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Abstract

This paper addresses two aspects of the model of rational addiction: forward looking behavior and time consistent preferences. It explores smoking by women before, during and after pregnancy using the European Community Household Panel (ECHP). Pregnancy is used as an instrument for a partially predictable future decrease in smoking. Women reduce the average number of cigarettes they smoke and many quit in the period 10 to 15 months before the birth of a child. Our analysis suggests that this effect may be stronger for married than for unmarried women, corresponding to the higher probability that the pregnancies of married women are planned. Pregnancy is also used as an instrument to estimate the parameters of a structural model of addiction. The estimates imply that cigarettes are highly addictive. Finally, we present statistically significant evidence that, even when the expected number of cigarettes smoked one month after the interview is taken into account, expected smoking further in the future has an independent effect on current consumption. This effect remains even when we impose the highest theoretically possible coefficient on expected cigarettes smoked one month after the interview. This means that the null of time consistency is (barely) rejected against the alternative of time inconsistency.

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1 Introduction

The consumption of a good can be termed an addiction if an increase in its past consumption leads to an increase of its current consumption. The explicit recognition of such a relationship is the main feature of the first generation of models of addiction. These introduced three notions that are essential in every model of addiction: tolerance (or gradual adaptation), withdrawal (or irreversibility) and reinforcement (or positive habit effects). Tolerance suggests that the higher past consumption causes lower satisfaction from a given level of current consumption. Withdrawal refers to the disutility associated with cessation or interruption of consumption. Finally, reinforcement implies a positive response to past consumption, so that higher current consumption implies higher future consumption.

These models came to be collectively called the myopic model of addiction, because they assume that consumers ignore the dependence of future consumption on current and past consumption, when choosing consumption. The first examples were Houthakker and Taylor (1970) and Pollack (1970). Baltagi and Levin (1986,1992) applied this model to cigarette consumption.

In 1988, Becker and Murphy introduced their famous Rational addiction model based on the idea that rational agents take into account future shocks when they determine the optimal level of consumption of an addictive good in the present. They demonstrate that several of the phenomena classified as irrational were consistent with a model of inter-temporal optimizing behavior of farsighted consumers endowed with time consistent preferences. If preferences are time consistent, agents' future behavior coincides with their currently desired future behavior. Under the assumption that preferences can be represented by a quadratic utility function, the model implies a closed form demand equation in which the current consumption of the addictive good positively depends on lagged consumption and one lead of expected consumption:

$$C_t = \alpha + \theta C_{t-1} + \beta\theta C_{t+1} + \theta_1 P_t + \theta_2 e_t + \theta_3 e_{t+1} \qquad (1)$$

where C_t indicates cigarette consumption in period t, β is the discount factor, P_t indicates price of cigarettes in period t and e_t and e_{t+1} are shift variables accounting for the impact of unmeasured variables on utility.

The simple testable implication, $\theta > 0$, first considered by Becker, Grossman and Murphy (1991) has been widely exploited to investigate the consumption of several addictive goods. Cigarette consumption was investigated by Baltagi and Griffin (2001), Becker, Grossman and Murphy (1994), Chaloupka (1991) among others.[1] The literature recognizes that lead and lagged consumption are endogenous. Most authors use lagged and future prices as instruments and analyze aggregate data at the state or regional level. The test of forward looking behavior has reduced to assessing whether higher prices next year are correlated with lower current consumption.

Gruber and Koszegi (2001) argue that, even if forward looking behavior can be convincingly supported, it provides no evidence in favor of the rational addiction model against a model with dynamic inconsistency. Dynamic inconsistency is considered in a third generation of models called imperfectly rational models of addiction, in which the individual is both a farsighted planner and a myopic doer. Planner and doer are in conflict. Examples are Schelling (1978), Thaler and Sheffrin (1981), Gul and Pesendorfer (2004, 2001) and Laibson (2001) for models of "temptation", O'Donoghue and Rabin (2002, 1999) and Gruber and Koszegi (2001) for models with "present bias preference", Lowestein (1999, 1996), and Lowestein O'Donoghue and Rabin (2003) for models with "Projection bias" and Bernheim and Rangel (2004, 2002) for models of "cue-conditioned cognitive processes". Gruber and Koszegi (2001) has an application to cigarette consumption and will be the major reference of our effort. These models rely on evidence coming from psychology and cognitive science to explain real world phenomena such as the inability to implement the stated desire to quit smoking and the resulting demand for self-control devices. Gruber and Mullainathan (2002) find evidence that cigarette excise taxes increase the self reported happiness of people who they calculate are likely to smoke. Models with dynamic inconsistency can deliver radically different implications for government policy, but have not been tested, using data on smoking, against models of rational addiction.

This paper addresses the endogeneity problem with an alternative valid instrument, and tests the null of dynamic consistency using individual level data on cigarette consumption. We begin by testing the null of myopia using pregnancy as an instrument.[2] The intuition is that a farsighted woman trying to get pregnant would reduce consumption in advance anticipating future reduction in smoking while pregnant. The description of cigarette con-

[1]Other papers on the topic are Tiezzi (2005) with evidence on Italian smokers, Escario and Molina (2001) on Spanish smokers, and Cameron (1998) on Greek smokers. Chaloupka and Warner (2000) and Cameron (1998) are two useful surveys on the argument.

[2]Cigarettes consumption by pregnant women has been the theme of Evans et al. (1999), Evans and Ringel (1999), Ringel and Evans (2001), Colman et al. (2003) and Bradford (2003). They describe cigarette consumption and its response to price and tax changes measuring the elasticity of participation.

sumption by pregnant women is a by product of our investigation, hence the paper should be of some interest also to those who are involved in this literature. We perform the test with reduced form estimates using data from the most recent 4 waves of the European Community Household Panel (ECHP) which contain information on respondents' cigarette consumption. We find robust evidence of forward looking behavior. Women sharply reduce cigarette consumption starting more than six months before they get pregnant and continuing for the duration of the pregnancy. This definitely rules out myopic models.

To determine whether preferences are dynamically consistent, we rely on the fact that women in the sample were interviewed at different distances from the baby's birth date allowing the comparison of current consumption with changes in future consumption at different points in time. This makes possible to test dynamic consistency by simply looking at estimated coefficients on consumption two periods and more in the future, after including consumption one period in the future in the regression or imposing the highest theoretically possible coefficient on consumption one period in the future. We discuss our evidence in the context of Gruber and Koszegi's model because it can generate radically different policy implication by simply allowing for quasi-hyperbolic discounting in the Becker and Murphy framework, but our test is sufficiently general for the result to be generated by other and more sophisticated models of dynamic inconsistency.

The structure of the paper is as follows. In section 2 we describe the data and justify the use of pregnancy as an instrument. In section 3 we illustrate the dramatic effect of pregnancy on smoking. Section 4 is devoted to the estimates of the Becker and Murphy model, while the test on dynamic inconsistency is performed in section 5. Section 6 uses a variety of estimators to see if the results in earlier sections could be caused by improper use of 2SLS. Section 7 concludes.

2 The data

The ECHP is an harmonized cross-country annual survey on living conditions, with information at both the household and the individual level covering the period 1994-2001. The survey is carried out by national statistical institutions under the supervision of Eurostat, the leading statistical office of the European community. Some countries have participated in the survey since the beginning (Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Spain, Portugal, and the United Kingdom) others only in subsequent years (Austria, Finland and Sweden joined the ECHP starting, respectively, in 1995, 1996, and 1997).[3]

The statistical units are households and, within them, individuals who are at least 16 years old. In the first wave (1994) about 60 thousand households and 130 thousand individuals were interviewed.

The main focus of the survey is on household income and living conditions. Household level data include basic demographic information, sources of incomes and financial positions, housing, purchases of durable goods, and some data on children under 16. Individual level data include labor market status, sources of income, educational levels and training. Finally the health section reports the number of cigarettes smoked per day by daily smokers. Unfortunately, the latter variable is only available in the ECHP for the 1998-2001 waves and for a subset of European countries: Austria, Belgium, Denmark, Finland, Greece, Ireland, Italy, Portugal, and Spain.

The ECHP data set is useful for our purposes partly because it was collected without a specific focus on smoking and pregnancy. This means that the timing of questions about smoking is unrelated to the timing of births, so the possible effect of anticipated pregnancy on smoking can be studied. On the other hand, this also means that our useful sample is effectively small, even though the total sample of the pooled ECHP is huge. There are relatively few pregnancies in the sample and even fewer pregnancies of women who smoke. Thus we will not be able to obtain precise estimates. We can precisely estimate baseline smoking behavior of women who are not pregnant, do not have newborn children and are not about to become pregnant, but we cannot precisely estimate the behavior of women who are about to become pregnant. Another way of describing the problem is that the fitted variance of future smoking instrumented by future pregnancy is very low since the variance of the indicator variable for pregnancy is very low. In that sense, pregnancy is a poor instrument.

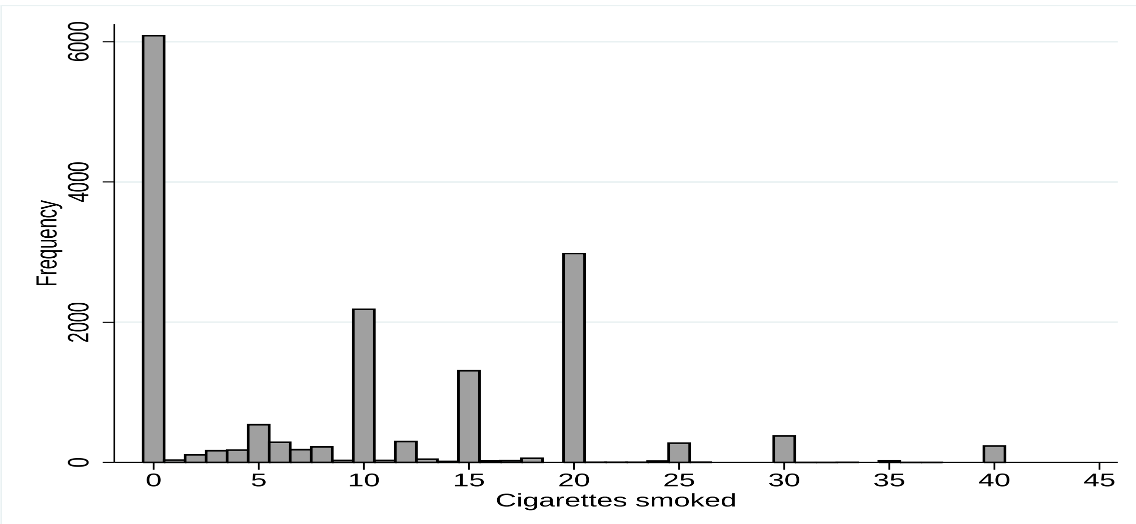
In the ECHP sample survey, individuals were asked: *Do you smoke or did you ever smoke ?* The five possible answers in the form were: 1-Smoke daily, 2-Smoke occasionally, 3-Do not smoke, used to smoke daily, 4-Do not smoke, used to smoke occasionally, 5-Never smoked. Respondents reporting 1 or 3 to the previous question were asked to report the

[3]Our brief description of the ECHP is especially based on the official documentation provided by the Eurostat and refers to the so called User Data Base (UDB). For confidentiality reasons, the complete Production Data Base (PBD) is in fact generally not be accessible to researchers. We also referred to Peracchi (2002) which contains a detailed analysis of statistical aspects of the survey. The Statistics on Income and Living Conditions (SILC), will replace the ECHP as the main source of micro data for the country members of the European Union.

Number of cigarettes smoked per day (currently or in the past).

As expected, the self reported data on cigarettes smoked per day suffer from bunching or heaping. The extent of bunching in our data is illustrated in Figure 1 which reports the frequency distribution of cigarettes consumed by women who smoked daily or did not smoke at all. As it is evident, there is a huge mass of respondents reporting that they don't smoke, while those who smoke have bunched their answers around multiples of 5 with a peak at 20 (the number of cigarettes typically contained in one pack).

Figure 1: Bunching of self-reported cigarettes data



This makes statistical inference tricky and is especially problematic since the coefficient of interest is effectively estimated with a small sample. For example, we estimated quantile regressions using high quantiles to deal with censoring at zero cigarettes per day. These estimates were extremely uninteresting, since large changes in the fraction of smokers and in the average number of cigarettes smoked by each smoker leave the 95th percentile of the distribution of cigarettes smoked at 20.

Heaping is normally ascribed to rounding errors in self reported averages. In this case, the true number of cigarettes smoked may include spikes at multiples of 5 or 10. Many smokers report that they have dynamically inconsistent preferences and are struggling with their addiction (without usually using the words dynamic or inconsistent). In such a case holding the line at 20 cigarettes may be a strategy to avoid ever increasing smoking. Thus a true spike in the distribution of cigarettes smoked may occur.

The reporting of cigarettes smoked is probably biased as well as rounded. It seems likely that people under-report smoking.

True spikes, rounding errors and reporting bias make it very difficult to believe that simple models of addiction correspond to our data. In any case, they give linear predictors (see Equation 1) because they have been designed for simplicity and not because people consider such predictors more realistic than others.

Given the difficulty of modelling even the reporting process, we estimate reduced form smoking equations with a number of different estimators. Each is subject to severe valid criticisms, but the fact that we find similar results with OLS and all of the other estimators reassures us that 2SLS can be used for structural estimates.

In addition to heaping, there is also a sample selection problem based on the number of cigarettes smoked per day. This information was asked of women who reported smoking daily and is clearly zero for women who don't smoke. However the average number of cigarettes per day is missing for women who smoke "occasionally". Thus when we use the number of cigarettes smoked per day, we have to drop those observations. This is selection based on the dependent variable. Five of the estimators which we use address this issue.

3 Evidence of forward looking behavior

In the model of rational addiction (Equation (1)) the shift variable e_t has an effect on the marginal utility of smoking in each period and thus influences consumption at all dates. Hence, C_{t-1} and C_{t+1} are endogenous. Becker, Grossman and Murphy (1991) propose an instrumental variable estimator which, after refinement in subsequent research, uses future prices as instruments for future consumption and lagged prices as instruments for lagged consumption. Thus the test of the myopic null hypothesis against the rational addiction model as an alternative hypothesis consists in testing whether smoking is reduced when next year prices are increased. As pointed out by Gruber and Koszegi (2001), there are a number of problems with this test. First, it requires that agents are able to accurately forecast price changes at least one year in advance, although price changes are rarely announced so far in advance.[4] Second, because of stockpiling, there isn't a clear interpretation of the coefficients when current sales instead of current consumption are regressed on future prices. Third, there may be endogeneity bias in regressing cigarettes consumed on the price of cigarettes, because the true exogenous variation which should be used to identify the model is the

[4]Gruber and Koszegi (2001) documented that only 8 out of 160 tax changes have been announced at least one year in advance over the period 1973-1996.

excise tax. Fourth, evidence of forward looking behavior could also be interpreted as a failure of the specification of the model. Fifth, prices are not useful instruments when dealing with micro data. To address these issues, we propose an alternative test on forward looking behavior which is suitable when micro data are available.

The intuition for the test is straightforward, women who are farsighted and trying to have a child will start reducing cigarettes consumption before getting pregnant because they anticipate lower consumption levels during pregnancy.

Even though the ECHP does not collect information on people aged less than 16, birth date of all members of the family are reported in the "register file". Using new babies' birth dates we construct a variable measuring the distance between the interview and the birth date. We named this variable *MonthSB* which stays for "months since birth". The variable measures the distance in months since the birth of the baby and takes negative values when the woman is interviewed before the birth date. Consequently, the data on cigarettes smoked at the date of the interview can also be thought as cigarettes smoked at a certain distance from the birth. Women begin to reduce smoking before they become pregnant as is shown by Figures 2 and 3.

Figure 2: Lowess estimation and quarterly mean of cigarettes smoked on months since birth by women who did smoke

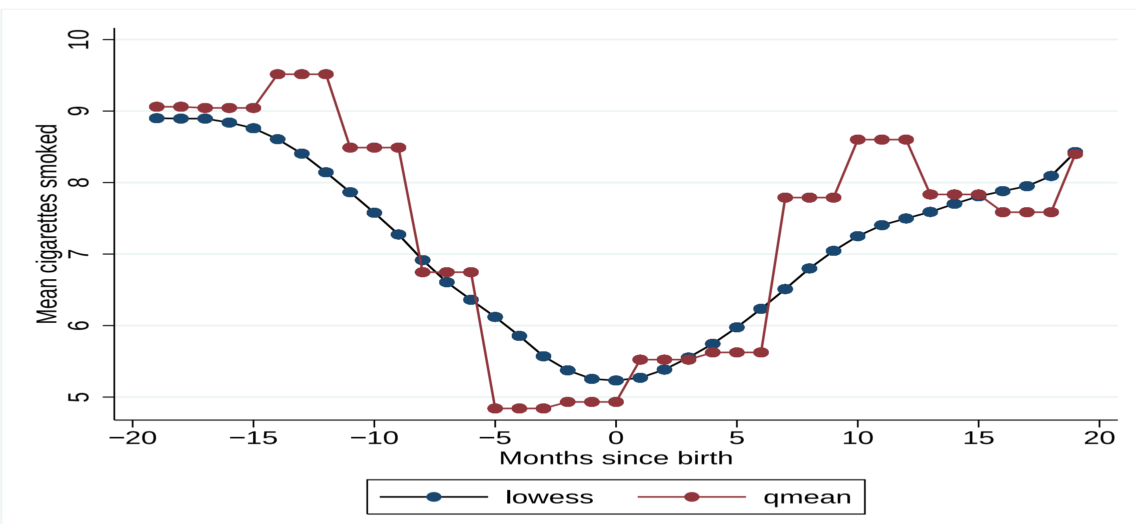
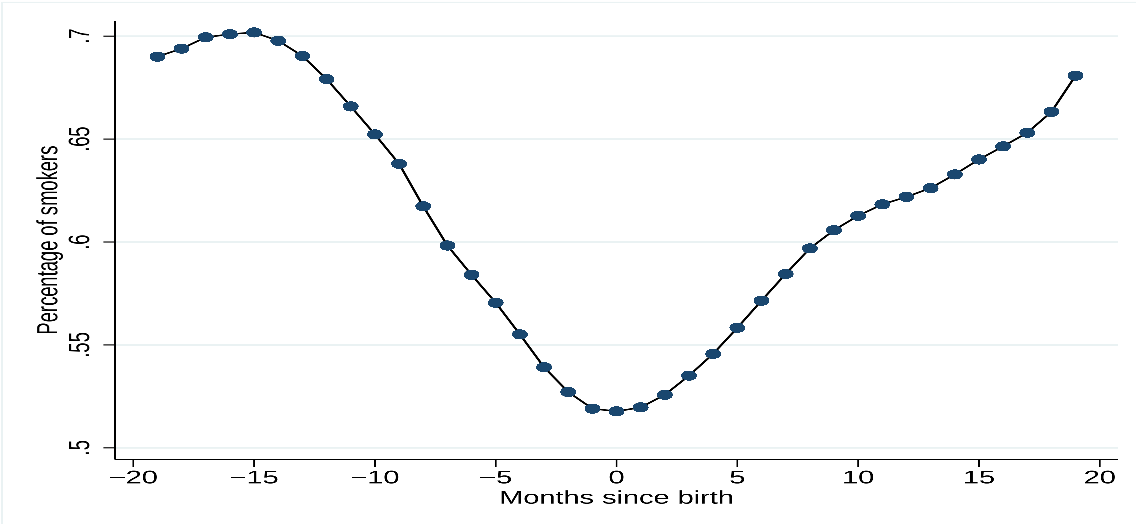


Figure 2 reports a lowess estimation of cigarettes smoked on months since birth that shows that women begin to reduce cigarette consumption at least 15 months before the birth date, hence at least 6 months before getting pregnant. The decline in the average

Figure 3: Lowess estimation of percentage of smokers by women who did smoke



number of cigarettes smoked continues for the entire pregnancy.[5] To avoid the artificial smoothing effects due to the lowess estimator, the same figure shows the quarterly mean of the cigarettes smoked. The pattern remains. In particular the average number of cigarettes smoked daily by women who did smoke decreases from a 9 to 5. Average daily cigarette consumption increases back to 8 one year after the birth of the baby.

Figure 3 shows a pre-pregnancy reduction of the percentage of women who smoke. 15 months before the birth date, the percentage of the women who smoked in the previous interview and that report smoking at least occasionally is 70%. The percentage decreases to 53% in the month of the birth. Both figures illustrate the intuition behind our test and the importance of pregnancy as a cause of quitting or of reducing smoking.

The same figure shows that, 20 months after birth, the percentage of women who declare that they smoke at least occasionally is back to the same value as 20 months before birth. Probit analysis of smoking behavior reveals that, among women who once smoked but do not report smoking in the previous interview, those who gave birth to a child 9 to 15 months in the past have a statistically significant 10% higher probability of smoking. The effect of past pregnancy is still significant and increases the probability by about 7%, when the birth is 20 to 24 months in the past. Further analysis on relapsing behavior reveals that having

[5]Figures 2 and 3 were created using the `lowess` command as implemented in Stata 9.2 SE. The smooth curves were in particular obtained by locally fitting a first order polynomial (weighted least squares smoothing) with a bandwidth equal to 0.5 and a tricubic weighting function given by $w(x) = (1 - |x|^3)^3$ if $|x| < 1$, and 0 otherwise.

at least one other smoker in the family results in a significant increase in the probability of smoking by 62%. However, smoking does not appear to be significantly correlated with weight gain during pregnancy.

The fact that we have only 4 waves of data on smoking, the relative rarity both of smoking and pregnancy, and panel attrition, means that our efforts to follow individual women's smoking histories did not give estimates precise enough to be at all interesting. Thus, all results reported below are for the pooled panel treated as a cross section. We consider only the most recent pregnancy per woman.

4 Estimating the parameters of a model of rational addiction

We attempt to estimate the parameters of Equation (1) via two stage least squares using a pseudo panel approach.

In the first stage we regress cigarettes smoked (C_t) on age, age squared, an indicator for married women, an indicator for university graduates, an indicator for high school graduates (all contained in X_t) country dummies (CD) and 49 indicator variables ($MonthSB[\#]$). This corresponds to estimating a regression of the following form

$$C_t = \alpha + \beta_1 X_t + \beta_2 MonthSB[\#] + \beta_3 CD + \epsilon_t \quad (2)$$

$MonthSB[\#]$ is an indicator variable that takes value 1 if the interview is # months since birth. The interval covered by the entire set of indicators goes from -24 months since birth to 24 months since birth. The excluded category related to pregnancy is no birth within 2 years of the interview.

To generate predicted cigarettes smoked by a woman one month after her interview (C^e_{t+1}), we calculated the fitted values using actual values of variables other than the indicator of $MonthSB$, setting the indicator which was actually 1 to zero and setting the next indicator of $MonthSB$ to one. The coefficient on this last indicator variable is estimated using data on women other than the one whose cigarette consumption is the dependent variable. This is important, since the coefficients on the indicators for $MonthSB$ are very imprecisely estimated implying measurement error in the predicted cigarettes smoked. We calculate, by an analogous procedure, C^e_{t+2}, C^e_{t+3}, C^e_{t+4}, respectively the predicted cigarettes smoked 2, 3 and 4 months ahead, C^e_{t-1}, C^e_{t-2}, and C^e_{t-3}, the predicted cigarettes smoked 2 and 3 months in the past.

In the second stage we estimate a version of Equation (1) that considers age, age squared, an indicator for married women, an indicator for university graduates, an indicator for high school graduates, country dummies, an indicator for being pregnant, indicators for the presence of young children in the household, and one fitted value of past and future smoking, for example the fitted values for C^e_{t+1} and C^e_{t-1} as regressors. In all regressions we exclude data on women who will not give birth for two years and do not have children under age 2. Indicator variables on pregnancy and the presence of young children in the household have been introduced to take into account the direct effect of pregnancy and young children on smoking as opposed to the indirect effect via past smoking and anticipated future smoking. In different regressions, we consider two indicators of the presence of young children – $Baby1$ which is an indicator of a baby aged 2 years or less in the household and $Baby2$ which is an indicator of a child aged 6 months or less in the household.

Given the results reported below in section 6, we are convinced that we can use least squares, since reduced form estimates are similar with different estimators as long as occasional smokers are excluded or occasional smoking is coded as not smoking. In particular, OLS coefficients are close to Tobit coefficients times the fraction of uncensored observations.

The extremely imprecise estimates in the first stage due to our small sample definitely creates bias. Since our errors in predicted future and lagged cigarettes smoked are uncorrelated with the dependent variable, coefficients will be biased towards zero.

Column 1 of Table 1 reports results on the classical formalization of the Becker and Murphy model. The coefficients on C^e_{t+1} and C^e_{t-1} (0.244 and 0.228) are both significantly greater than zero. This demonstrates forward looking behavior once again. The coefficient on C^e_{t+1} is slightly greater than the coefficient on C^e_{t-1} implying a negative estimated rate of time preference, which is clearly not statistically significantly different from zero. We are sure that the coefficients are biased down, since resolving the quadratic equation in the lag operator implies rapid reversion to the mean of cigarettes smoked.

Column 2 of Table 1 reports an estimate of the effect of censoring on our estimates. We repeat both stages of the regression excluding data on women who report that they have never smoked. This enormously reduces the fraction of censored observations but has only a tiny effect on the coefficients of interest.

Columns 3 and 4 of Table 1 shows the results of a regression where, in an effort to increase the signal to noise ratio, we replace C^e_{t+1} with the average of C^e_{t+1}, C^e_{t+2}, and C^e_{t+3} and replace C^e_{t-1} with the average of C^e_{t-1}, C^e_{t-2}, and C^e_{t-3}, ($C^e_{(t+1,t+2,t+3)}$ and $C^e_{(t-1,t-2,t-3)}$

respectively). As expected the coefficients of interest become much larger. The estimated quadratic in the lag operator implies two roots of almost exactly 1 roughly corresponding to a random walk with drift. This seems very reasonable given that we have used monthly data.

In column 4 we add $Baby2$, the indicator that there is a child aged 6 months or less in the household. The coefficient is negative and statistically significant, corresponding to a greater perceived cost of passive smoking by newborns compared to toddlers. Inclusion of $Baby2$ causes a statistically insignificant decline in the coefficient on $C^e_{(t-1,t-2,t-3)}$.

In the estimates above, we have implicitly assumed that women have perfect foresight about future pregnancies. This is clearly not realistic. We expected that the coefficient on our prediction of future cigarettes smoked would be smaller for women who are not yet pregnant, since our prediction is based on our knowledge of the date of birth of a not yet conceived child. Thus we include a separate variable ($NpyC^e_{t+1}$) for future cigarettes smoked predicted for women who are not pregnant yet. The results reported in column 5 of Table1 do not reject the null hypothesis of perfect foresight, presumably due to the low power of our test.

The pseudo panel approach to estimation of dynamics is no longer new (Moffit (1993)). However our application is somewhat unusual as we (effectively) group women based on months till or since a birth. A more common approach is to group based on cohorts. Fortunately, this means that we do not need to be concerned about otherwise important econometric issues. The fact that women are grouped based on the month of birth of their children and the month in which they are interviewed makes it very unlikely that variables are correlated for women with slightly different $MonthSB$. Such correlation, as noted by Verbeeck and Vella (2005), can lead to inconsistent estimates of coefficients on variables which are only included in the second stage of the regression. The only variables which we include in the second stage and not the first stage are *pregnancy*, *baby1* and *baby2* which are functions of $MonthSB$ which is included with complete flexibility in the first stage.

Furthermore while important variables are, no doubt, missing from both stages of our regression, it is very hard to see how their omission could cause inconsistent estimates of the parameters of interest. For example, we do not use any information on the price of cigarettes. However, there is no reason to assume that there is any particular correlation between prices paid by women who are 3 months pregnant and women who are four months pregnant. Prices vary over time and across regions but have no particular association with the month of birth of the smoker's child.

Table 1: Structural estimations on Becker and Murphy model

	(1a) Coeff./t	(1b) Coeff./t	(1c) Coeff./t	(1d) Coeff./t	(1e) Coeff./t
Age	–.046	–.349	–.030	–.044	–.040
	(–.45)	(–1.22)	(–.30)	(–.43)	(–.40)
Age^2	.001	.005	.002	.001	.001
	(.88)	(1.10)	(.99)	(.80)	(.78)
Married	–1.683**	–1.239	–.755	-1.639**	-1.578**
	(–4.01)	(–1.82)	(–1.76)	(–2.82)	(–2.70)
University	–2.057**	–3.052**	–1.728**	–2.017**	–2.001**
	(–7.84)	(–4.37)	(–7.08)	(–7.32)	(–7.24)
HighSchool	–1.162**	–1.695**	–1.238**	–1.165**	–1.170**
	(–5.79)	(–3.41)	(–6.85)	(–6.35)	(–6.38)
Pregnancy	–.520	–1.324	–.138	–.502	–.194
	(–1.86)	(–1.84)	(–.49)	(–1.54)	(–.41)
$Baby1$	–.249	–.401	–.150	–.104	.204
	(–1.17)	(–.81)	(–.71)	(–.49)	(.51)
$Baby2$				–.663*	–.658*
				(–2.26)	(–2.24)
C^e_{t+1}	.244*	.224			
	(2.23)	(1.88)			
C^e_{t-1}	.228*	.186			
	(2.06)	(1.65)			
$C^e_{(t+1,t+2,t+3)}$			.459**	.317*	.310*
			(3.24)	(2.04)	(1.99)
$C^e_{(t-1,t-2,t-3)}$			.349*	.131	.142
			(2.27)	(.73)	(.78)
$NpyC^e_{t+1}$					.099
					(.91)
Constant	4.047*	11.193**	1.665	3.989	3.549
	(2.27)	(2.66)	(.93)	(1.93)	(1.67)
Adj. R^2	.09	.13	.09	.09	.09
No. of cases	7334	2531	7334	7334	7334

Notes: $^*P < 0.05$ and $^{**}P < 0.01$. Indicators for countries included as controls but not reported. Robust standard errors reported. Model (1a) is estimated on women who smoke or did smoke. $Baby1$ is a variable indicating the presence of a child aged less than 24 months in the family. $Baby2$ is a variable indicating the presence of a child aged less than 6 months in the family. $C^e_{(t+1,t+2,t+3)}$ is the mean of C^e_{t+1}, C^e_{t+2} and C^e_{t+3}.$C^e_{(t-1,t-2,t-3)}$ is the mean of C^e_{t-1}, C^e_{t-2} and C^e_{t-3}. $npyC^e_{t+1}$ is future cigarettes smoked predicted for women who are not pregnant yet. *Pregnancy* is a indicator variable of pregnancy.

5 Testing dynamic inconsistency

The Becker and Murphy model of "Rational Addiction" is based on two key assumptions: forward looking behavior and time consistency. The first assumption is shared by competing models and is supported by evidence reported below. Gruber and Koszegi (2001) note that estimates of equation (1) test the null of myopia, but provides no evidence on the relative merits of models with consistent and with inconsistent preferences. Psychologists and cognitive scientists have cast doubt on the second assumption with evidence that consumers have dynamically inconsistent preferences. Experiments have shown that agents apply a lower rate when discounting decisions that are farther in the future with respect to decisions that are closer in the future. This generates an internal conflict, when they make decision about future prospects. At every point in time, the agent is both a farsighted planner and a myopic doer. Planner and doer are in conflict, making short term preferences inconsistent with long term preferences. Such a situation is often modelled as an hyperbolic or quasi-hyperbolic discount rate or by mean of a game played by the agent with his future-self in which the agent tries to implement some form of pre-commitment.

Despite the huge amount of experimental evidence, little empirical evidence exist on time inconsistency of economic agents living their normal lives and dealing with problems with which they have years or decades of experience. The point is that after Gruber and Koszegi have shown that testing Equation (1) is not a test of the rational addiction hypothesis but a test of forward looking behavior, we are also left without evidence on time consistency. In particular they have demonstrated that the huge mass of empirical evidence accumulated on the classical Becker and Murphy model is consistent with a model slightly different from the original one where *sophisticated* consumers are endowed with quasi-hyperbolic discounting.

The use of self-control devices is indirect evidence that consumers have time inconsistent preferences. Time consistent agents will use a quitting aid, that lowers the dis-utility from not smoking, but not a self-control device that lowers the utility from smoking.[6]

Other anecdotal evidence in favor of time inconsistency comes from attempted quits. This is theoretically consistent with time consistency if the model incorporates learning and uncertainty, but it also implies a very slow learning process or a high variability of relevant circumstances.

[6] Citations of empirical evidence coming from medical literature can be found in Gruber and Koszegi (2001).

For agents with quasi-hyperbolic discounting, modeled as in Laibson (1997), the stream of future utilities is discounted in the following way

$$U_t = \beta \sum_{i=1}^{T-t} \delta^i U_{t+1} \tag{3}$$

β and δ usually assumed to be in the interval $[0;1]$. β also capture hyperbolic discounting making the discount factor between consecutive future periods (δ) larger then the discount between current period and the next in the future ($\delta\beta$). We consider agents that realize their self-control problem and named them *sophisticated*.[7]

When the Becker and Murphy model is modified to consider the time discount structure presented above, we are left with results that are summarized in Table 2.[8]

Table 2: Summary of price responses in Gruber and Koszegi (2001)

	Next period	Two periods ahead
Time consistent	> 0	0
Sophisticated	> 0	> 0

Current consumption negatively responds to pregnancy one period in the future. The point is that this prediction is implied by both the model of time consistent and the model of sophisticated consumers. Hence measurement of the effect of next years cigarettes consumption on current consumption is not conclusive. The two models predict different behavior starting two periods before a predictable shock.

If preferences are time consistent, the level of addiction can be described with a single real number and addiction is the only form of non time separability, smoking at $t+1$ is a sufficient statistic for the whole stream of future smoking, that is, expected smoking lead more than one period should have no independent effect on smoking.

A brief heuristic explanation of this mathematical result might be useful. Consider an optimal smoking plan and a variation which involves slightly more smoking in period t and a reduced smoking in $t+1$ such that the levels of addiction in period $t+2$ are the same with the two plans. Provided that the level of addiction can be described with a single real number and is a continuous function of, among other things, the past period's

[7]It is theoretically possible to consider agents that do not realize their self control problem, *naive* in terms of Gruber and Koszegi taxonomy, but their behavior is similar in this setting. O'Donoghue and Rabin (1999) have excellently discussed how *naive* and *sophisticated* agents behave differently in other contexts.

[8]Table 2 is equivalent to the Table reported in appendix 3 of Gruber and Koszegi (2001).

smoking, it is possible to find such a reduction in smoking in period $t+1$. Assume also that consumption of other goods is modified so that wealth at the end of period $t+1$ is the same for the original and the modified plan. Optimality and dynamic consistency implies that the first order effect of such a modification on welfare must be zero. The derivative of welfare expected at t with respect to a small change in smoking in period t balanced by a change in non smoking consumption must be zero for optimality. If preferences are time consistent, the derivative of welfare expected at t with respect to a small change in smoking in period $t+1$ balanced by a change in non smoking consumption must also be zero. Since consumption changes only in periods t and $t+1$ and the level of addiction changes only in period $t+1$, the change in welfare from the original plan to the modified plan can not depend on variables dated $t+2$ and higher. Thus a necessary first order condition for optimality depends only on smoking at $t+1$. Any variation in the plan which does not involve a permanent shift in the level of addiction can be built up from such small variations so, given concavity of the utility function, a sufficient condition for optimality consists of satisfaction of the necessary first order condition each period and a transversality condition that the present value at t of addiction at $t+s$ must go to zero as s goes to infinity. The transversality condition has no implications which can be tested with a finite data set, so, as claimed above, for time consistent agents in which the level of addiction can be described with a single real number and the utility function is time separable except for addiction, smoking at $t+1$ is a sufficient statistics for the whole stream of future smoking.

In contrast, if consumers have time inconsistent preferences, it is possible for predicted smoking two periods and more ahead to help explain current smoking, even though consumption one period ahead has been considered.

This is the intuition for our test. The response to future consumption at different points in the future can be used, in principle, to obtained the parameters δ and β. The small dimension of our sample prevents us from estimating the parameters consistently. For our purposes a simple test on the coefficient of future consumption will be sufficient to distinguish the two models. In our first exploration of the issue we estimate

$$C_t = \alpha + \gamma C_{t+3} + \psi X_t + \theta_2 e_t + \theta_3 e_{t+1} \tag{4}$$

where the vector X_t includes pregnancy, baby1, age, age squared, an indicator for married women, an indicator for university graduates, an indicator for high school graduates and country dummies, C^e_{t+1}, C^e_{t+2}, C^e_{t-1}, C^e_{t-2} and C^e_{t-3}. The coefficient on C^e_{t+3} (0.326) is significantly different from zero with a t-statistic of 2.54. This result reported in Col. 1 of Table 3 is an apparent rejection of time consistency. However, it is clearly not a valid test of the Becker and Murphy model. The insignificance of the coefficients on C^e_{t+1}, and C^e_{t-1} creates suspicion since all models imply that these coefficients are positive. More formally, the downward bias in the coefficients on C^e_{t+1}, and C^e_{t-1} due to the imprecise first stage which creates, in effect, measurement error, implies an upward bias (analogous to omitted variables bias) in the coefficients on C^e_{t+3} and C^e_{t-3}.

In order to address this issue, we impose the highest plausible coefficient (0.5) on C^e_{t+1} and the highest coefficient consistent with this imposition on C^e_{t-1} (also 0.5). Which means that we use $Cdif \equiv C_t - 0.5C^e_{t+1} - 0.5C^e_{t-1}$ as our dependent variable. Since these coefficients add to zero, theory implies that variables which do not change month to month should not be correlated with this variable. All such variables are excluded from the regressions. This also implies that we do not need to worry about omitted variables bias, since plausible omitted variables should not be correlated with months since birth.

Thus we test Becker and Murphy's model with a simple regression of $Cdif$ on C^e_{t+3}. As reported in Table 3, we reject the null hypothesis of time consistency. In similar simple regressions of $Cdif$ on C^e_{t+2} and C^e_{t+4} we obtain positive coefficients, which are not statistically significantly different from zero.

To check that the result in column 4 of Table 3 is not due to a few outliers, we repeat both stages of the regression excluding observations in which women claimed to smoke 60 or more cigarettes a day. The coefficient on C^e_{t+3} barely changes.

In the last column of Table 3 we have excluded respondents interviewed at critical dates (0 or –9 months since birth).Also in this case, the coefficient on C^e_{t+3} does not significantly changes.

Table 3: Evidence on dynamic inconsistency

	(3a) Coeff./t	(3b) Coeff./t	(3c) Coeff./t	(3d) Coeff./t	(3e) Coeff./t	(3f) Coeff./t	(3g) Coeff./t
Age	–.364	–.359					
	(–1.29)	(–1.25)					
Age^2	.005	.005					
	(1.09)	(1.07)					
Married	–.045	–.103					
	(–.04)	(–.10)					
University	–1.934*	–1.976*					
	(–2.01)	(–2.03)					
HighSchool	–1.243*	–1.260*					
	(–2.25)	(–2.12)					
Pregnancy	–.817	–.837					
	(–.98)	(–.99)					
*Baby*1	–.754	–.780					
	(–1.05)	(–1.14)					
C^e_{t+1}	.032						
	(.23)						
C^e_{t+2}	.075		.054				
	(.52)		(1.09)				
C^e_{t+3}	.326*	.322*		.123*		.108*	.125*
	(2.54)	(2.53)		(2.42)		(2.21)	(1.97)
C^e_{t-1}	–.046						
	(–.36)						
C^e_{t-2}	.057						
	(.45)						
C^e_{t-3}	.324**	.324**					
	(2.92)	(2.82)					
$C^e_{(t+1,t+2)}$		.097					
		(.49)					
$C^e_{(t-1,t-2)}$		.011					
		(.07)					
C^e_{t+4}					.039		
					(.78)		
Constant	8.573*	8.637	–.380	–.903*	–.264	–.777	–.952
	(1.98)	(1.96)	(–1.06)	(–2.49)	(–.73)	(-2.10)	(–1.72)
Adj. R^2	.14	.14	.00	.00	–.00	.00	.00
No. of cases	2531	2531	2531	2531	2531	2351	1626

Notes: $^*P < 0.05$ and $^{**}P < 0.01$. Countries dummies included as controls but not reported. Robust standard errors reported. *Baby*1 is an indicator variable indicating the presence of a child aged less than 6 months in the family. $C^e_{(t+1,t+2)}$ is the mean of C^e_{t+1} and C^e_{t+2}. $C^e_{(t-1,t-2)}$ is the mean of C^e_{t-1} and C^e_{t-2}. *Pregnancy* is an indicator variable of pregnancy. The dependent variable of models (3c)-(3g) is $C_t - 0.5(C^e_{t+1} + C^e_{t-1})$. In Model (3g) interviews at critical distances (0 or 9 months since birth) have not been considered.

6 Reduced form estimates with various estimators

Given the distribution of cigarettes smoked reported in section 3, we are concerned about our use of 2SLS in the structural estimates and test of dynamic consistency. In this section we estimate reduced form smoking equations with a variety of estimators designed to address the censoring and bunching of data on cigarettes smoked per day. The fact that OLS coefficients are similar to Tobit estimates times the fraction censored is reassuring. More generally, for the different estimators, the t-statistics on indicators of intervals of time since birth are similar provided occasional smokers are excluded or occasional smoking is coded as not smoking, reassuring us that our 2SLS estimates are informative.

We estimate regressions of the following form,

$$C_t = \alpha + \beta_1 C_L + \beta_2 Smoke_L + \delta MonthSB[\#/\#] + \gamma_1 X_t + \gamma_2 CD + \epsilon_t \tag{5}$$

where C_t is cigarettes currently smoked per day, C_L is lagged consumption (as reported in the previous interview), $Smoke_L$ is an indicator which takes the value 1 if the woman reported that she smoked in the past interview, $MonthSB[\#/\#]$ are indicator variables corresponding to being interviewed during a particular interval of months since birth (for example $MonthSB[-15/-10]$ takes the value 1 if the woman gives birth 10 to 15 months after the interview) X_t is a vector of socioeconomic characteristics of the respondent and CD is a vector of country dummies. Finland is the excluded country.

Since we are not principally interested in estimating the effect of past smoking on current smoking, we will use lagged smoking both as an explanatory variable and to pick up the effects of unobserved heterogeneity. Thus we will not even attempt to include all available relevant explanatory variables. Our results are not particularly sensitive to the set of explanatory variables included in the estimates. They are more sensitive to the choice of the dependent variable and statistical technique.

In column 1 of Table 4 we present the results of simple OLS estimation using the number of cigarettes smoked by women who smoke daily or not at all as the dependent variable.[9]

Since consumption is censored at zero cigarettes per day and 82% of the of women in the sample do not smoke, such estimates are biased down compared to estimates of theoretical interest. One of our aims in this section is to provide evidence on whether the use of OLS distorts our structural estimates and test of dynamic consistency. For this reason we

[9] The OLS test statistics reported in Table 4 are based on robust estimates of the standard errors, obtained by specifying the `robust` option to the `regress` command in Stata 9.2 SE.

compare OLS estimates of the reduced form to more sophisticated estimates.

We include the number of cigarettes smoked per day reported in the preceding interview, C_L and its square (C_L^2). Thus we lose one wave and 16846 other observations including 1077 observations for which the woman reported being an occasional smoker in the previous interview. Thus our sample is selected using the dependent variable. We also include an indicator variable for did smoke ($Smoke_L$), which implies that they smoked daily since we don't observe C_L for women who said they smoked occasionally. Both coefficients are strongly significant. Squared cigarettes smoked as of the last interview (C_L^2) is also strongly significant with a negative sign. This, the fact that the coefficient on C_L is less than one, and the positive coefficient on $Smoke_L$ imply that the number of cigarettes smoked shows mean reversion. We also include age, an indicator of marital status and indicators of education.

The variables of interest are indicators of months till birth or age of a newborn child. The most interesting period is 10 to 15 months before the birth ($MonthSB[-15/-10]$), that is, before pregnancy but when upcoming pregnancy might be planned. The negative coefficient implies that the average woman smokes 0.84 fewer cigarettes per day in this period compared to what one would expect given her country of residence and previously reported smoking. The coefficient is small since most women in the sample are non smokers. This shows that women begin to reduce smoking before getting pregnant, which is evidence of forward looking behavior. Other possible explanations are that women imagine that lagged smoking affects the health of their fetus or that smoking has an effect on fertility. We know of no medical evidence supporting either concern, but women might still be concerned.

Similar results were obtained in more parsimonious regressions with fewer explanatory variables. The coefficient of interest and its t-statistic got larger when variables were added (results not shown).

One interesting feature of the data is that there is no sign that the actual birth has much of an effect on smoking. This seems reasonable, since fear of passive smoking by a newborn could be roughly as strong a disincentive as fear of damage to a fetus. Notice from model (4b) that the coefficient becomes much larger, as expected, if we only use data on women who reported that they smoked daily in the previous interview ($Smoke_L$=1).

As noted above, our dependent variable is censored and bunched making OLS inappropriate. The bunching process is complicated, uninteresting and, by definition unobservable, so we do not attempt to model it. Instead we consider a variety of estimators each of which is not optimal and note that they give similar results.

The third column of Table 4 presents the outcomes of fitting a Tobit model to the same sample. It is well known that Tobit parameter estimates are not consistent in the presence of heteroskedasticity and non normality in the data. The normality assumption is clearly unrealistic in our case, so that the evidence provided by the Tobit estimates must be considered only as a robustness check of our OLS results.[10] The t-statistics on $MonthSB[-15/-10]$ is reassuringly similar to the corresponding OLS results.

Column 4 of Table 4 reports the estimation of a Probit model in which the binary dependent variable is an indicator of being a smoker, at least occasionally ($Smoke$). The coefficient on $MonthSB[-15/-10]$ is insignificantly different from zero. This is a hint that women anticipating pregnancy cut back on smoking but don't quit completely. Given the very small sample size, it is not surprising that the evidence of such behavior is not statistically significant.

Column 5 of Table 4 reports the estimation of a Probit model in which the binary dependent variable is an indicator of smoking daily, so occasional smokers and non-smokers are classified together. In this case, the coefficient on $MonthSB[-15/-10]$ is negative and significantly different from zero.[11]

Column 6 of Table 4 reports the estimation of an Ordered Probit model, in which the dependent variable is an element of the vector (does not smoke, smokes occasionally, daily smokes less than 6 cigarettes, daily smokes 6 to 15 cigarettes, daily smokes 16 to 25 cigarettes, daily smokes more than 25 cigarettes). We generated this variable in order to complete the process of rounding which seems to have occurred. Thus we use intervals centered around multiples of ten. This approach has the advantage that we can treat smoking occasionally as an intermediate category between never smoking and smoking daily. Thus, as in our Probit estimates, we do not select observations based on the dependent variable. The coefficient on $MonthSB[-15/-10]$ is negative and significantly different from zero. The estimator also reports cut points which can be interpreted as follows - if the latent variable is less than cut1=0.964, the woman reports that she never smokes, if it is between cut1 and cut2=1.253 she reports that she smokes occasionally.

[10]The Tobit test statistics reported in Table 4 are based on bootstrap estimates of the standard errors, with 100 iterations, obtained by specifying the `vce(bootstrap)` option to the `tobit` command in Stata 9.2 SE.

[11]The Probit test statistics reported in Table 4 are based on robust estimates of the standard errors, obtained by specifying the `robust` option to the `Probit` command in Stata 9.2 SE.

Table 4: Evidence on forward looking behavior based on alternative estimators

	(4a) Coeff./t	(4b) Coeff./t	(4c) Coeff./t	(4d) Coeff./t	(4e) Coeff./t	(4f) Coeff./t	(4g) Coeff./t	(4h) Coeff./t
$Smoke_L$	2.211**		19.704**	2.464**	2.249**	1.545**	1.227**	1.307**
	(7.11)		(42.23)	(42.12)	(41.63)	(36.30)	(27.58)	(29.24)
$MonthSB[-15/-10]$	–.849**	–2.575*	–3.984**	–.112	–.385**	–.262**	–.140	–.418**
	(–2.83)	(–2.24)	(–3.31)	(–.98)	(–2.78)	(–2.74)	(–1.83)	(–3.66)
$MonthSB[-9/-4]$	–.956**	–3.675**	–4.897**	–.522**	–.536**	–.503**	–.446**	–.556**
	(–4.70)	(–4.43)	(–4.12)	(–5.29)	(–4.93)	(–6.11)	(–5.09)	(–5.77)
$MonthSB[-3/2]$	–1.381**	–5.049**	–8.186**	–.789**	–.988**	–.739**	–.539**	–.703**
	(–7.72)	(–6.73)	(–7.74)	(–8.47)	(–9.47)	(–9.38)	(–6.74)	(–7.92)
$MonthSB[3/8]$	–.552**	–2.538**	–2.195**	–.170*	–.217**	–.181**	–.070	–.130
	(–4.15)	(–3.97)	(–2.96)	(–2.49)	(–2.74)	(–3.07)	(–1.33)	(–1.57)
Age	–.017**	–.015	–.148**	–.018**	–.015**	–.015**	–.009**	–.006**
	(–11.27)	(–1.60)	(–17.17)	(–18.37)	(–13.39)	(–18.51)	(–14.04)	(–7.29)
$Married$	–.381**	–.701**	–1.660**	–.217**	–.179**	–.166**	–.088**	–.078**
	(–6.49)	(–3.24)	(–6.24)	(–7.53)	(–5.66)	(–7.40	(–4.72)	(–3.65)
$University$	–.165*	–.601*	–.450	–.016	–.084*	–.018	–.009	–.050
	(–2.43)	(–2.28)	(–1.23)	(–.46)	(–2.21)	(–.67)	(–.42)	(–1.83)
$HighSchool$	–.055	–.574**	.186	.053*	.027	.023	.005	–.031
	(–.95)	(–2.93)	(.83)	(1.96)	(.89)	(1.08)	(.30)	(–1.52)
C_L	.800**	.783**	.885**	.045**	.074**	.105**	.155**	.155**
	(19.35)	(19.00)	(17.70)	(7.59)	(13.48)	(23.96)	(38.29)	(37.48)
C_L^2	–.002*	–.002*	–.004**	–.001**	–.001**	–.001**	–.001**	–.001**
	(–2.02)	(–2.05)	(–2.64)	(–5.75)	(–9.21)	(–6.85)	(–16.92)	(–17.90)
$Constant$	1.363**	4.282**	–11.944**	–.815**	–1.166**			
	(10.20)	(7.34)	(–19.44)	(–11.85)	(–15.33)			
$cut1$						.964	.964	1.301
$cut2$						1.253	1.393	1.780
$cut3$						1.455	1.766	3.228
$cut4$						2.543	3.191	4.560
$cut5$						4.057	4.577	
$Pseudo.\,R^2$	.73	.42	.32	.61	.67	.44		
$Log-likelihood$			–28516	–7511	–5934	–16829	–15505	–11599
$No.\ of\ cases$	38041	6789	38041	39118	39118	39118	39118	39118

Notes: $^*P < 0.05$ and $^{**}P < 0.01$. Robust standard errors reported. Country dummies included as controls but not reported. Model (4a) is estimated with OLS. Model (4b) is estimated with OLS only on those women who did smoke in last interview. Model (4c) is estimated with a Tobit on cigarettes smoked (robust standard errors obtained by 100 bootstrap replications). Model (4d) is a Probit on the indicator variable 1 smoke (daily or occasionally), 0 otherwise. Model (4e) is a Probit on the indicator variable 1 smoke daily, 0 otherwise. Model (4f) is an Ordered Probit on the variable: 0 don't smoke, 1 smoke occasionally, 2 smoke daily less than 6, 3 smoke daily 6 to 15, 4 smoke daily 16 to 25, 5 smoke daily more than 25. Model (4g) is a semi-parametric estimation of an Extended Ordered Probit model on the variable considered in model (4f). Model (4h) is a semi-parametric estimation of an Extended Ordered Probit model on the variable: 0 don't smoke or smoke occasionally, 1 smoke daily less than 6, 2 smoke daily 6 to 15, 3 smoke daily 16 to 25, 4 smoke daily more than 25. $MonthSB[\#/\#]$ are dummies for the considered interval of months since birth. C_L is self-reported cigarette consumption in last in the previous interview. $Smoke_L$ is an indicator variable of smoking in the previous interview.

Here the strong tendency of self reported smoking to bunch at 20 cigarettes is reflected by the large gap between cut4=2.543 and cut5=4.057. The estimated cut points and the assumption that the latent variable has a normally distributed disturbance are a very crude estimate of the combined process of true bunching, rounding by the respondents, and, finally, our rounding.

We have also estimated an Ordered Probit model in which the dependent variable is an element of the vector (does not smoke or smokes occasionally , daily smokes less than 6 cigarettes, daily smokes 6 to 15 cigarettes, daily smokes 16 to 25 cigarettes, daily smokes more than 25 cigarettes). The coefficient of $MonthSB[-15/-10]$, that is the estimated effect of anticipated pregnancy on smoking by forward looking women, becomes markedly larger (-0.451 instead of -0.262) . As in the case of the simple Probit models, classification of occasional smoking with non smoking causes a larger estimated effect of anticipated pregnancy. This is again a statistically insignificant hint that women who are trying to quit smoking pass through a stage of occasional smoking.

Finally, the last two columns of Table 4 report the semi non-parametric estimations of an Extended Ordered Probit model. The dependent variables are those considered in column 5 and (does not smoke or smokes occasionally , daily smokes less than 6 cigarettes, daily smokes 6 to 15 cigarettes, daily smokes 16 to 25 cigarettes, daily smokes more than 25 cigarettes) respectively. Estimates have been obtained considering an Hermite polynomial of order 5.[12] Estimated coefficients are in line with those obtained applying the Ordered Probit. The t-statistic of the coefficient on $MonthSB[-15/-10]$ remains significant. We have also estimated both models allowing for polynomials of order 3, 7 and 9. Results are similar to those presented in Table 4 except that Model (4f) with a polynomial of order 3 gave an insignificant negative coefficient on $MonthSB[-15/-10]$. Likelihood ratio tests of Ordered Probit model against the semi non-parametric ones rejected the null in favor of the latter.

Overall, Table 4 suggests that the choice of estimators is not critical to our results. The t-statistics of $MonthSB[-15/-10]$ are similar in each column, except for column 3. Coefficients scale as would be expected due to censoring alone. None of our efforts to deal with bunching is entirely convincing in itself, but the similarity of results based on different approaches is very reassuring. In particular it gives us some confidence that our structural estimates and test of dynamic consistency based on OLS are valid.

[12]The reported semi non-parametric estimates are based on the `sneop` command implemented in Stata 9.2 SE by Mark Stewart.

Table 5: Ordered probit regressions on forward looking behavior - marital status effect

	(5a) Coeff./t	(5b) Coeff./t	(5c) Coeff./t	(5d) Coeff./t	(5e) Coeff./t	(5f) Coeff./t
$Smoke_L$	1.483**	1.545**	1.483**	1.486**	1.545**	1.545**
	(33.00)	(36.38)	(33.01)	(33.06)	(36.38)	(36.38)
$MonthSB[-12/-10]$	–.340**					
	(–2.72)					
$MonthSB[-12/-11]$		–.308*				.179
		(–1.98)				(.80)
$MonthSB[-15/-13]$	–.640**					
	(–2.77)					
$MonthSB[-9/-4]$	–.503**	–.499**	–.503**	–.491**	–.498**	–.498**
	(–4.39)	(–4.90)	(–4.39)	(–4.27)	(–4.89)	(–4.89)
$MonthSB[-3/2]$	–.849**	–.735**	–.849**	–.838**	–.735**	–.735**
	(–8.61)	–8.31	(–8.61)	(–8.47)	–8.31	–8.31
$MonthSB[3/8]$	–.215**	–.177**	–.215**	–.202*	–.177**	–.177**
	(–2.73)	(–2.67)	(–2.73)	(–2.56)	(–2.66)	(–2.66)
Age	–.013**	–.015**	–.013**	–.013**	–.015**	–.015**
	(–14.38)	(–18.64)	(–14.37)	(–13.16)	(–18.59)	(–18.59)
C_L	.112**	.105**	.112**	.113**	.105**	.105**
	(20.28)	(18.92)	(20.28)	(20.35)	(18.93)	(18.93)
C_L^2	–.001**	–.001**	–.001**	–.001**	–.001**	–.001**
	(–5.11)	(–4.42)	(–5.10)	(–5.15)	(–4.42)	(–4.42)
$Married$	–.153**	–.165**	–.152**	–.151**	–.162**	–.162**
	(–6.04)	(–7.17)	(–5.98)	(–5.90)	(–7.02)	(–7.02)
$University$	–.050	–.019	–.049	–.051	–.019	–.019
	(–1.61)	(–.68)	(–1.59)	(–1.66)	(–.68)	(–.68)
$HighSchool$	.006	.023	.006	.005	.023	.023
	(.26)	(1.01)	(.24)	(.21)	(1.01)	(1.01)
$Nonmarried[-15/-10]$			–.398*	–.385*		
			(–2.33)	(–2.25)		
$Married[-15/-10]$			–.474**	–.462**		
			(–3.17)	(–3.08)		
$Nonmarried[-12/-11]$					.179	
					(.80)	
$Married[-12/-11]$					–.521**	–.700*
					(–2.64)	(–2.34)
$MonthSB[-27/-22]$				–.369		
				(–1.96)		
$MonthSB[-21/-16]$				–.075		
				(–.64)		
$MonthSB[9/14]$				.137*		
				(1.98)		
$MonthSB[15/20]$				.076		
				(1.15)		
$cut1$	1.301**	.974**	1.302**	1.333**	.980**	.980**
$cut2$	1.502**	1.263**	1.503**	1.534**	1.269**	1.269**
$cut3$	2.599**	1.464**	2.599**	2.631**	1.469**	1.469**
$cut4$	4.122**	2.552**	4.123**	4.154**	2.558**	2.558**
$cut5$		4.065**			4.071**	4.071**
$Pseudo.R^2$	.50	.44	.50	.50	.44	.44
$Log-likelihood$	–12895	–16831	–12896	–12891	–16828	–16828
$No.\ of\ cases$	39118	39118	39118	39118	39118	39118

Notes: $^*P < 0.05$ and $^{**}P < 0.01$. Indicators for countries included as controls but not reported. Robust standard errors reported. $MonthSB$[#/#] are indicators of the considered interval of months since birth. C_L is self-reported cigarette consumption in last in the previous interview. $Smoke_L$ is an indicator variable of smoking in the previous interview. $Married$[#/#] is an interaction variable created as $MonthSB$[#/#]*$Married$. $Nonmarried$[#/#] is an interaction variable created as $MonthSB$[#/#]*(1-$Married$).

Table 5 aims to address the theoretically different forward looking behavior of married and unmarried women. In particular unmarried women are less likely to have planned their pregnancies than married women. To investigate this issue, we have considered the interaction of the indicator for marital status with $MonthSB[-15/-10]$. Our regressions do not yield a clear result. When the entire period from -15 months to -10 months is considered, the difference in smoking reduction between married and unmarried women is not statistically significant. In contrast, if the period is reduced to -12 months to -11 months since birth there is statistically significant evidence that married women reducing smoke more than unmarried ones. This could be due to different probabilities that pregnancies are planned or could be indirect evidence of the role of husbands as a control device.[13]

Finally, Tables 4 and 5 shown some of the patterns typically found in this literature: older women smoke less than younger women, married women smoke less than unmarried women and smoking declines as the educational level increases.

7 Conclusions

The ECHP contains strong evidence of forward looking behavior by women smokers who are about to become pregnant. There is a statistical significant decline in the fraction of women who smoke daily and the average number of cigarettes smoked in the period 10 to 15 months before the birth of a child. This result is robust to different specifications of the econometric model. There is some weak evidence that the effect is stronger for married women corresponding to a higher probability that their pregnancies are planned.

Estimates of parameters of a Becker and Murphy (1988) type model of addiction by two stage least squares analysis is hampered by the small size of the sample of women smokers who give birth. In particular, the first stage of estimation involves estimating parameters on an indicator of months since (or till) birth with very few useful observations per cell. Since we use a pseudo panel approach, imprecise estimation of first stage parameters has an effect analogous to measurement error on the second stage. Thus estimates should be biased towards zero, and, indeed, the parameter estimates imply implausibly fast mean reversion of smoking behavior.

A three months moving average of predicted future smoking and fitted past smoking appears to increase the signal to noise ratio in the second stage yielding estimates which would imply that smoking is highly persistent. Oddly, the null of perfect foresight of future

[13]Results report in columns 5 and 6 of Table 5 were the first to be obtained.

pregnancy is not rejected, presumably because of the low power of our test with a small sample.

Finally, we find borderline statistically significant evidence that expected smoking further in the future has an independent effect on current smoking. This means that the null of time consistency is (barely) rejected against the alternative of time inconsistency.

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