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ABSTRACT

A panel of Italian single households is used to test for rational addiction in alcohol consumption. These monthly consumption data raise problems of measurement errors and unobservable heterogeneity. To deal with the zeros in the dependent variable we adopt a specification based on infrequency of purchase. GMM estimators are used to deal with errors in variables and unobserved heterogeneity. There is evidence that alcohol consumers are actually forward-looking. Past consumption is also significant in explaining current consumption thus detecting the addictive nature of alcohol. Discount rates, the strength of addiction, short and long run price and income elasticities are significant and in line with the theoretical predictions. These results and the inclusion of a number of demographic and geographic characters deliver valuable information for public policy purposes and suggest significant differences driven by individual heterogeneity.

JEL codes: C23, D12

Keywords: rational addiction; infrequency of purchase; GMM

1. INTRODUCTION

Alcohol consumption has negative current and inter temporal consequences. It is an intoxicant: consumed in sufficient quantity in a single session it impairs mental and physical functioning and it is potentially toxic, generating important social costs such as: alcohol related violence and crime, road accidents and extra costs to the health and social security system. It also has direct inter temporal consequences: past consumption generates habit formation and addiction. Moreover, chronic alcohol use affects physical and mental health over the course of years or decades. For these reasons alcoholic beverages are subject to restrictions in most western societies. Since alcohol demand is typically assumed to be price inelastic, regulation, rather than economic incentives, has been the preferred policy measure to reduce consumption in most countries.

To explain alcohol consumption we use the theory of rational addiction developed by Becker and Murphy (1988). The theoretical model assumes forward-looking, utility maximizing consumers who may become addicted to the consumption of a good. Consumers are rational in that they anticipate the expected future consequences of their current actions. They may recognize the addictive nature of their choices, but decide to make them because the gains from the activity exceed the costs of possible future addiction. The rational addiction model is not just another theoretical model, but it has important policy implications. The two most important ones are the following. First, rational addiction models assign an important role to price changes (Becker and Murphy, 1988; Becker, Grossman, Murphy, 1991) and recover an important role for taxation not only for public revenue raising, but also for reducing consumption, thus questioning the common sense idea according to which the demand for addictive goods is price inelastic. Second, optimal taxation of harmful goods must include only the external costs that this behavior causes on other members of society.

This theory is not without criticisms (Winston, 1980; Akerlof, 1991; Orphanides and Zervos, 1995; Gruber and Koszegi, 2001), but the seminal paper of Becker and Murphy (1988) remains the starting point in most addiction theories (Bernheim and Rangel, 2004). The theoretical model lends itself to a simple empirical formulation in which current alcohol consumption is a function of past and future alcohol consumption, own current price and unmeasured life-cycle variables. This empirical equation allows testing five important predictions of the theory with the availability of at least 3 years of data over several individuals or States. The first prediction is that the effect of lagged consumption must be positive and statistically significant, which confirms that alcohol is addictive. The second requires the estimated coefficient for future consumption to be positive and significant, which clearly indicates that future consumption of alcohol affects current consumption. Third, long-run price elasticity must be larger than short-run price elasticity, implying, crucially, that price policies may be effective in curbing alcohol consumption in the long-run. Fourth, the roots of the second difference equation representing the empirical version of the Becker and Murphy demand function (see, Becker, Grossman and Murphy, 1994, appendix A or Baltagi, 2007, p. 4 for a discussion of this issue), must be real. Finally, the inter temporal rate of time preference obtained as a derived parameter of the empirical model, must be positive and take on values in line with the real interest rate. This requires that the ratio of lagged to lead consumption coefficient be greater than one.

This model has been applied extensively to explain consumption of a number of legal and illegal substances of abuse (see Picone, 2005, and Baltagi, 2007, for a review), but these studies have seldom produced results satisfying all the five predictions. A number of researchers has questioned their empirical relevance. The main criticisms are that the model implies implausible discount rates, a wide range of demand elasticities and results often critically depend on the set of instrumental variables used. Another criticism is that this model is not empirically distinguishable from models with forward looking behavior, but with time inconsistent preferences (Gruber and Koszegi, 2001). Concerns have also arisen about the econometric strategy usually adopted to estimate these models (Baltagi and Griffin, 2001) and about the interpretation of zero observations in the dependent variable (Jones and Labeaga, 2003). Whether the data support the rational addiction theory and its empirical predictions remains an empirical question.

This applied paper makes three distinct contributions to the existing literature on rational addiction. First, using individual level panel data on monthly alcohol consumption and sound econometric techniques it provides new and convincing evidence that Italian alcohol consumers are forward looking in their decisions to consume alcohol. Second, we present results satisfying all five predictions of the theoretical model including plausible estimates of discount rates, short and long run price elasticities of demand, the income elasticity of demand and strength of addiction. Finally, thanks to the inclusion of a number of demographic covariates in our empirical specification, we calculate short and long-run price elasticities of demand by gender, age, employment condition, education level and geographic location of individuals. This individual heterogeneity allows for interesting public policy implications to be drawn from the results.

The remaining of the paper is organized as follows. In section 2 we present the theoretical model and compare its policy implication with those stemming from more recent behavioral economics models of addiction. We also motivate the use of the model in the context of household panel data. Section 3 describes the data and the selection of the sample. The econometric methods are introduced in section 4. Section 5 describes the main results and the estimated elasticities by demographic characteristic. Section 6 concludes.

2. THE MODEL

Our model is a variant of the rational addiction equation for current consumption (C_{it}), as developed by Becker and Murphy (1988) and applied to alcohol consumption by Baltagi and Geishecker (2006), Baltagi and Griffin (2002), Bentzen *et al*. (1999), Grossman *et al*. (1998), Waters and Sloan (1995) among others:

$$C_{it} = \alpha_i + \beta_1 + \beta_2 C_{it-1} + \beta_3 C_{it+1} + \beta_4 P_{it} + \beta_5^{'} X_{it} + \beta_6 u_{it} + \beta_7 u_{it+1} \tag{1}$$

Where *i* is the individual, *t* is time, *X* includes relevant time varying and time invariant socio-demographic variables that may affect the consumption of alcohol and α_i is an unobservable effect intended to encompass idiosyncratic characteristics that can be expected to be correlated with lead and lagged consumption and probably with other determinants of consumption. This equation is derived from the optimality condition for inter temporal utility maximization based on a quadratic instantaneous utility function. Although equation (1) follows from a clearly specified utility maximization problem it is not sufficient to identify all of the structural parameters from the original model. Moreover some of the coefficients (β_4 and β_5) depend on the marginal utility of wealth which may not be completely fixed across time if there are unexpected changes in income or prices and it will change across individuals. Following Becker et al. (1994) we interpret the estimates of β_4 and β_5 as linear approximations to the true values.

Equation (1) is straightforward to estimate using standard econometric methods, which has contributed to the popularity of testing this model by applied economists and researchers. Underlying the rational addiction model are several assumptions: 1) the individual consumes positive amounts of the good; 2) she can accurately predict future prices and other demand shifters; 3) she is not only rational and forward looking but also time consistent (Gruber and Koszegi, 2001); she does not have self-control problems (Elster, 1999). Despite these assumptions, the empirical literature has been highly supportive of the main prediction of the rational addiction model, namely that future consumption of an addictive good is positively associated with current consumption.

The empirical formulations of the model have a number of critical points too. First the discount rates implied by the estimated coefficient on future consumption are often implausible which has led many researchers to impose the constraint of a sensible discount rate. However, such a restriction does not allow to test whether current consumption depends on future consumption independently of the effect of past consumption.

Second, the standard equation used to estimate rational addiction models cannot identify between time consistent and time inconsistent rational addicts[1]. While these two models are empirically undistinguishable they have radically different policy implications (Gruber and Koszegy, 2001). If individuals are time consistent taxation should include only the values of externalities. However, if individuals are time inconsistent taxation should also include the private costs giving rise to a much higher rate of taxation (Picone, 2005, p. 10). Although the standard rational addiction model cannot distinguish between time consistent versus time inconsistent rational addicts, still it may allow us to test for forward looking behavior and to estimate price elasticities in the short and in the long run.

Finally, a further empirical point relates to the type of data. In practice many applications have used cross-section data that cannot capture the dynamics in the model, or aggregate time series data. Auld and Grootendorst (2004) showed empirical estimates of the rational addiction equation using aggregate time series data tend to find spurious evidence in favor of the rational addiction because time-series data is unable to discriminate between rational addiction and correlation in the consumption series. Since the theoretical model was developed for an individual representative consumer it is not clear whether State level aggregated panel data can be used either. The most appropriate form of data to capture the key features of these dynamic models with unobserved heterogeneity is therefore individual level panel data. Except for the problem of identification of time consistent versus inconsistent consumers, in this paper we address each of the mentioned empirical issues.

In the context of household survey data, $C_{it}, C_{it-1}, C_{it+1}$ could each be subject to censoring. In this case measures of actual consumption C in equation (1) would be replaced by latent variables (C^*). Under abstention and corner solution, all the three variables would be latent. Under infrequency of purchase, i.e., when the survey period is too short to allow the consumers

[1] Laibson (1997), Harris and Laibson (2001) and O'Donoghue and Rabin (1999) are among some of the most important papers on hyperbolic discounting.

to report any purchase of a specific product, none of the variables are censored but they are measured with errors. Following Jones and Labeaga (2003, p. 160) we assume some observability rule to link observed and latent consumption is:

$$C_{it-s} = f(C^{*}_{it-s}), \quad s = \text{-}1, 0, 1 \qquad (2)$$

Where $f(.)$ is a function linking observed and unobserved variables. In the case when C is infrequently observed, $f(.)$ is linear in the latent variable and in the measurement error so that, for example, $C_{it-s} = C^{*}_{it-s} + r_{it-s}$ where r is the measurement error and C^{*} is the planned alcohol consumption. Actual consumption C can differ from the planned consumption due to infrequency of purchase, causing a measurement error. In the case where C is censored, instead, $f(.)$ follows a Tobit-type observability rule. In this paper we assume that zeroes are attributable to infrequency of purchase only and that the purchase policy is time-invariant. In this case we only need to deal with the problem of errors-in-variables during estimation.

3. DATA AND SAMPLE SELECTION

We use monthly cross sections from January 1999 to December 2006 of individual Italian households current expenditures on alcoholic beverages (wine, beer and liquors) collected by the Istituto Nazionale di Statistica (ISTAT) through a specific and routinely repeated survey[2]. Current expenditures are collected on a weekly basis and then transformed to monthly expenditures by ISTAT. In this survey, current expenditures are classified in about 200 elementary goods and services with the exact number changing from year to year due to minor adjustments in the item's list. The survey also includes detailed information on the household structure, so that relevant data on demographic characteristics (such as location on a regional basis, number of household members, sex, age and employment condition of each) are available. All annual samples are independently drawn according to a two stage design[3].

Given the availability of a series of independent cross-sections instead of a panel data, it is impossible to track individual households overtime and, therefore, to estimate a dynamic model. To overcome this problem, starting from the series of independent cross-sections of micro-data for the period 1999(1)-2006(12), we construct a pseudo-panel using cell averages, identifying household types. Households in each cell are selected on the basis of 12 combinations of a set of available demographic characteristics plus one residual category and sample averages for each type in each month and in each region have been computed. Since the survey does not provide information on the presence of drinkers in the household, households with one member only have been selected to ensure a unique correspondence between the recorded expenditure on alcoholic beverages and the individual in the household. Finally, for the purposes of the current research, we restrict the analysis to wine consumption. Table 1 contains a description of each average household.

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

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

Table 1 – Single household types

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

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

Our dependent variable, the quantity of wine (QW) , has been obtained implicitly as the ratio between monthly wine expenditure (in Euros) and the wine price index. In order to introduce some individual variation, the price of wine (PW) is constructed by deflating the retail price index for wine by a weighted average of nine broad categories of the retail price index (RPI), as in Labeaga (1999), where the weights are the shares of expenditure devoted to each good in each household. A set of dummy variables is included to account for demographic and geographic factors: location (North-West (NW), North-East (NE), Centre (CE) and South and Islands (SI)); gender (MALE, FEMA); employment status (employed (EMP), unemployed (UNE)); education level (higher education (HED), lower education (LED)); income level (RICH, POOR, MIDL); age (less than 24 years (YOU); between 25 and 65 years (ADU) and more than 65 years (SEN)); household type (HT1 to HT13) based on gender, age, employment condition and education level of the single member of the household according to combinations displayed in table 1. We also add total current monthly expenditure (YT) as a proxy of disposable income[4]. Summary statistics of the data are shown in table 2.

[4] We have tried alternative specifications of equation (1) including interactions between wine price and demographic characteristics and between total current expenditure and demographic characteristics. We do not report results of these alternative estimations to save space, but they are available to the interested reader upon request.

A few comments about the data are worth making at this stage. The descriptive statistics reveal that almost 22% of the single households report zero wine expenditures during the survey period. On average, wine consuming singles have slightly higher total expenditures than non consuming ones. Non consuming females are more numerous than non consuming males.

Table 2 - The Data

Variable	Full Sample	Consuming Households	Non Consuming Households
Sample size	4,259	3,329	930
Wine expenditures[a]	7.984 (11.612)[b]	10.215 (12.236)	0
Price of wine	106.189 (3.421)	106.139 (3.216)	106.367 (4.067)
Retail price index	110.527 (5.905)	110.622 (5.872)	110.189 (6.012)
Total household expenditures	1414.426 (544.657)	1432.014 (523.085)	1351.467 (611.891)
Dummy variables (yes = 1, no = 0)			
North West	0.255 (0.436)	0.270 (0.444)	0.203 (0.403)
North East	0.2444 (0.429)	0.244 (0.429)	0.244 (0.429)
Centre	0.241 (0.428)	0.245 (0.430)	0.229 (0.420)
South & Islands	0.259 (0.438)	0.241 (0.427)	0.324 (0.468)
Male	0.449 (0.497)	0.481 (0.499)	0.339 (0.473)
Female	0.469 (0.499)	0.449 (0.498)	0.538 (0.499)
Unemployed	0.312 (0.464)	0.281 (0.449)	0.427 (0.495)
Employed	0.359 (0.479)	0.394 (0.489)	0.232 (0.422)
Young (< 24)	0.067 (0.250)	0.028 (0.164)	0.209 (0.406)
Adult	0.671 (0.469)	0.675 (0.468)	0.659 (0.474)
Senior (>65)	0.180 (0.384)	0.228 (0.419)	0.009 (0.092)
Low Education	0.355 (0.478)	0.377 (0.485)	0.275 (0.447)
High Education	0.317 (0.465)	0.298 (0.457)	0.384 (0.487)
Poor	0.249 (0.433)	0.223 (0.416)	0.345 (0.476)
Rich	0.249 (0.433)	0.255 (0.436)	0.231 (0.422)
Middle	0.500 (0.500)	0.522 (0.499)	0.424 (0.494)

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

When looking at age, young consumers are less represented than older ones in our data, but among non consuming households the young are more numerous than the old. Non consuming households are also more numerous among highly educated in comparison with less educated individuals and among unemployed rather than employed ones.

4. ESTIMATION METHOD

Under the assumption of infrequency of purchase, with a time-invariant purchase policy, the model to be estimated is the linear equation (1). Even though we have numerous months, the assumption about the invariability of the purchase policy looks quite reasonable given that wine is usually consumed during meals and its daily consumption is a well established life style in Italy. There are two problems that prevent the linear expression (1) from being estimated by ordinary least squares. First, there is an omitted variable bias due to unexplained demand shifters that may also be serially correlated (Becker et al., 1991). Second, infrequency of purchase accounts for errors-in-variables since, even considering the heterogeneity, lag and lead consumption are measured with errors and are correlated with the mixed error terms. Measurement errors lead to the classical error-in-variables model (CEV). CEV causes an attenuation bias in the estimated coefficients and this problem is worsened using panel data[5]. To correct for this endogeneity bias we follow Arellano and Bond (1991) in using a GMM procedure to obtain the vector of parameters:

$$\hat{\beta}_{GMM} = \left[\left(\sum_{i=1}^{N} V_i' K' W_i\right)\hat{A}\left(\sum_{i=1}^{N} W_i' K V_i\right)\right]^{-1}\left(\sum_{i=1}^{N} V_i' K' W_i\right)\hat{A}\left(\sum_{i=1}^{N} W_i' K C_i\right) \quad (3)$$

Where $V_i = [C_{it-1}, C_{it+1}, P_{it}, X_{it}]$, K is a transformation matrix to get rid of the individual unobservable effects, W_i is the matrix of instruments and the weighting matrix $\hat{A}$ is a consistent estimate of the inverse of the covariance matrix of the empirical moments given by $\hat{A} = [W_i' K \hat{u}_i \hat{u}_i' K' W_i]^{1}$, where $\hat{u}_i = C_i - \hat{\beta}' V_i$ is a consistent estimate of the disturbance. Since the weighting matrix is a function of $\hat{\beta}$, we need a two-step procedure. In the first step, we obtain a preliminary estimate of the parameter vector using an arbitrary positive definite and symmetric weighting matrix which does not depend on $\hat{\beta}$. In the second step, the preliminary estimate of β is used to form $\hat{A}$ and obtain $\hat{\beta}_{GMM}$.

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

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

instruments (Picone, 2005). Once we have identified valid instruments given the type of regressors included in the model and the auto correlated errors in equation (1), estimation using (3) is straightforward.

Additional restrictions that could lead to more efficient GMM estimators can be obtained incorporating the orthogonality conditions for the equations in levels into the above procedure, see Blundell and Bond (1998) for the system-GMM method, which allows for orthogonality conditions of both types of equations, transformed $(K \neq I)$ and in levels $(K = I)$.

Whether we actually need all these moment conditions is not clear. For example, Ziliak (1997) showed that GMM may perform better with suboptimal instruments and argued against using all available moments in panel data estimation, especially when N is relatively small and T is relatively large. In our case, e.g., $N = 52$ and $T = 96$, there is a large number of orthogonality conditions to use, hence we consider only a subset of them, testing their validity with the Sargan over-identification test (Baltagi and Griffin, 2001).

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

The use of prices alone to instrument consumption can induce problems of weak instruments and of estimators that can be biased towards ordinary least squares ones (see Jones and Labeaga (2003) for a discussion of this issue). Time invariant demographic variables can also be used as instruments in any transformation of the model that rules out time invariant explanatory variables. After some experimentation with the matrix of instruments W_i, we use lag and lead prices, the proxy of disposable income as well as a dummy variable (RICH) for the presence of rich households, i.e. households belonging to the highest quartile in the distribution of disposable income. One way to decide about the set of instruments is to perform a Hausman test of the null hypothesis that future prices are legitimate instruments. [6]

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

5. EMPIRICAL SPECIFICATION AND RESULTS

In the empirical specification of model (1) we use the quantity of wine consumed per month as the dependent variable. The right-hand side variables are the lead and lag consumption, the real price of wine, the proxy of disposable income and the following socio-demographic characteristics: gender, geographical area, age, high education level, high income level and a dummy variable accounting for whether a specific combination of demographic variables can explain some of the variation in wine consumption. We use all available instruments of prices to improve the efficiency of the GMM estimator. Table 3 presents results under the infrequency of purchase interpretation for the zeros. Column 1 gives the estimates of equation (1) in levels. The problem with this set of estimates is that, although they take into account errors-in-variables, they do not control for individual heterogeneity and the possibility of correlated individual effects could lead to spurious evidence in favor of the rational addiction model. The results in column 2 are estimated by GMM on the deviations from the mean, which eliminates these fixed effects. Finally, results in column 3 are obtained using the system–GMM (Blundell and Bond, 1998). This unifying GMM framework incorporates orthogonality conditions for equations in deviations and levels and performs significantly better in terms of efficiency as compared to other IV estimators of dynamic panel data models. We estimate both one step and two step GMM estimators, but we only report two step estimates with a robust covariance matrix[7].

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

Table 3 – Estimation for rational addiction models (infrequency or misreporting)

Parameter	Model 1: GMM-levels	Model 2: GMM-deviations	Model 3: GMM-system	Model 4: GMM-system
C(-1)	0.523	0.511	0.446	0.446
	(0.001)	(0.004)	(0.012)	(0.019)
C(+1)	0.438	0.446	0.372	0.345
	(0.001)	(0.003)	(0.011)	(0.018)
Real price of wine	-0.008	-0.006	-0.015	-0.016
	(0.0003)	(0.0007)	(0.002)	(0.003)
Real disposable income	0.001		0.002	0.003
	(0.00003)		(0.0002)	(0.0003)
Demographic structure	0.001			
	(0.001)			
Geographic area	0.033			
	(0.002)			
Male	0.230			
	(0.007)			
Employed	-0.194			
	(0.006)			
Adult	-0.068			
	(0.007)			
High Education	-0.268			
	(0.006)			
Rich	0.041			
	(0.025)			
p-value Sargan test	0.599	0.459	0.232	0.169

Notes:
1. Model 1 estimated in levels. Model 2 estimated in deviations. Model 3 and Model 4 estimated combining levels and deviations.
2. Instrument set: lagged and lead prices, lagged real disposable income and demographic dummies for lagged and lead consumption. Future prices are excluded from the set of instruments in Model 4.
3. Consistent standard errors robust to heteroscedasticity are in parentheses.

According to the estimates of the equation in levels, the behavior of Italian consumers seems to be consistent with the rational addiction framework. When we rule out the presence of unobserved effects using quasi-time demeaning (column 2) the lag and lead consumption variables remain significant even though the real price of wine is no more significant. GMM-system estimates (Model 3 and Model 4) are to be considered our reference results. One formal way to choose between them is to perform a Hausman test. Under the null of perfect foresight both set of estimates are consistent but those in Model 3 are more efficient. Under the alternative only Model 4 estimates are consistent. The statistics is a quadratic form, which is asymptotically chi-squared with four degrees of freedom, i.e., the number of instruments excluded when future prices are discarded. The computed p-value is 0.36, hence the empirical χ^2 does not exceed the critical value at any reasonable significance level. This implies that the null of consumers that can fully anticipate future prices without measurement errors cannot be rejected.

Given the validity of future prices as instruments, in the following we'll comment the results of Model 3. As predicted by the theory, both the lag and the lead consumption term are positive and highly significant in the wine demand equation suggesting, respectively, habit formation and forward looking behavior. We will return to this issue below when commenting on the implied discount rates and the strength of the estimated addiction effects. Moreover, the lead consumption parameter is smaller in magnitude than the lagged consumption parameter giving rise to a positive discount rate. The proxy of disposable income, added as a covariate to the model, is also highly significant and has the expected sign. In terms of adherence to the theory's predictions, our findings perform well and compare favorably with other works. In their study on tobacco expenditure, Jones and Labeaga (2003) obtain theoretically consistent results only for the equations in levels, whereas the real price of tobacco is never statistically significant when using GMM in deviations or system-GMM. Baltagi and Geisheker (2006) find substantial evidence that Russian drinkers are forward looking consumers, but their implied discount rate is negative and insignificant; the full sample yields an insignificant coefficient estimate of lagged consumption, too.

5.1 Behavioural implications

Although the empirical specification of the rational addiction model cannot distinguish between time consistent and time inconsistent addicts it still can be used to test for forward looking behavior and to calculate short and long price elasticities of demand which can be of interest for policy purposes.

All our estimates are consistent with the rational addiction framework. First, past consumption has a significant positive effect. Second, future consumption has a significant positive effect, supporting the idea that behavior is forward looking. Third, the coefficient of lag consumption is always greater than the coefficient of lead consumption giving rise to a positive discount rate. Fourth, our results fulfill the stability condition[8] as both roots are positive and $4\beta_2\beta_3 < 1$ (Becker *et al.*, 1994). Finally, we obtain a sensible value of the discount rate. These findings are also true in Jones and Labeaga (2003) with the exception of the stability condition derived by their GMM-sys set of estimates.

These results are further explored in table 4, which reports the estimated roots of the second order difference equation implied by the standard specification: $\left[1 \pm \left(1 - 4\beta_2\beta_3\right)^{.5}\right] / 2\beta_2$. The reciprocal of the larger root measures the impact of an exogenous shock to past consumption on current consumption and can be interpreted as the strength of the addiction effect. The smaller root gives the impact of an exogenous shock to future consumption on current consumption, and can be interpreted as the forward looking effect. The first and second row of table 4 show that the model estimated in deviation and levels (GMM-sys), gives a smaller estimate of both effects. Apparently, the failure to account for heterogeneity (GMM-levels) may lead to over-estimate the impact of the forward looking effect, while it does not seem to have notable consequences on the addiction effect. This is not in line with the results of Jones and Labeaga (2003, p. 172, table V) or Chaloupka (1991).

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

Table 4 – Discount rate and strength of addiction

Derived parameter	Model 1: GMM-levels	Model 2: GMM-deviations	Model 3: GMM-system	Model 4: GMM-system
(Larger root)$^{-1}$	2.964 (0.008)	3.019 (0.021)	2.836 (0.069)	2.768 (0.105)
Smaller root	0.186 (0.001)	0.180 (0.002)	0.094 (0.006)	0.085 (0.009)
Monthly discount factor	0.836 (0.004)	0.872 (0.013)	0.833 (0 .040)	0.774 (0.059)
Monthly discount rate	0.196 (0.005)	0.146 (0.017)	0.201 (0.058)	0.292 (0.098)

Notes:
1. Model 1 estimated in levels. Model 2 estimated in deviations. Model 3 and Model 4 estimated combining levels and deviations.
2. Instrument set: lagged and lead prices, lagged real disposable income and demographic dummies for lagged and lead consumption. Future prices are excluded from the set of instruments in Model 4.
3. Consistent standard errors robust to heteroscedasticity are in parentheses.

The implied discount factor, (β_3 / β_2), is the weight given to future utility, from which one can derive the discount rate, $(\beta_2 / \beta_3)-1$. Concerning discount rates, there is not a marked difference between GMM-levels and GMM-system estimates, both assume a reasonable value of about 20%. Compared with the existing literature producing very high discount rates ranging from 4.175 and 0.165 (Jones and Labeaga, 2003, infrequency specifications); 0.255 to 0.695 (Chaloupka, 1991); 0.892 to 0.939 (Labeaga, 1999); 0.31 to 0.64 (Becker et al, 1994); or negative discount rates (Baltagi and Geisheker, 2006), our results appear plausible and do not require imposing the constraint of a given discount rate.

5.2 Short and Long Run Demand Elasticities

Becker *et al.* (1994) have derived formulas to compute short (SRE) and long run (LRE) price elasticities of demand. Taking into account equation (1), the resulting short and long run elasticities at the sample mean are, respectively:

$$SRE = \frac{dQW}{dPW}\frac{PW_m}{QW_m} = \frac{2\beta_4}{[1-2\beta_3+(1-4\beta_2\beta_3)^{0.5}]}\frac{PW_m}{QW_m} \tag{4}$$

$$LRE = \frac{dQW_\infty}{dPW}\frac{PW_m}{QW_m} = \frac{\beta_4}{[1-\beta_2-\beta_3]}\frac{PW_m}{QW_m} \tag{5}$$

The short run elasticity gives the permanent variation in wine consumption in the first year after a permanent change in current and all future prices, with past consumption held constant. The long run price elasticity gives, instead, the percent change in wine consumption following a permanent price change in all time periods (Becker, Grossman and Murphy, 1994, p. 240). The implied SRE and LRE price elasticities at the sample mean are, respectively, - 0.477 and -1.096. The long run price elasticity of demand for wine is of particular interest for policy purposes. Wine demand appears elastic in the long run in Italy, meaning that a permanent price increase of 10%, for example, would produce a decrease in wine demand by approximately 10%. Up until now only liquors, among alcoholic beverages, have been highly taxed with wine being subject to a lower level of taxation as a way of subsidizing wine production. Our elasticities suggest this is a reasonable way of maximizing public revenues. To obtain additional insights regarding the optimal taxation policy for alcoholic beverages it would be useful to compare the long run prices elasticities of both wine and liquors.

Tables 5 and 6 show short run and long run price and expenditure elasticities (along with their standard errors) by some demographic characteristics. The rows convey information on the differences in elasticities across geographic macro-areas of Italy. The columns detect demographic differences within each area. A few comments on demand responses to price and expenditure variations are noteworthy. As far as geographic differences are concerned, singles in the North are less reactive to price changes than in the South, across all demographic characters. A plausible interpretation of this result is the following. In the rational addiction model, the marginal utility of income is a multiplying factor in the current price coefficient, so that an increase in the marginal utility of income will produce a greater increase in the price coefficient. This implies that wealthy people, with a lower marginal utility of income, will be less sensitive to price changes than people with lower incomes and a higher marginal utility of income. Thus, we expect that price elasticities of demand will be higher in the South of Italy, characterised by a lower per-capita income, and lower in the North. This information can be useful for policy purposes, because it suggests that a regionally differentiated taxation policy could pursue the double objective of increasing public revenues while not decreasing sales, if targeted at the more inelastic areas.

Looking at gender, females are more reactive than males to price variations, both in the short and in the long run. A tentative interpretation of this difference is the following. Habit formation may be weaker for women, i.e. they may be more ready to change their habits following a price change and to reallocate their budget across the bundle of consumption goods. They are also generally considered more careful than males regarding food and drink purchases and therefore more sensitive to a change in the price of wine. Unemployed single households are also more reactive to price changes than employed ones, with the exception of those living in the North. In this case one might consider that individuals with a less stable income over time may be more reactive to the price change of a luxury good (see comments below) than the employed ones who benefit from a more stable pattern of income.

Table 5 – Short and long run price elasticities of wine demand

Price elasticity	Short run			Long run		
	North	Centre	South	North	Centre	South
Gender						
Male	-0.398	-0.370	-0.565	-0.914	-0.852	-1.298
	(0.065)	(0.060)	(0.092)	(0.152)	(0.142)	(0.216)
Female	-0.574	-0.576	-1.241	-1.319	-1.325	-2.852
	(0.093)	(0.094)	(0.201)	(0.219)	(0.220)	(0.474)
Employment						
Unemployed	-0.348	-0.433	-0.885	-0.799	-0.996	-2.033
	(0.056)	(0.070)	(0.144)	(0.133)	(0.166)	(0.338)
Employed	-0.461	-0.404	-0.812	-1.059	-0.929	-1.867
	(0.075)	(0.066)	(0.132)	(0.176)	(0.155)	(0.310)
Age						
Young	-0.853	-0.609	-0.878	-1.962	-1.399	-2.019
	(0.138)	(0.099)	(0.143)	(0.326)	(0.233)	(0.336)
Adult	-0.412	-0.446	-0.907	-0.948	-1.026	-2.086
	(0.067)	(0.072)	(0.147)	(0.158)	(0.072)	(0.347)
Education						
Low	-0.435	-0.416	-0.910	-1.001	-0.955	-2.092
	(0.071)	(0.067)	(0.148)	(0.166)	(0.159)	(0.348)
High	-0.373	-0.422	-0.787	-0.858	-0.970	-1.809
	(0.061)	(0.068)	(0.128)	(0.143)	(0.161)	(0.301)

Notes: Consistent standard errors in parentheses.

Finally, young single households are more price elastic than adults and seniors. Even in this case an interpretation in terms of weaker habits sounds reasonable, considering that, generally, younger generations have looser habits, as far as food and drinks consumption are concerned, than adults or seniors. Differences in the level of education do not look remarkable. Among the binary demographic variables considered, gender seems the character displaying the largest within variation in elasticities. Females elasticities are at least 20% higher than male ones across geographic areas and both in the short and long run.

When looking at expenditure elasticities of demand, a similar pattern emerges as far as gender and age are concerned. Females and young individuals' wine consumption is more income elastic than their male and non-young counterparts. As far as the employment condition of individuals is concerned, being employed increases the income elasticity of demand. For all characteristics and all geographic areas wine is a luxury good in the long run, as its demand increases more than proportionally as income increases. When considering differences across areas, the South is more income elastic than the North, both in the short and in the long run and across each demographic character except age.

Table 6 – Short and long run expenditure elasticities of wine demand

Expenditure elasticity	Short run			Long run		
	North	Centre	South	North	Centre	South
Gender						
Male	0.927 (0.081)	0.872 (0.076)	0.955 (0.084)	2.131 (0.186)	2.003 (0.175)	2.195 (0.191)
Female	1.331 (0.117)	1.260 (0.111)	2.036 (0.179)	3.060 (0.267)	2.897 (0.253)	4.680 (0.408)
Employment						
Unemployed	0.812 (0.071)	0.964 (0.084)	1.435 (0.126)	1.867 (0.163)	2.215 (0.193)	3.299 (0.288)
Employed	1.187 (0.104)	1.015 (0.089)	1.621 (0.142)	2.730 (0.238)	2.334 (0.203)	3.727 (0.325)
Age						
Young	1.975 (0.173)	1.495 (0.131)	1.431 (0.125)	4.539 (0.396)	3.436 (0.300)	3.290 (0.287)
Adult	0.960 (0.084)	0.980 (0.086)	1.508 (0.132)	2.207 (0.192)	2.253 (0.196)	3.467 (0.302)
Education						
Low	0.955 (0.084)	0.884 (0.077)	1.348 (0.118)	2.195 (0.191)	2.031 (0.177)	3.010 (0.270)
High	1.045 (0.092)	1.096 (0.096)	1.708 (0.150)	2.402 (0.209)	2.518 (0.220)	3.926 (0.342)

Notes: Consistent standard errors in parentheses.

6. Conclusion

We use a pseudo panel of singles Italian households to test the rational addiction model proposed by Becker and Murphy (1988) and Becker *et al.* (1994). The dependent variable in our model, wine consumption, raises the problem of zero observations. To deal with these zeros we assume that they are generated by infrequency of purchase and errors-in-variables. There is evidence that the rational addiction specification is sensitive to unobserved heterogeneity. We also provide sound econometric evidence for all the main predictions of the rational addiction model. Habit formation in wine consumption is very strong and Italian wine consumers are forward looking in their decisions. Moreover, the roots of the estimated second order difference equation are real, as required by the theory, and we find plausible estimates of the monthly discount rate. These findings suggest a number of policy implications and interesting extensions. The implementation of appropriate public policies to control the consumption of alcoholic beverages requires reliable estimates of the price and income elasticities taking habits' formation into account. Our results suggest that increased government taxation would be an effective tool for curtailing the consumption of alcohol – wine in this case - at least in the long run. Geographic differences in price elasticities suggest, in addition, that the level of taxation could be space-differentiated. Differences in price elasticities of demand by gender, age and employment condition suggest that price policy measures could be targeted at specific groups in society. Finally, this article can be extended in at least three ways. First, since censoring is another plausible interpretations of zeroes in the dependent variable we will deal with this hypothesis following Chamberlain (1984) and adopting a three stage estimator and we will then compare the two alternative interpretations of zeroes. Second, given that individual data on Beer, Spirits and Tobacco are also available, it would be worthwhile to examine the demand for Beer, Spirits and Tobacco using the same theoretical and methodological framework. The associated price elasticities for different addictive goods could be compared. Interesting policy suggestions could emerge from such comparison as to which is the good that could be taxed the most as a function of the policy target. For example, the optimal strategy for maximizing public revenues would be to raise the price of the most price inelastic good. Third, there may be current and inter temporal interactions (e.g. complementarities and substitutions) between alcoholic beverage and between alcoholic beverages and Tobacco. Information on the way these "sin goods" are related, given by the cross-price elasticities of demand, may allow a better coordination of public policies. If they are complements, for instance, we could obtain a reduction in consumption of both goods by raising the price of just one of them. On the other hand, if they are substitutes, measures aimed at reducing one of them could produce undesired effects. Such current and inter temporal interactions could be investigated within an extended version of the empirical rational addiction equation (Pierani and Tiezzi, 2009), but using individual level data and adapting the methodological framework used in this paper to the case of two (or more) addictive goods.

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