{P}(t)$ in equation 25 shows that optimal consumption depends on the current price $p(t)$, as well as on the history of past and future prices. Past prices matter because they influence past consumption choices, which determine the current taste for addiction; future prices matter because the agent is forward-looking and takes into account future utility (which is discounted at rate $\beta \in (0,1)$ because of the uncertainty about future lifetime). We require $\sum_{s=1}^{\infty} \lambda^s \left[p(t-s) + \beta^s p(t+s) \right]$ to exist and be finite for all t. Since parameter g_1 is negative, consumption is predicted to respect the law of demand with respect to simultaneous price changes. Note, however, that this is not necessarily true for non-contemporaneous price shocks, because the coefficient g_2 can be either positive or negative.

If the good displays reinforcement, the roots λ and λ_1 of the Euler equation are positive. Note that $\lambda_1 = 1/(\beta\lambda) > 1$, which qualifies it as the unstable root of the dynamic process. We need to assess whether $\lambda < 1$ to avoid the dynamic process to be explosive. Three cases can occur:

1. If $0 < \theta < \frac{1}{1+\beta}$ both roots are reals with $\lambda < 1 < \lambda_1$: saddle-point dynamics,
2. If $\frac{1}{1+\beta} < \theta < \frac{1}{2\sqrt{\beta}}$, both roots are real but larger than one: explosive trajectories,
3. If $\frac{1}{2\sqrt{\beta}} < \theta$, both roots are complex and with modulus larger than one: explosive oscillations.

The second and third type of trajectories imply that the modulus of both λ and λ_1 is larger than one, hence they cannot be estimated with standard techniques. In the first type of trajectories, instead, λ is smaller than one, hence stationarity can be exploited for the empirical estimation. The corresponding condition $0 < \theta < \frac{1}{1+\beta}$ can be rewritten as $u_{cA} < \frac{\beta u_{AA} + \delta(1-\beta+\delta\beta)u_{cc}}{(1-2\delta)\beta - 1}$, which implies an upper bound on reinforcement.

The general solution 24 satisfies the necessary conditions for optimality (including the Euler equation) and it nests the solution presented in Becker et al. (1994), who restricts the attention to the special case $\delta = 1$. The selection of the particular solution depends on the transversality condition, which determines the value of the constant K. To eliminate the impact of the explosive root λ_1, we select $K = 0$. Hence the solution of the rational addiction model is the saddle path to the steady state

$$c(t) = [c(0) - \mathcal{P}(0)]\lambda^t + \mathcal{P}(t), \tag{29}$$

which can be expressed as a function of initial consumption, time and prices in all periods. This demand function asymptotically converges to the steady state c^{ss}; it essentially represents the discrete-time equivalent of the theoretical solution of the deterministic rational addiction model presented in Becker and Murphy (1988). This can be appreciated fixing $p(t)$ for all t, in which case $\mathcal{P}(0) = \mathcal{P}(t) = c^{ss}$ and the demand function becomes $c(t) = [c(0) - c^{ss}]\lambda^t + c^{ss}$. In contrast with the general solution 24 of the Euler equation, the saddle path does not contain explosive roots.

A.2 Deriving the AR(1) representation of the saddle path

To obtain the AR(1) version of the demand for addiction described in equation 8, shift equation 29 one period backward and solve for $c(0)$. Replacing it back into 29 and rearranging yields the AR(1) empirical model:

$$c(t) = \lambda c(t-1) + \varphi_1 p(t-1) + \varphi_2 p(t) + \sum_{s=1}^{\infty} \varphi_3(s)\, p(t+s) + \varphi_0 \tag{30}$$

where

$$\lambda \in (0,1); \qquad \varphi_1 = (g_2 - g_1)\lambda \geq 0; \qquad \varphi_2 = g_1 - \beta\lambda^2 g_2 < 0; \tag{31}$$

$$\varphi_3(s) = g_2\left(1 - \beta\lambda^2\right)(\beta\lambda)^s; \qquad \varphi_0 = (1-\lambda)\, g_0. \tag{32}$$

The key terms for testing rational addiction are λ and $\varphi_3(s)$. Note that $\varphi_3(s)$ is zero in absence of forward-looking behavior ($\beta = 0$). When $\beta \neq 0$, it can either have a positive or a negative sign, depending on the sign of g_2 (see 28). When $\delta = 1$, then $\varphi_1 = 0$. It can be shown that $\varphi_1 > \varphi_3(1)$.[12]

As an analytical exercise, one can compute the discount factor from the definition of $\varphi_3(1)$

$$\beta = \frac{\varphi_3(1)}{\varphi_1 + \lambda\varphi_2}. \tag{33}$$

However, this expression is highly non-linear, which may result in very unstable (and possibly non meaningful) empirical estimates of β.[13]

[12] The term φ_1 in equation 30 is non negative. This apparently counterintuitive result is a mathematical artifact due to keeping yesterday's consumption fixed (see Becker et al., 1990, Chaloupka, 1991, Becker et al., 1994).

[13] Alternatively, using $\varphi_3(1)$ and $\varphi_3(2)$, one can compute $\beta = \varphi_3(2)/(\lambda\varphi_3(1))$, which is also non-linear and possibly unstable.

B Empirical analysis: Supplementary material

B.1 Unit-root, cointegration tests

Table 2 shows the results of the the Augmented Dickey-Fuller test (ADF, Dickey and Fuller, 1979), the GLS Dickey-Fuller test (DF-GLS, Cheung and Lai, 1995; Elliot et al., 1996), and the Zivot-Andrews tests (ZA, Zivot and Andrews, 1992), to check for unit-roots in the data considered in the empirical analysis of Section 5. The optimal number of lags is automatically selected. Since trends appear to be non relevant, in the ZA test we allow for structural breaks only for the intercept.

Table 2: Unit-root and cointegration tests

	Cigarettes		Milk		Eggs		Oranges	
	price	cons.	price	cons.	price	cons.	price	cons.
ADF test	-1.208	0.355	-1.745	-1.791	-1.518	-1.533	-3.268	-2.954
z crit. value	-2.623	-2.623	-2.614	-2.614	-2.616	-2.614	-2.613	-2.613
DF-GLS test	-2.008	-1.107	-1.329	-0.349	-1.811	-1.599	-3.798	-3.016
z crit. value	-3.020	-3.020	-2.960	-2.960	-2.960	-2.960	-2.952	-2.952
ZA test	-3.227	-2.857	-2.769	-2.998	-3.559	-1.667	-6.635	-5.524
z crit. value	-4.58	-4.58	-4.58	-4.58	-4.58	-4.58	-4.58	-4.58
Stationary?	No	No	No	No	No	No	Yes	Yes
GH/EG test	-5.39		-3.651		-3.816		–	
z crit. value	-4.99		-3.497		-3.497		–	
Cointegrated?	Yes		Yes		Yes		–	

Notes: Unit-root and cointegration tests for prices and consumption; z is the critical value of each test (10% for the unit-root tests, 5% for the cointegration tests).

For cigarettes we use the Gregory-Hansen cointegration test (GH, Gregory and Hansen, 1996) to account for potential structural breaks due to the antismuggling policies implemented in the early 1990s (Gruber et al., 2003). The p-values are smaller than 10% and allow to reject the no-cointegration hypothesis. Similarly, for milk and eggs the Engle-Granger test (EG, Engle and Granger, 1987) allows to reject no-cointegration at the 5% significance level.

B.2 AR(1) model and error correction mechanism

Based on the results presented in Table 2, consumption and prices of cigarettes, milk and eggs are cointegrated. Accordingly, we follow the two-step Engel-Granger procedure for cointegration modeling. We consider the Error Correction Mechanism (ECM) representation of the AR(1) model 11 and we apply Dynamic OLS for estimation (Stock and Watson, 1993), as explained below.

As a starting point, consider the AR(1) model 11

$$c_t = \rho c_{t-1} + \gamma_1 p_{t-1} + \gamma_2 p_t + \gamma_3 p_{t+1} + \gamma_0 + \xi_t. \tag{34}$$

Subtracting c_{t-1} and manipulating the above equation allows for the following Error Correction Mechanism representation

$$\Delta c_t = \mu \left(c_{t-1} - \gamma_0 + \omega p_{t-1}\right) + \gamma_0 \rho + \gamma_2 \Delta p_t + \gamma_3 \Delta_2 p_{t+1} + \epsilon_t. \tag{35}$$

where $\mu \equiv \rho - 1$, $\omega \equiv \frac{\gamma_1+\gamma_2+\gamma_3}{\mu}$, Δ is the difference operator, and $\Delta_2 p_{t+1} \equiv p_{t+1} - p_{t-1}$. This representation allows to describe consumption as a combination of a long run relationship $\left(c_{t-1} = \gamma_0 - \omega p_{t-1}\right)$, and a short run relationship $\left(\gamma_0 \rho + \gamma_2 \Delta p_t + \gamma_3 \Delta_2 p_{t+1}\right)$ between consumption and prices.

Considering equation 35, estimates and inference for the parameters can be derived through the two-step procedure described in Engle and Granger (1987). First, the long run relationship $c_{t-1} = \gamma_0 - \omega p_{t-1}$ is estimated using the Dynamic OLS procedure of Stock and Watson (1993), which produces super-consistent estimators of γ_0 and ω. The lagged residuals are then plugged into equation 35 to obtain estimates of γ_2, γ_3 and ρ. Finally, using the definition of ω and μ, the point estimate of γ_1 can be computed as $\gamma_1 = \mu\omega - \gamma_2 - \gamma_3$