

Smoking within the Household: Spousal Peer Effects and Children's Health Implications*

Chiara Canta[†] and Pierre Dubois[‡]

This version: October 2011

Abstract

This paper studies spousal peer effects on the smoking behaviour and their implication for the health of children through passive smoking. Smoking decisions are modeled as equilibrium strategies of an incomplete information game within the couple. Using data from the French Health Survey 2002-2003, we identify two distinct effects linked to spousal behaviour: a smoking enhancing effect of smoking partners and a smoking deterring effect of non smoking partners. On the one hand, having a smoking partner might make smoking more valuable because of the possibility of smoking together. On the other hand, having a non smoking partner might reduce the utility of smoking because the smoker partially internalises the nuisance imposed on the partner. An implication of these findings is that the smoking behaviour could differ qualitatively in couples in which both partners smoke and in which just one partner smokes. This interpretation is supported by our finding that the respiratory health of children is negatively affected only if both parents smoke.

JEL Code: C31, D10, I12.

Keywords: Smoking, Social Interaction, Simultaneous Game Model, Health.

*We thank Jerome Adda, Magnus Johannesson, and workshop and conference participants at Toulouse School of Economics, Stockholm School of Economics, the ASHE Conference 2010, the European Economic Association Congress 2010 for useful comments.

[†]Université Catholique de Louvain, CORE.

[‡]Toulouse School of Economics.

1 Introduction

The determinants of smoking behaviour are the object of many studies aimed at improving the understanding of a phenomenon that imposes high costs on societies. An important question in this context is how social interactions affect smoking decisions. Peer effects have been shown to play an important role in individual smoking decisions. The behaviour of peers might convey information about the costs and benefits of smoking, or affect directly the benefit that an individual derives from tobacco consumption. A number of studies provide evidence of peer effects on teenagers' tobacco consumption (Powell *et al.*, 2005, Lundborg, 2006, Harris and González López-Valcàrcel, 2008). Harris and González López-Valcàrcel (2008), for instance, separately identify the impacts of peer group smoking prevalence and peer group non smoking prevalence using a cross-section of US young people. A peer group is constituted by young people living in the same household (“siblings”). The main finding of the paper is that the pro-smoking influence of a smoking sibling is twice as big as the deterrence effect exerted by a non smoking sibling. The authors interpret these effects in terms of learning: siblings' smoking and non smoking behaviour do not convey the same kind of information about the “coolness” of smoking. Concerning intra-household peer effects, Jones (1994) finds a significant impact of the presence of other smokers in the household on individuals' probability of succeeding in giving up. Cutler and Glaeser (2007) study spousal peer effects on smoking decisions, as well as the impact of other kinds of social interactions. Using instruments in order to tackle selection problems, they show the existence of such effects. These findings have important implications: they suggest that measuring the impact of smoking containment policies at the individual level is not appropriate, because of the multiplier effect due to social interactions. Conversely, Clark and Etilé (2006) look at the effect of the lagged spousal smoking behaviour on current smoking status and find no significant effect once all the individual characteristics are controlled for.

This paper contributes to the literature by disaggregating the spousal peer effect on individual

smoking, in the lines of Harris and González López-Valcárcel (2008). In contrast to their work, however, we assume that partners share the same kind of information and that “being cool” is not an issue. In our paper peer effects work through the impact of social interactions on individuals’ utility function and not through learning (as it is more natural to assume in the case of teenagers). We allow the partner’s smoking behaviour to affect the utility from smoking in two different ways. With respect to singles, on the one hand, having a smoking partner could make smoking more valuable because of the possibility of smoking together. On the other hand, having a non smoking partner could reduce the utility of smoking, because of the (partial) internalization of some of the nuisance imposed on the partner.

We model smoking decisions as the equilibrium strategies of an incomplete information game within the couple. We identify two distinct effects of spousal behaviour: a smoking enhancing effect of smoking partners and a smoking deterring effect of non smoking partners. The latter effect is interpreted as a cost imposed by the non smokers on the smokers. Studying the presence of these effects in the context of couples is interesting because the deterrence effect might have an impact on the nature of the smoking behaviour. For instance, a smoker living with a non smoker could smoke less than she would like to, or decide to smoke outside (bearing thus a transportation cost) in order to avoid the complaints of the partner.

We use data from the French Health Survey 2002-2003 carried out by the French National Statistical Institute (INSEE). To our knowledge there is no study of intra-couple peer effects on smoking using French data. The literature deals mainly with U.S. or U.K. data. Smoking decisions in different countries might be subject to different social norms. Our results, however, are in line with the existing literature on the determinants of smoking.

We look at the smoking behaviour as a game of incomplete information in the case of couples, and as a simple individual decision in the case of singles. Each individual observes a number of

characteristics of her partner (if any), but not all the variables influencing the smoking decision of the partner. She forms a prior on the probability that the partner smokes, which can be the probability that the partner quits smoking or starts smoking given her observation of past behaviour. This prior is a function of the characteristics of the partner, and in particular of his past smoking behaviour. The assumptions that the smoking game is non cooperative and that information is incomplete within the couple might sound unusual. However, smoking is addictive and it might be difficult for an individual to commit to a particular behaviour. In addition to that, adults are not likely to start smoking, but they might quit if they were smokers in the past. Succeeding in giving up smoking is not perfectly predictable *ex ante* and might depend on random individual shocks that the partner cannot observe or predict (for instance, health, taste or psychological shocks). Thus, at each instant in time, the smoking decision of the spouse can be considered as uncertain and based on private information.

In order to identify the model we use the methodology proposed by Bajari *et al.* (2009). This method permits to estimate peer effects in incomplete information games, when the equilibrium probabilities of choosing a particular strategy are unobserved to the econometrician. We include in our sample individuals that play a game with their partner (couples) and individuals whose smoking behaviour is determined individually (singles). This permits us to identify both the negative and positive peer effects that are at work in the smoking game.

The main problem in estimating household decision-making models is related to assortative matching (Becker, 1974), leading to the well known correlated effects (Manski, 1995). For instance, Clark and Etilé (2006) consider a complete information framework and find that the correlation between spouses smoking decisions is entirely due to the correlation between individual random effects, not to peer effects. We use a different strategy in order to tackle this problem: we consider an incomplete information game and we control for a number of partners characteristics influencing the

beliefs about the partner's decisions. In our model, each individual takes her instantaneous smoking decision in order to maximise her expected utility, knowing the socioeconomic characteristics of the partner she has. In addition to that, we control for past smoking behaviours. Thus, our model does not predict the probability of smoking of an individual, but the probability of smoking given her past smoking behaviour and the partner she lives with. Controlling for the past smoking decision of both partners permits to take into account the correlation across partners' unobservables, if this correlation is constant over time.

The main empirical result of the paper is that both a smoking enhancing and a smoking deterring effect are at work in the spousal smoking game. Having a smoking partner encourages tobacco consumption, while having a non smoking partner has the opposite impact. As it was mentioned earlier, our interpretation of this result is that a non smoking partner might reduce the utility enjoyed from smoking. A smoker could change the way she consumes cigarettes depending on the partner's smoking status. For instance, she could be forced to smoke outside home by a non smoking partner which reduces her utility. This should have an impact on the exposure to passive smoking of other family members, and ultimately on their health status. As passive smoking exposure is not observable, we cannot test directly the hypothesis that having a non smoking partner imposes a reduction in utility to the smoker through the obligation to smoke outside the house. However, using data on the respiratory diseases of children, we find evidence supporting this interpretation of the smoking game.

A relatively large literature has studied the effect of passive smoking on the health of children. For instance, Mannino *et al.* (2001) showed that an high level of exposure to tobacco smoke (measured by the cotinine levels in body fluids) increases the numbers of sick days in school for U.S. children. Adda and Cornaglia (2009), showed that smoking bans in public place increase the exposure of children with smoking parents. However, these studies do not look at the interaction of smoking

and non smoking parents. According to our results, a non smoking parent could play a control role and push the smoking parent to smoke outside. This would imply that, controlling for the overall quantities smoked, the respiratory diseases affect more the children whose both parents smoke than the ones with just one smoking parent. Using the French health survey 2002-2003, we find that only the fact that both parents smoke affects negatively the health of children. This is consistent with the smoking game model. Non smoking parents seem to play a control role on their smoking spouses, possibly reducing the utility of smokers by imposing less smoke at home. This translates in the reduction of respiratory diseases of children that we observe in our data.

The paper is structured as follows: in Section 2 we describe the theoretical model and in Section 3 we discuss the estimation strategy. In Section 4 we present the data and we describe the results concerning both the equilibrium smoking behaviour and the effect of smoking on the respiratory diseases of children. Section 5 concludes.

2 Explaining Smoking behaviour: A Theoretical Model

We consider a model in which individuals living in a couple choose their smoking behaviour simultaneously, taking into account the expected decision of the partner. Singles take their decision individually.

Let us first consider the utility of an individual i living with a partner j . The benefit that this individual obtains from smoking depends on her taste for smoking f_i and on the smoking behaviour of her partner. Let $a_i \in \{0, 1\}$ be the smoking decision of individual i , where $a_i = 1$ means that the individual smokes. The partner makes the same dichotomous decision denoted by a_j . The utility of individual i if she smokes is:

$$f_i + sa_j - p(1 - a_j),$$

where f_i is the private benefit from smoking, p is the disutility due to the presence of a non smoking partner and s is the extra utility from smoking if the partner smokes as well. Both parameters

are assumed to be non negative in the theoretical model. They capture, respectively, a smoking enhancing and a smoking deterring effect related to the partner's behaviour.

The utility of a non smoker is normalised to zero up to the disutility linked to passive smoking when the partner smokes. It is thus equal to:

$$-ra_j,$$

where r is a positive parameter quantifying the disutility imposed by a smoking partner on a non smoker.

The utility from smoking of a single is simply f_i , while her utility from non smoking is normalised to zero. Using the dummy variable D_i taking value one if the individual lives with a partner and zero otherwise, we can write the utility from smoking in a more general form as:

$$f_i + sa_jD_i - p(1 - a_j)D_i.$$

In the same way, the utility of a non smoker is thus equal to:

$$-ra_jD_i.$$

We assume that the private benefit from smoking is a linear function of a vector of observed variables \tilde{x}_i , and of an individual shock, unobservable by the econometrician, ϵ_i :

$$f_i = \lambda\tilde{x}_i + \epsilon_i.$$

The past smoking behaviour is an important characteristic to be included in \tilde{x}_i , given the addictive nature of tobacco consumption.

The utility U_i of individual i can be written as a function of the individual's decision to smoke a_i , the partner's decision to smoke a_j and the individual characteristics:

$$U_i(a_i, a_j, x_i, \epsilon_i) = a_i [\lambda\tilde{x}_i + \epsilon_i + sa_jD_i - p(1 - a_j)D_i] - [1 - a_i] ra_jD_i$$

$$\begin{aligned}
&= a_i [\lambda \tilde{x}_i - p D_i + \epsilon_i] - r a_j D_i + a_i a_j [s + p + r] D_i \\
&= \lambda_1 a_i x_i + \lambda_2 a_j D_i + \lambda_3 a_i a_j D_i + a_i \epsilon_i,
\end{aligned}$$

where $x_i = (\tilde{x}_i, D_i)$, $\lambda_1 = (\lambda, -p)$, $\lambda_2 = -r$, $\lambda_3 = p + r + s$. As the parameters s , r and p should be non negative, we expect in particular that $\lambda_3 \geq 0$.

We assume that both partners take their decision simultaneously. The assumption that the game is non cooperative can be justified by the fact that commitment to a smoking behaviour might be impossible. The decision is taken under incomplete information because the attitude of both partners towards smoking might depend on idiosyncratic shocks on their preferences that are private information. Think about smoking cessation (which is empirically very relevant in our sample as will be illustrated in the following): this choice might depend on some health or taste or psychological shock. Thus, ϵ_j is assumed to be unobservable by the partner and the expected payoff of individual i depends on the probability that the other partner smokes which we denote $\sigma_j(x_i, x_j) = Pr(a_j = 1 | x_i, x_j)$. The belief of each individual about the partner's probability of smoking is constructed using all the available information. In other words, beliefs are contingent to (x_i, x_j) , the set of both the individual's and the partner's characteristics, which is publicly known within the household. We thus look at a Bayesian Nash equilibrium.

An individual i does smoke ($a_i = 1$) if and only if

$$\Delta E U_i \equiv E_{a_j} [U_i(1, a_j, x_i, \epsilon_i)] - E_{a_j} [U_i(0, a_j, x_i, \epsilon_i)] > 0. \quad (1)$$

Since $U_i(a_i, a_j, x_i, \epsilon_i)$ is linear in the unknown action a_j , in equilibrium the expected payoff of strategy a_i can be written as

$$E_{a_j} [U_i(a_i, a_j, x_i, \epsilon_i)] = \lambda_1 a_i x_i + \lambda_2 \sigma_j(x_j, x_i) D_i + \lambda_3 a_i \sigma_j(x_j, x_i) D_i + a_i \epsilon_i,$$

where $\sigma_j(x_j, x_i)$ is the equilibrium probability that the partner smokes. Substituting this expression

in (1) one can rewrite the smoking condition for individual i as

$$\Delta EU_i = \lambda_1 x_i + \lambda_3 \sigma_j(x_j, x_i) D_i + \epsilon_i > 0.$$

This condition shows that it will be impossible to identify the parameter $\lambda_2 = -r$. The model only permits to identify $\lambda_1 = (\lambda, -p)$, and $\lambda_3 = p + r + s$. Our estimation will thus permit to recover the structural parameters p and $r + s$.

3 Identification and Estimation strategy

Given the availability of data on both the smoking behaviour within households and the characteristics of the members of the households, we first study how to identify and estimate the model parameters.

Our theoretical model shows that the decision to smoke of individual i depends on whether $\lambda_1 x_i + \lambda_3 \sigma_j(x_j, x_i) D_i + \epsilon_i$ is positive or not. Under the assumption that the preference shocks ϵ follow a logistic distribution, we obtain the following expression for the probability that individual i smokes conditional on the individual's and the partner's characteristics, $\sigma_i(x_i, x_j)$:

$$\begin{aligned} \sigma_i(x_i, x_j) &= Pr(a_i = 1 | x_i, x_j) = Pr(\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i + \epsilon_i > 0) \\ &= \frac{\exp(\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i)}{1 + \exp(\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i)} \\ &= \frac{\exp \Delta EU_i(x_i, x_j)}{1 + \exp \Delta EU_i(x_i, x_j)} \end{aligned}$$

and the same holds for the partner j .

We thus obtain the following system of equations for couples

$$\begin{aligned} \sigma_i(x_i, x_j) &= \frac{\exp(\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i)}{1 + \exp(\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i)} \\ \sigma_j(x_i, x_j) &= \frac{\exp(\lambda_1 x_j + \lambda_3 \sigma_i(x_i, x_j) D_j)}{1 + \exp(\lambda_1 x_j + \lambda_3 \sigma_i(x_i, x_j) D_j)} \end{aligned}$$

We can prove that this system admits at least one solution $(\sigma_i^*(x_i, x_j), \sigma_j^*(x_i, x_j))$ such that $\sigma_i^*(x_i, x_j) \in (0, 1)$ and $\sigma_j^*(x_i, x_j) \in (0, 1)$. Furthermore, this system has a unique solution if $|\lambda_3| < 4$. This solution thus corresponds to a Bayesian Nash equilibrium of our model.

To prove this result, let us denote by F the logistic function ($F(Z) = \exp(Z)/(1 + \exp(Z))$). Note that $F' = F(1 - F)$ and define $G(z) = z - F(\lambda_1 x_i + \lambda_3 F(\lambda_1 x_j + \lambda_3 z D_j) D_i)$ for all z and $H(z) = z - F(\lambda_1 x_j + \lambda_3 F(\lambda_1 x_i + \lambda_3 z D_i) D_j)$. The two equations of our system can be rewritten as $G(\sigma_i(x_i, x_j)) = 0$ and $H(\sigma_j(x_i, x_j)) = 0$. Both $G(\cdot)$ and $H(\cdot)$ are continuous functions; furthermore, $G(0) < 0$, $G(1) > 0$. Then, there exists at least one $\sigma_i^*(x_i, x_j) \in (0, 1)$ such that $G(\sigma_i^*(x_i, x_j)) = 0$. Similarly, it can be shown that there exists at least one $\sigma_j^*(x_i, x_j)$ such that $H(\sigma_j^*(x_i, x_j)) = 0$. Consequently, there exist at least one Bayesian Nash equilibrium such that $\sigma_i^*(x_i, x_j) \in (0, 1)$ and $\sigma_j^*(x_i, x_j) \in (0, 1)$. To show that the system has a unique solution, it is sufficient to prove that both $G(\cdot)$ and $H(\cdot)$ are strictly increasing. The first derivative of $G(z)$ is

$$G'(z) = 1 - \lambda_3^2 D_i D_j [F'(\lambda_1 + \lambda_3 F(\lambda_1 x_j + \lambda_3 z D_j) D_i)] F'(\lambda_1 x_j + \lambda_3 z D_j) \geq 1 - D_i D_j \left(\frac{\lambda_3}{4}\right)^2,$$

since $0 \leq F'(Z) \leq \frac{1}{4}$ for all z . Then, $G'(\cdot)$ is strictly positive if $|\lambda_3| < 4$. In this range of parameters, the equation $G(\sigma_i(x_i, x_j)) = 0$ has a unique solution. In the same way, it can be shown that $H'(\cdot)$ is strictly positive whenever $|\lambda_3| < 4$, so that the system admits a unique solution $(\sigma_i^*(x_i, x_j), \sigma_j^*(x_i, x_j))$.

The problem in estimating such a model is that the equilibrium probabilities $\sigma_i(x_i, x_j)$ and $\sigma_j(x_i, x_j)$ are unknown. In order to estimate the model parameters, we use a two-step procedure as in Bajari *et al.* (2009). In this paper the authors estimate a similar model of simultaneous decisions under incomplete information. We first estimate $\hat{\sigma}_i(x_i, x_j)$ and $\hat{\sigma}_j(x_i, x_j)$ using a logit regression. Under the assumption that individuals do not have better information than the econometrician (that is to say, the partner's ϵ is unknown to each individual), $\hat{\sigma}_j$ corresponds to the belief that individual i holds about the partner's smoking decision. Since at equilibrium the believed probabilities are

equal to the equilibrium ones, $\hat{\sigma}_i(x_i, x_j)$ and $\hat{\sigma}_j(x_i, x_j)$ are unbiased estimates of the probability of smoking.

Then we use the "Hotz-Miller" (1993) inversion to obtain:

$$\begin{aligned}\Delta \widehat{EU}_i(x_i, x_j) &= \ln \hat{\sigma}_i(x_i, x_j) - \ln(1 - \hat{\sigma}_i(x_i, x_j)) \\ \Delta \widehat{EU}_j(x_i, x_j) &= \ln \hat{\sigma}_j(x_i, x_j) - \ln(1 - \hat{\sigma}_j(x_i, x_j)).\end{aligned}$$

These are the empirical counterparts for the expected utility from smoking of individuals i and j . In equilibrium, these estimated expected utilities must coincide with the true expected utility of smoking $\lambda_1 x_i + \lambda_3 \sigma_j(x_i, x_j) D_i + \epsilon_i$. To identify the structural parameters we can then use the following moment conditions

$$E \left[\left(\Delta \widehat{EU}_i(x_i, x_j) - \lambda_1 x_i - \lambda_3 \hat{\sigma}_j(x_i, x_j) D_i \right) \right] = 0,$$

and minimise in λ_1 and λ_3 the empirical counterpart of this moment condition across individuals.

Note that the structural model parameters are identified if and only if some variables affect only the individual smoking behaviour. In particular, in the utility function of individual i , we need that x_j enters only through $\hat{\sigma}_j(x_i, x_j)$ and is excluded from the direct utility function of individual i .

As mentioned above, a crucial assumption in the model is that both the spouses and the econometrician share the same information on the characteristics of each individual. That is to say, we assume that what is unobservable for us is not reciprocally observable for the spouses and is not correlated across them. This is of course a strong assumption.

In this kind of models, assortative matching might lead to biased estimates of the peer effects parameters. The bias might come from two channels. First of all, any correlation of spouses smoking behaviours might be explained by the correlation of unobservable characteristics of the partners. Clark and Etilé (2006), for instance, study how the present smoking status depends on the past smoking status of the partner and they conclude that the correlation between smoking behaviours

is explained solely by the correlation of unobservables across spouses. Our strategy is to control for a number of characteristics of the partner, which enter the belief of the probability of smoking. Our approach can be motivated as follows. Suppose for instance that young people tend to smoke more. Since young people have a good chance to match, regressing the smoking behaviour of an individual on the smoking behaviour of her partner would lead to biased results since the correlation between behaviours could be driven by the simple fact that young people are more likely to be matched with young people. However, controlling for the age of the partner takes away this bias.

Assortative matching would also lead to biased estimates if tobacco consumption was a relevant characteristic in the choice of a partner. To tackle this problem, we control for the past smoking behaviour of each partner. Under the assumption that the couple was already formed in the previous period, controlling for past smoking decisions permits to take into account the endogeneity due to assortative matching. The resulting peer effect parameter can thus be interpreted as the effect of the expected smoking behaviour of the partner on the own decision to smoke today, *given* the individual past smoking status and *given* the characteristics of the partner the individual is assigned to. So the decision to smoke will be akin to a decision to quit smoking or start smoking.

4 Empirical Estimation and Results

4.1 Data description

The French health survey 2002-2003 includes data on the demography, socioeconomic status, health status, and health consumption of 25,000 households in France. Data were collected on about 40,797 individuals, interviewed three successive times. Adult individuals (over eighteen) were also required to fill an auto-evaluation, in which they were asked to report their perceived health and their prevention behaviour, including alcohol and tobacco consumption. A similar but adapted questionnaire was proposed to kids aged between 11 and 17. Out of 30,997 adults in the survey, 25,931 complied and returned an auto-evaluation. We dropped the observations containing missing

values either on the reported smoking habit or on the socio-demographic variables of interest. We also limit the analysis to adults being the household reference person or the partner of the reference person and in this subgroup, we consider only individuals with an age between 18 and 60. In the case of couples we drop the households in which the husband is more than 60 years old. Our sample reduces this way to 13,406 adult individuals, 10,862 of which live in couple.

Our endogenous variable is the smoking behaviour. We construct a dummy equal to one if the individual reports being a smoker. An individual is considered a smoker if she reports to be smoking every day.

Individual variables include the age, a dummy equal to one if the level of education is above high school (HS), and the body mass index (BMI). Descriptive statistics on the whole adult population of the survey point to a negative correlation between smoking and BMI. Another variable susceptible to influence smoking behaviour is the exposure to smoke at the workplace. This variable is self reported by each individual and takes the form of a dummy equal to one if the individual is currently exposed to smoke at work. It is worth noticing that in France smoking bans in public places were not as strict in 2002 as they are today. Consequently the exposure to work variable exhibits some variability, and almost 15 percent of the individuals in our sample reported to be exposed to smoke at the workplace. Finally, the past smoking behaviour is included in the analysis: in particular, we use the two years lagged smoking behaviour. A two years period is short enough to reasonably assume that most couples did not change their partner; at the same time it is a period large enough to have some variation between past and current smoking behaviours. Taking longer lags would raise the problem of having to deal with individuals changing partner or moving from single to couple. We do not include in the explanatory variables the price of cigarettes for the simple reason that this price in France is regulated and homogeneous at the national level. Another variable that is often used in smoking models is the price (or the price variation) of cigarettes during the adolescence of the

individual, that is to say when the individual was more likely to start smoking.¹ We refrain from using this variable, since it would be the same for all individuals in the same age cohort, and thus reduce to a mere proxy for age.

Household specific variables include the family income adjusted for the number of people in the household, according to the OECD-modified scale (assigning a weight of 1 to the household head, of 0.5 to each additional adult, and of 0.3 to each child), and a dummy variable taking value 1 if at least one child under the age of 15 belongs to the household. Note that the presence of children does not mean that these are the children of the reference individuals (they could be the children of just one of the two partners). For our purposes, this is not problematic, since we want to estimate the impact of the presence of children in the same household on the smoking behaviour. Finally, we control for the number of children under age 15 living in the household.

4.2 Reduced Form Results on Smoking behaviour

In the first stage of the empirical analysis we estimate a reduced form model in order to recover the estimated probability of smoking of each individual and the empirical analogue of her expected utility.

We run a logit regression where the endogenous variable is the smoking dummy. We include in the explanatory variables individual characteristics of both the individual and her partner, if any. In particular we include the past smoking behaviour, in the form of a dummy taking value one if the individual smoked two years ago. We use a two years lag to have more variation across present and past smoking status without having to deal with changing partners. Remark that the correlation across past and present behaviour is very high, probably because of addiction. In particular, in our sample, the probability of being a smoker is equal to 26.51%. However this probability is equal to 85.8% for past smokers and to just 1.17% for people who never smoked in the past. This piece of

¹See for instance Douglas and Hariharan (1994).

evidence shows that among adults quitting smoking is much more frequent than starting smoking. Since we control for the past smoking behaviour, we will be able to look at the impact of spousal smoking on the probability of switching behaviours and in particular on the probability of smoking cessation.

We also include in the analysis the sex, the age, the education level and the current work exposure to smoke of the individual. Some household characteristics are also taken into account: for instance, we distinguish among individuals being singles and the ones living in couple. The number of children under 15 and the presence of at least one child under 15 are variables that are susceptible to influence smoking behaviour. Finally, we include the family income, adjusted for the size of the household. Descriptive statistics for people living in couple and singles are reported in Tables 1 and 2.

[INSERT TABLE 1 HERE]

[INSERT TABLE 2 HERE]

The results of the reduced form logit regression are reported in Table 3. Heteroscedasticity-robust standard errors allowing for clustering at the household level are reported in parentheses.

[INSERT TABLE 3 HERE]

The current smoking behaviour is strongly correlated with the past smoking behaviour, as expected. The level of education correlates negatively with the probability to smoke, as well as the BMI for people living in a couple. The income and the presence of children do not display any correlation with the probability of smoking. For couples, the past smoking behaviour of the partner has a positive and highly significant effect on the probability of smoking, while the partner's level of education affects negatively the probability of smoking. These parameters, however do not correspond to the structural model parameters.

Through this first step estimation, we get the estimated probability $\widehat{\sigma}_i(x_i, x_j)$ that individual i smokes conditional on the observables. In order to recover the structural parameters, we use the Hotz-Miller inversion and we obtain an estimate of the expected utility from smoking for each of individual i :

$$\Delta \widehat{EU}_i(x_i, x_j) = \ln \widehat{\sigma}_i(x_i, x_j) - \ln(1 - \widehat{\sigma}_i(x_i, x_j))$$

Remind that, under our assumptions, $\widehat{\sigma}_j(x_i, x_j)$ is a consistent estimate of the beliefs that individual i holds about the probability of smoking of her partner. In equilibrium the beliefs coincide with the true probabilities. Thus, $\Delta \widehat{EU}_i(x_i, x_j)$ is the empirical analogue of the expected utility of individual i . We can then proceed with the second step of our analysis.

4.3 Structural Estimation of Smoking behaviour

Once an unbiased estimation of the expected utility from smoking has been recovered, it is possible to recover the parameters of the structural model under the sole moment condition discussed above, $E \left[\left(\Delta \widehat{EU}_i(x_i, x_j) - \lambda_1 x_i - \lambda_3 \widehat{\sigma}_j(x_i, x_j) \right) D_i \right] = 0$. In particular, we obtain estimates of the coefficients $\lambda_1 = (\lambda, -p)$ and $\lambda_3 = p + r + s$. Both p and $r + s$ are identified.

Remark that the assumption that allows us to recover these parameters is that partner's characteristics x_j enter the individual expected utility function only through the beliefs about the partner's smoking behaviour $\widehat{\sigma}_j(x_i, x_j)$ and thus are excluded from the direct utility of the individual.

The results of the described regression are reported in Table 4. Bootstrap standard errors are reported in brackets.² The past smoking behaviour affects positively the utility of smoking.

[INSERT TABLE 4 HERE]

The corresponding parameter is strongly significant and quantitatively important. This is not surprising, since the smoking behaviour is persistent over time. Remember that, on the one hand, only

²A bootstrap procedure was motivated by the fact that in the second stage we include estimated variables. The bootstrapping procedure was performed at the household level, in order to preserve the information concerning both partners in each resample.

about 15% of past smokers succeeded in giving up smoking by the time of the interview. On the other hand, individuals that were non smokers two years before are very unlikely to start smoking. This explains the explanatory power of the past smoking behaviour.

However, given the past smoking behaviour, other variables significantly affect the present utility from smoking. Males seem to be more prone to smoke than women. The BMI is negatively correlated with the utility of smoking. This piece of evidence suggests that overweight people might be more concerned about the health damages of smoking; the fact that obesity and tobacco consumption could be substitute and not complements is not new to the literature (see for instance, Gruber and Frakes, 2006, and Flegal *et al.*, 1995). Of course, the BMI is potentially an endogenous variable. Smoking might substitute excessive eating and affect individual weight. However, the causal relationship between BMI and tobacco consumption goes beyond the scope of this paper, and the cross-sectional nature of our data does not permit us to trace back the evolution of the BMI, which is the result of long term decisions. The level of education is negatively correlated with the expected utility of smoking. This is an intuitive result in line with previous findings from the literature (see for instance Kenkel *et al.*, 2006). The exposure to smoke at work has also a significant (at the 90% confidence level) and positive effect on the utility of smoking. The results also suggest that the utility from smoking decreases as family income increases, which is in line with previous findings. The presence of at least one child and the number of children in the household do not have any significant effect on individual smoking. This result is counter intuitive but quite robust to different specifications. Parents do not seem to perceive an extra cost of smoking with respect to non parents.

Let us now discuss the parameters corresponding to peer effects. On the one hand, the impact of the probability of smoking of the partner is positive and strongly significant. This effect corresponds in the theoretical model to $p + r + s$ and is estimated to be 0.82. On the other hand, living in a couple has a negative and significant (at the 95% confidence level) effect estimated to be -0.38. The

absolute value of this parameter corresponds to the cost of smoking when the partner does not, p . We can thus identify $r + s$. If the partner has a probability to smoke close to one, the individual expected utility function increases of around 0.8 in absolute value with respect to the case in which it is very unlikely that the partner will smoke. In the model, the presence of single individuals permits to decompose this effect. With respect to a single, an individual with a partner who smokes gets an extra utility from smoking. This extra utility is modeled through the parameter $r + s$ and is estimated to be about 0.4. Also with respect to a single, an individual with a non smoking partner gets a loss of utility if she smokes. This loss, corresponding to the parameter p in the model, is estimated to be equal to -0.4.

These findings suggest that the smoking behaviour of the partner influences the utility from smoking in two distinct ways. First, if both partners smoke, this increases the benefit that they can both extract from tobacco consumption. This is a smoking enhancing effect linked to the presence of a smoker in the household. Second, if just one partner smokes, she will have to bear a cost due to the fact that she lives with a non smoker. This extra cost might be linked to the partner complaints, or to the internalization of some of the passive smoke externality. Furthermore, it could be due to the fact that a smoker matched with a non smoker might have to smoke outside the house or reduce her tobacco consumption.

Finally, note that the estimated $\lambda_3 = r + p + s$ is smaller than four in absolute value. As shown in Section 3, this ensures that the Bayesian Nash equilibrium that we have empirically characterised is indeed unique.

The coefficients listed in Table 4 give us a qualitative idea of spousal peer effects. However, the results refer to the impact on the utility from smoking which is an ordinal quantity. Thus, they do not allow us to quantify the magnitude of the peer effects. As pointed out before, these magnitudes are important in order to measure the impact of smoking containment measures. In

the next section, we present the marginal effects of spousal smoking behaviour on the individual probability of smoking.

4.4 Marginal effects

Given the estimated parameters, we now analyse the marginal effects of x_i or x_j (the characteristics of the partner of i) on the probability of smoking of an individual i . This probability is equal to

$$\sigma_i(x_i, x_j) = F(\Delta EU_i(x_i, x_j)),$$

where F is the logistic function satisfying $F'(u) = F(u)(1 - F(u))$ for all u .

Thus, we have

$$\frac{\partial}{\partial x_i} \sigma_i(x_i, x_j) = \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] \left[\lambda_1 + \lambda_3 \frac{\partial}{\partial x_i} \sigma_j(x_i, x_j) D_i \right]$$

for the marginal effect of an individual characteristic on its own likelihood to smoke, and

$$\frac{\partial}{\partial x_j} \sigma_i(x_i, x_j) = \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] \left[\lambda_3 \frac{\partial}{\partial x_j} \sigma_j(x_i, x_j) D_i \right]$$

for the marginal effect of a partner characteristic on the own likelihood to smoke.

Note that each individual characteristic has both a direct effect on the probability of smoking and an indirect effect through the partner's probability of smoking. The direct effect of x_i on the probability of smoking of i is $\lambda_1 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)]$. The indirect effect due to the implied change in the probability of smoking of the partner is equal to $\lambda_3 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] \frac{\partial}{\partial x_i} \sigma_j(x_i, x_j)$. This indirect effect can either reinforce or reduce the effect of x_i on the probability to smoke.

Substituting the same expressions for $\frac{\partial}{\partial x_i} \sigma_j(x_i, x_j)$ and $\frac{\partial}{\partial x_j} \sigma_j(x_i, x_j)$ in the previous equations, after some rearrangements we get:

$$\frac{\partial}{\partial x_i} \sigma_i(x_i, x_j) = \frac{\lambda_1 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)]}{1 - \lambda_3^2 \sigma_j(x_i, x_j) [1 - \sigma_j(x_i, x_j)] \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] D_i},$$

and

$$\begin{aligned}\frac{\partial}{\partial x_j} \sigma_i(x_i, x_j) &= \frac{\lambda_1 \lambda_3 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] \sigma_j(x_i, x_j) [1 - \sigma_j(x_i, x_j)] D_i}{1 - \lambda_3^2 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] \sigma_j(x_i, x_j) [1 - \sigma_j(x_i, x_j)] D_i} \\ &= \frac{\partial}{\partial x_i} \sigma_i(x_i, x_j) [\lambda_3 \sigma_j(x_i, x_j) [1 - \sigma_j(x_i, x_j)] D_i].\end{aligned}$$

The interaction effect increases the marginal effect of the own individual characteristics on the probability to smoke since

$$1 - \lambda_3^2 \sigma_j(x_i, x_j) [1 - \sigma_j(x_i, x_j)] \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)] D_i < 1$$

whenever $|\lambda_3| < 4$, which is the case empirically.

We estimated the marginal effect of continuous variables for each individual, and we take the averages on the whole sample. Concerning the BMI, for a person measuring 1m70 the effect of a 3 kilos weight increase reduces the probability of smoking by a factor equal to 0.30 percentage points on average (ranging from -1 to 0). An increase in annual income of 10,000 euros corresponds to a decrease in the probability of smoking of 4 percentage points on average.

In Table 5 we report the average marginal effect for the peer effect parameters. The standard deviations are obtained by bootstrap. For individuals living in couple, the effect of the probability that the partner smokes $s + r + p$ is equal to

$$\frac{\partial}{\partial \sigma_j} \sigma_i(x_i, x_j) = \lambda_3 \sigma_i(x_i, x_j) [1 - \sigma_i(x_i, x_j)],$$

and is estimated to be equal to 0.03 for individuals living in couple. This effect ranges from 0 to 0.20 depending on the value of σ_i . This effect seems low, compared to the existing empirical literature; for instance, Cutler and Glaeser (2007) find that a smoking partner increases the individual probability of smoking of 40 percent. However, we are already controlling for the past smoking behaviour for which we know that there is a strong path dependence. Thus, marginal effects on transitions from smoking to non smoking are generally low. In addition to that, the average marginal effect for

individuals that smoked in the past (t-2) goes up to 9.1 percent. The interpretation of this number is that a smoker is about 9 percentage points less likely to give up smoking if her partner smoking probability moves from zero to one. Remember that the unconditional probability to quit smoking is equal to 15 percent. The estimated peer effect is therefore relatively important.

The marginal effect p of being in a couple on the probability of smoking is calculated as the difference in the probability of smoking of individual i when the couple dummy, D_i , passes from zero to one. Since for singles $\hat{\sigma}_j = 0$, in order to evaluate this marginal effect separately from the effect of $\hat{\sigma}_j$, one has to keep $\hat{\sigma}_j$ fixed and equal for all the individuals in the sample. First, we impose $\hat{\sigma}_j = 0$. The average marginal effect over the full sample is equal to -1.5 percent. This figure goes up to -4.3 percent for individuals who smoked two years before. This result suggests that smokers living in a couple and expecting the partner not to smoke are 4.3 percentage points more likely to give up smoking than singles.

We also look at the marginal effect of being in couple imposing $\hat{\sigma}_j = 1$. The effect is much smaller than the previous one both for smokers and the full sample. As one would expect, the negative effect of living in a couple on smoking is smaller if the partner is expected to smoke with probability one. Living with a smoking partner increases the probability of smoking by a number (corresponding to $s + r$ in the theoretical model) equal to the difference between the marginal effect of $\hat{\sigma}_j$ (corresponding to $s + r + p$) and the marginal effect of the couple dummy calculated at $\hat{\sigma}_j = 1$ (corresponding to $-p$). For past smokers, this increase is estimated to be equal to 8 percentage points.

[INSERT TABLE 5 HERE]

The results from this section suggest that a non smoking partner might have some control role on the tobacco consumption of her spouse. In particular the non smoker could impose a cost on the smoker, sometimes succeeding in having the latter quit. For instance, he could require the smoker to

smoke less or to leave the house in order to smoke. We cannot observe these qualitative aspects of the smoking behaviour and our interpretation is not directly testable. However, in the next section, we look at partners with children and analyse the effects of parental smoking on the health of their children. If the deterring effect identified in this section reduces the individual utility through an obligation for the smoker not to smoke at home, we should find that, everything else equal, children whose both parents smoke are more exposed to passive smoking than children with a non smoking parent. This constitutes a testable prediction of our model.

4.5 Gender specific peer effects

In a couple, male and female partners might be affected in different ways by the behaviour of the partner. In this section we consider a different setting where the structural parameters p , r and s depend on gender. We denote the gender by $g \in \{f, m\}$ where m refers to male individuals and f to female ones. The utility of individual i of gender g equals:

$$\begin{aligned}
U_{ig}(a_i, a_j, x_i, \epsilon_i) &= a_i [\lambda_g \tilde{x}_i + \epsilon_i + s_g a_j D_i - p_g (1 - a_j) D_i] - [1 - a_i] r_g a_j D_i \\
&= a_i [\lambda_g \tilde{x}_i - p_g D_i + \epsilon_i] - r_g a_j D_i + a_i a_j [s_g + p_g + r_g] D_i \\
&= \lambda_{1g} a_i x_i + \lambda_{2g} a_j D_i + \lambda_{3g} a_i a_j D_i + a_i \epsilon_i,
\end{aligned}$$

where $x_i = (\tilde{x}_i, D_i)$, $\lambda_1 = (\lambda_g, -p_g)$, $\lambda_2 = -r_g$, $\lambda_3 = p_g + r_g + s_g$. The parameters s_g , r_g and p_g are expected to be non negative for $g = f, m$.

We apply the same estimation method as in the previous sections. In the first stage regression (the results are omitted), we allow the parameters to be different for men and women. In the second stage we estimate the gender specific peer effects, by interacting the variables of interest, $\hat{\sigma}_j$ and Couple, with a dummy taking value one if the individual is male. The results of the analysis are reported in Table 6.

The results for the individual characteristics are very similar to the ones reported in Table 5,

with the important exception of the sex dummy. Concerning the peer effects, however there are some noticeable differences. Women seem to feel a higher peer pressure. In particular, the so-called smoking enhancing effect is greater for women than for men. The difference is statistically significant. In order to have a sense of the magnitude of these different effects, we calculated the average marginal effect of a smoking partner on the own probability of smoking. For women, the probability of smoking is 3.8 percentage points higher if their partner smokes (the standard deviation is equal to 0.0043). For men, the increase in the probability of smoking is only equal to 2.1 percentage points (standard deviation of 0.0071).

Also in this case, we consider the average marginal effect of σ_j for the subsample of past smokers. This is very high for women: a woman living in a couple is 12 percentage points less likely to give up smoking if her partner's smoking probability goes from zero to one (with standard deviation equal to 0.0173). For past smoking men, this figure is only of 5.5 percentage points (standard deviation of 0.0189). Under our interpretation, these results suggest that women get more pleasure from smoking with their partner, or internalise more the externality imposed on their partner.

Concerning the smoking deterring effect, represented by the parameter p , the results suggest that there are no significant differences between men and women.

The sex dummy has no significant explanatory power in this specification, while in the previous one it was significant at the 95% confidence level. This suggests sex affects the smoking behaviour only through the interaction with the expectations on the partner's smoking behaviour.

[INSERT TABLE 6 HERE]

4.6 Children's health and parents' behaviour

In this section, we study the relationship between the smoking behaviour of parents and the number of non chronic respiratory diseases of their children. We only include households in which the reference person lives in a couple. We also limit the analysis to the case in which the reference

person is a man (only 10 households are removed) and is between the age of 18 and 60. There are 5,431 such households. For simplicity, in the following we will define the reference person as the husband and his partner as the wife, even though we do not control for their effective marital status. Overall, 2,824 such households have at least one child under the age of 15; 4897 children live in these families. In these household, 1,511 husbands and 1,183 wives reported being smokers. In 658 cases both parents smoke.

[INSERT TABLE 7 HERE]

We regress the number of non chronic respiratory diseases on a set of individual variables, such as the age, the sex, the BMI of the child and a dummy equal to one if she is affected by chronic respiratory condition; we also include in the regressors the number of children under 15 present in the household. The education level of both the mother and the father and their BMI are also taken into account, since these characteristics may influence the way parents care about the health of their children. Finally, we include two dummy variables summarizing parents' smoking behaviour: we distinguish the case in which both parents smoke and the one in which just one parent smokes.

In our data set the number of sicknesses and the level of health care consumption of children is reported by parents. This can lead to measurement problems if parents tend to misreport the health status of their children. In the case of respiratory diseases, this difficulty seems to be particularly strong since some parents might report to the interviewer problems such as a light flu, while others would not. If this reporting bias is correlated with the variables of interest, this can lead to a misinterpretation of the coefficients. For instance, if smoking parents tend to underestimate the health problems of their children, we might find no effect of smoking on the non chronic respiratory diseases of children, even though passive tobacco exposure actually affects their health. In order to reduce this bias, we control for the total number of non respiratory diseases and the total number of doctor visits for health matters different from the respiratory ones. These variables are useful to

control the global health of the child and might capture the reporting bias of parents, if the latter is systematically the same for any health condition.

Another problem to take into account is endogeneity. On the one hand if a parent observes that her children are often sick, this may affect her smoking behaviour. On the other hand, even though we control for chronic respiratory conditions, which have a high chance to affect both the parents' behaviour and the occurrence of non chronic respiratory diseases, there could still be some correlation between our measures of parents' tobacco consumption and some unobservables affecting the occurrence of non chronic respiratory diseases. For instance, smoking parents might be less concerned with the health status of their children as they are less by their own health. This would lead to an overestimation of the effect of smoking on children's health. Regressing naively the health status of children on the smoking behaviour of parents might thus lead to biased results. In particular, the impact of smoking on children respiratory health could be underestimated. We try to overcome this problem using instruments. We use as instrument the age of both parents and their exposure to smoke at the workplace. The age of parents does not appear to be correlated with the error term once one controls for the age of children. We think that it is quite reasonable to consider the exposure to smoke at the workplace as exogenous to the health care of children by parents. Evans *et al.* (1999) using U.S. data, showed that the sorting across jobs based on smoking status seems to be relatively weak. We perform an OLS and 2SLS regression. We run a Sargan test suggesting that the instruments are indeed valid (see Table 8).

[INSERT TABLE 8 HERE]

Since we are dealing with count data (the number of respiratory diseases in the period of interest ranges from 0 to 4), we also run a Poisson regression and a Poisson regression with control functions in order to account for endogeneity (using the same instrumental variables as in the 2SLS). The latter estimates are obtained by a technique suggested by Blundell and Powell (2003). We perform

a first stage regression of the endogenous variables on all exogenous variables and instruments and we use the residuals and polynomials of those residuals as additional control variables in the main regression. This seems to be a more appropriate estimation strategy, because of the zero inflated discrete distribution of the dependent variable.

Results of both the OLS and the IV regressions are reported in the first two columns of Table 8. Clustered standard errors at the household level are reported in brackets. The presence of chronic conditions seems not to influence the number of non chronic respiratory diseases. However, the total number of doctor visits and the number of diseases different than respiratory both present positive and highly significant effect on the endogenous variable. As pointed out before, this could be due to the fact that these variables are proxies for the general health of the child. However, their positive impact might be linked to a systematic reporting bias of the parents. The age of the child affects positively the respiratory health of the child, as expected. The square of the age, gender and BMI have a small or insignificant effect in both specifications. The variable controlling for the number of children in the household presents a negative estimated parameter. This result seems counter intuitive since one could expect the presence of siblings to increase the risk to fall sick. The father's education level seems to have a positive correlation with the respiratory diseases of children. The mother's education and BMI do not seem to have a significant effect. The fact that the father's education increases the number of non chronic respiratory condition is at first sight counter intuitive too. One explanation could be that more educated households tend to report more respiratory diseases. The family income has a positive and significant effect on the number of sicknesses in the OLS regression, but the significance vanishes in the IV specification.

The results on smoking variables are the ones presenting a particular interest in order to test our smoking model. In the OLS specification, the estimates suggest no significant effect of the smoking behaviour of parents. In the IV regression, however, the fact that both parents smoke

has a significant (at the 95% confidence interval) and positive effect on the respiratory diseases of children. Having just one parent smoking at home does not affect significantly the children's health. The impact of the fact that both parents smoke is quantitatively very high (0.598), considering that in the period of observation, the average number of non chronic respiratory diseases for children is equal to 0.3. If just one parent smokes, the effect of smoking on children seems to be null. This evidence supports the hypothesis that non smoking parents might have a control role inside the household, protecting children from passive tobacco exposure.

In the third and fourth columns of Table 8, we report the results of the Poisson regressions. For most variables the results of the least square regression are confirmed. However, the parameters corresponding to the smoking behaviour of parents are not significant in this specification.

These results weakly point towards a control role of a non smoking parent. However, this first analysis does not take into account the number of cigarettes effectively smoked by each parents and thus lacks precision. We refine the analysis by looking at the effect of each cigarette smoked per day by household members. In particular, we constructed a variable corresponding to the daily tobacco consumption of the smoking parent when just one parent smokes, and a variable corresponding to the daily aggregate consumption when both parents smoke. No information concerning where these cigarettes are consumed is available. In particular, the available data does not allow us to know whether the parents smoke at home or not. The estimates of the smoking game suggest that when an individual is in couple with a non smoker, this reduces its utility from smoking. Our interpretation is that this disutility might come from the fact that smokers living with non smokers and having kids may be forced to smoke less at home or leave the house in order to smoke. Thus, we expect to see a smaller effect of each cigarette on the respiratory health of children when just one parent smokes instead of both.

In columns (a) and (b) of Table 8 we report the results of the OLS and the IV regressions. In the OLS regression, no effect of the smoking behaviour is found. In the IV specification, the respiratory health of children seems to be affected by each extra cigarette that a parent smokes only if the other parent is also a smoker. The parameter is significant at the 95% confidence level. In column (3) of Table 8, we also include among the instrumented variables the square of the total number of cigarettes smoked by parents (if one or both smoke). This variable is meant to control for non linear effects of the number of cigarettes smoked. More precisely, we want to test for the hypothesis that the number of cigarettes matters only if a critical number of cigarettes is consumed (or that the negative effect on health is convex). The results seem to reject this hypothesis. Controlling for this variable, the marginal cigarette smoked leads to an increase of 0.05 in the number of respiratory diseases when both parents smoke. Again, no effect is detected in households where just one parent smokes. In columns (c) and (d), we report the results of a Poisson regression and of a Poisson with control functions (for endogeneity). The results are qualitatively similar to the previous ones. The number of cigarettes smoked in households where both parents smoke has a positive impact on the number of diseases.

Summarizing, there is some evidence that non smoking parents exert a control role over smoking ones, in particular in protecting children from passive smoking. This is in line with our interpretation of the empirical results of the smoking game. A related interpretation is that having one parent smoking 20 cigarettes a day is less detrimental than two parents smoking 10 cigarettes a day because of the unobserved change in behaviour concerning smoking inside or outside, the smoker with a non smoking partner being more likely to smoke outside.

[INSERT TABLE 9 HERE]

5 Conclusion

In this paper we analyse intra-couple peer effects on smoking. Our empirical results suggest that the smoking behaviour of the partner influences the individual probability of smoking in two ways. If the partner smokes, the individual utility from smoking is enhanced. If the partner does not smoke, the individual utility from smoking is smaller than the one of a single. We interpret this result as the effect of smoking externalities. Smoking together might be more pleasant than smoking alone. However, smoking alone as a single is better than smoking when living with a non smoker. This might be due to the fact that the non smoker imposes a cost on the smoking partner. This cost may materialise in a different smoking behaviour: for instance smoking outside the house.

We quantify the impact of spousal tobacco consumption on the individual probability of smoking. More particularly, we find that smokers living in couple and expecting the partner not to smoke are 4.3 percentage points more likely to give up smoking within a period of two years with respect to singles. This might be due to the fact that individuals anticipate some extra cost from smoking if their partner does not smoke. However, if the partner is likely to smoke, this situation is reversed, and smokers living in couple are 8 percentage points less likely to give up smoking with respect to singles. Having a smoking partner enhances the utility an individual can get from smoking. This effect is higher for women than for men.

Finally, we look at the impact of smoking on children respiratory diseases. There seems to be some effect of parental smoking on children health only when both parents smoke. This result is consistent with the evidence from the smoking game we modeled above, and in particular with the fact that, if only one parent smokes, she might be obliged by the partner to protect the children from passive smoke. In terms of policy, the results show the importance of peer effects within the family and the role of partner's behaviour in quitting smoking. It suggests that incentives to smoking cessation should be given in priority to couples of smokers specially if they have children and even

if they jointly do not smoke as much as singles.

References

- [1] Adda J. and F. Cornaglia, 2010, "The Effect of Taxes and Bans on Passive Smoking", *American Economic Journal Applied Economics*, 2 (1), 1–32.
- [2] Bajari P., H. Hong, J. Krainer and D. Nekipelov, 2010, "Estimating Static Models of Strategic Interactions", *Journal of Business and Economic Statistics*, 28 (4), 469-482.
- [3] Becker G.S., 1974, "A theory of marriage. Part I", *Journal of political Economy*, 81, 813-846.
- [4] Blundell R. and J. Powell, 2003, "Endogeneity in nonparametric and semiparametric regression models," in *Advances in Economics and Econometrics : Theory and Applications*, Dewatripont M., L.P. Hansen and S.J. Turnovsky (eds.), Eighth World Congress, Vol II, Cambridge : Cambridge University Press.
- [5] Clark A.E. and F. Etilé, 2006, "Don't give upon me baby: Spousal correlation in smoking behavior", *Journal of Health Economics*, 25 (5), 958-978.
- [6] Cutler D.M. and E.L. Glaeser, 2007, "Social interactions and smoking" NBER working paper W13477.
- [7] Douglas S. and G. Hariharan, 1994, "The hazard of starting smoking: Estimates from a split population duration model", *Journal of Health Economics*, 13 (2), 213-230.
- [8] Evans W.N., M.C. Farrelly and E.B. Montgomery, 1999, "Do workplace smoking bans reduce smoking?", *American Economic Review*, 85 (5), 729-747.
- [9] Flegal K.M., R.P. Troiano, E.R. Pamuk, R.G. Kuczmarski and S.M. Campbell, 1995, "The Influence of Smoking Cessation on the Prevalence of Overweight in the United States", *The New England Journal of Medicine*, 333 (18), 1165-1170.

- [10] Gruber J. and Frakes M., 2006, "Does Falling Smoking Lead To Rising Obesity?", *Journal of Health Economics*, 25 (2), 183-197.
- [11] Harris J.E. and B. González López-Valcàrcel, 2008, "Asymmetric peer effects in the analysis of cigarettes smoking among young people in the United States, 1992-1999", *Journal of Health Economics*, 27, 249-264.
- [12] Hotz V.J. and R.A. Miller, 1993, "Conditional Choice Probabilities and the Estimation of Dynamic Models", *The Review of Economics Studies*, 60, 497-529.
- [13] Jones A.M., 1994, "Health, addiction, social interaction and the decision to quit smoking", *Journal of Health Economics*, 13, 93-110.
- [14] Kenkel D., Lillard D. and Mathios A., 2006, "The Roles of High School Completion and GED Receipt in Smoking and Obesity" , *Journal of Labor Economics*, 24 (3), 635-660.
- [15] Lundborg P., 2006, "Having the wrong friends? Peer effects in adolescent substance use", *Journal of Labor Economics*, 25 (2), 214-233.
- [16] Mannino J.S., J.E. Moorman, B. Kingsley, D. Rose and J. Repace, 2001, "Health effects related to environmental tobacco smoke exposure in children in the United States: data from the third National Health and Nutrition Examination Survey ", *Archives of Pediatrics and Adolescent Medicine*, 155, 36-41.
- [17] Manski C., 1995, *Identification problems in the social sciences*, Harvard University Press, Cambridge, MA.
- [18] Powell L.M., J.A. Tauras and H. Ross, 2005, "The importance of peer effects, cigarette prices and tobacco control policies for youth smoking behavior", *Journal of Health Economics*, 24 (5), 950-968.

Tables

TABLE 1. Individuals in couple. Descriptive statistics

Variable	Mean	Std. Dev.
Smoking	0.248	0.431
Smoking two years before	0.284	0.4508
Sex	0.500	0.5000
Age	41.341	10.1168
Education>High School	0.385	0.4865
BMI	24.610	4.1067
Work exposure	0.146	0.3535
At least one child under 15 years	0.511	0.4996
Number of children under 15 years	0.900	1.0437
Income	17,767	11,190
Observations	10,862	

TABLE 2. Singles. Descriptive Statistics

Variable	Mean	Std. Dev.
Smoke	0.338	0.4731
Smoked two years before	0.366	0.4819
Gender (1: man, 0:woman)	0.3910	0.4899
Age	40.038	11.4990
Education higher than High School	0.477	0.4996
BMI	23.639	4.3127
Work exposure	0.152	0.3588
At least one child under 15	0.178	0.3826
Number of children under 15	0.264	0.6605
Income	16,121	11,743
Observations	2,544	

TABLE 3. Smoking behaviour: Logit Model

VARIABLES	Parameter	(Standard error)
Smoking at year-2*couple	6.075***	(0.1217)
Smoking at year-2*single	6.820***	(0.2779)
Gender ³ *couple	0.306***	(0.1115)
Gender*single	0.011	(0.2232)
Age*couple	0.048	(0.0409)
Age ² *couple	-0004	(0.0005)
Age*single	0.084	(0.0737)
Age ² *single	-0.0009	(0.0009)
Education higher than High School*couple	-0.357***	(0.1094)
Education higher than High School*single	-0.704***	(0.2331)
BMI*couple	-0.223***	(0.0921)
BMI ² *couple	0.002	(0.0017)
BMI*single	-0.193***	(0.0782)
BMI ² *single	0.003	(0.0012)
Work exposure*couple	0.160	(0.1110)
Work exposure*single	0.468*	(0.2885)
Partner smoking at year-2*couple	0.824***	(0.0995)
Partner's age*couple	0.002	(0.0105)
Partner's education>HS*couple	-0.243**	(0.1100)
Partner's BMI*couple	0.010	(0.0122)
Partner's work exposure*couple	-0.081	(0.1268)
Couple	0.730	(2.2483)
At least one child under 15*couple	-0.748	(0.8972)
At least one child under 15*single	0.336	(0.2911)
Number of children under 15*couple	-0.420*	(0.2815)
(Number of children under 15) ² *couple	0.108**	(0.0626)
Number of children under 15*single	0.432	(0.8821)
(Number of children under 15) ² *single	-0.041	(0.1751)
Income*couple	-2.59e-05***	(8.64e-06)
Income ² *couple	2.40e-10***	(9.86e-11)
Income*single	-4.29e-05***	(1.85e-05)
Income ² *single	4.40e-10***	(1.98e-10)
Constant	-2.509	(1.6730)
Observations	13406	

TABLE 4. Expected utility of smoking (OLS)

VARIABLES	Parameter	(Standard Error)
Smoked at t-2	6.252***	(0.1166)
$\hat{\sigma}_j$ (r+p+s)	0.823***	(0.1045)
Couple (-p)	-0.388**	(0.1974)
Age	0.049	(0.0359)
(Age)2	-0.0005	(0.0004)
Gender (1: man, 0 woman)	0.193**	(0.0876)
Education higher than High School	-0.535***	(0.0924)
BMI	-0.077***	(0.0114)
Work exposure	0.194*	(0.1127)
At least one child under 15	-0.126	(0.1608)
Number of children under 15	0.073	(0.0753)
Income	-1.13e-05***	(3.92e-06)
Constant	-3.365***	(0.7330)
Observations	13406	

TABLE 5. Marginal peer effects

	Marg. Eff.	Std. Dev.
<i>All individuals</i>		
$\hat{\sigma}_j$ (couples only)	0.032	0.0043
Couple (non smoking partner)	-0.015	0.0088
Couple (smoking partner)	-0.006	0.0074
<i>Past smokers</i>		
$\hat{\sigma}_j$ (couples only)	0.091	0.0125
Couple (non smoking partner)	-0.043	0.0239
Couple (smoking partner)	-0.007	0.0138

TABLE 6. Expected utility of smoking/Gender differences (OLS)

VARIABLES	Parameter	(Standard Error)
Smoked at t-2	6.303***	(0.1199)
$\hat{\sigma}_j$ (r+p+s)	1.087***	(0.1418)
$\hat{\sigma}_j$ *Sex	-0.566**	(0.2324)
Couple (-p)	-0.541**	(0.2258)
Couple*Sex	0.293	(0.2421)
Age	0.051	(0.0353)
(Age) ²	-0.0005	(0.0001)
Sex	0.063	(0.2141)
Education>HS	-0.540***	(0.0936)
BMI	-0.077***	(0.0115)
Work exposure	0.190*	(0.1131)
At least one child under 15	-0.127	(0.1613)
Number of children under 15	0.067	(0.0758)
Income	-1.11e-05***	(3.94e-06)
Constant	-3.386***	(0.7309)
Observations	13406	

TABLE 7. Children. Descriptive statistics

Variable	Obs	Mean	Std. Dev.
Non chronic respiratory diseases	4897	0.310	0.5789
At least one chronic condition	4897	0.084	0.2773
Doctor visits-else than respiratory	4897	0.402	0.8885
Sicknesses-else than respiratory	4897	0.928	1.0861
Age	4897	6.963	4.3458
Sex	4897	0.513	0.4999
BMI	4897	17.136	3.5302
Number of children under 15	4897	2.111	0.9245
Only one parent smokes	4897	0.268	0.4432
Both parents smoke	4897	0.134	0.3411
Cigarettes if one parent smokes	1315	14.829	7.9185
Cigarettes if both parents smoke	658	30.849	11.5561

TABLE 8. Children Respiratory Diseases (a)

VARIABLES	(a)	(b)	(c)	(d)
	OLS	2SLS	Poisson	CF Poisson
One parent smokes	-0.006 (0.0209)	-0.085 (0.4127)	-0.021 (0.0620)	2.487 (1.6281)
Both parents smoke	0.039 (0.0315)	0.598* (0.3325)	0.115 (0.0768)	1.612 (1.3978)
One chronic condition	-0.004 (0.0283)	-0.027 (0.3505)	-0.022 (0.0923)	-0.079 (0.1015)
Visits-else than respiratory	0.034*** (0.0125)	0.035*** (0.0148)	0.045* (0.0269)	0.044 (0.0295)
Sicknesses-else than respiratory	0.047*** (0.0095)	0.046*** (0.0136)	0.160*** (0.0270)	0.160*** (0.0339)
Age	-0.042*** (0.0077)	-0.041*** (0.0088)	-0.083*** (0.0226)	-0.082*** (0.0244)
(Age)2	0.0009* (0.0005)	0.001* (0.0006)	-0.0009 (0.0017)	-0.001 (0.0018)
Gender (1: man, 0:woman)	0.014 (0.0162)	0.010 (0.0201)	0.041 (0.0517)	0.036 (0.0566)
BMI	-0.0001 (0.0026)	-0.0004 (0.0031)	-0.0008 (0.0082)	-0.0031 (0.0095)
Number of children under 15	-0.029*** (0.0097)	-0.027*** (0.0115)	-0.095*** (0.0301)	-0.078*** (0.0315)
Mother's education higher than HS	0.023 (0.0225)	0.045* (0.0272)	0.084 (0.0609)	0.133** (0.0682)
Father's education higher than HS	0.051** (0.0234)	0.091*** (0.0360)	0.159*** (0.0618)	0.264*** (0.0876)
Mother's BMI	0.0004 (0.0022)	0.004 (0.0029)	0.001 (0.0065)	0.010 (0.0077)
Father's BMI	0.002 (0.0028)	0.006 (0.0036)	0.006 (0.0076)	0.015 (0.0091)
Income	-3.12e-06*** (1.03e-06)	-1.83e-06 (1.41e-06)	-1.07e-05*** (3.60e-06)	-7.40e-06* (4.48e-06)
Constant	0.493*** (0.0966)	0.220 (0.1548)	-0.751*** (0.2761)	-1.928*** (0.4827)
Observations	4897	4897	4897	4897
Sargan	.	0.892 (P val. 0.6403)	.	.
R^2	0.067	.	.	.

TABLE 9. Children Respiratory Diseases (b)

VARIABLES	(a)	(b)	(c)	(d)	(e)
	OLS	2SLS	2SLS	Poisson	CF Poisson
Cigarettes if one smokes	0.0002 (0.0012)	-0.010 (0.0170)	0.035 (0.0437)	0.002 (0.0052)	0.104 (0.1105)
Cigarettes if both smoke	0.001 (0.0009)	0.019** (0.0097)	0.053** (0.0300)	0.006 (0.0066)	0.141* (0.0816)
(Cigarettes)2			-0.001 (0.0010)	-0.001 (0.0001)	-0.004 (0.0027)
One chronic condition	-0.003 (0.0282)	-0.022 (0.0339)	-0.024 (0.0337)	-0.021 (0.0923)	-0.073 (0.0986)
Visits-else than respiratory	0.034*** (0.0124)	0.038*** (0.0151)	0.030* (0.0162)	0.45* (0.0269)	0.029 (0.0353)
Sicknesses-else than respiratory	0.047*** (0.0095)	0.042*** (0.0125)	0.057*** (0.0187)	0.160*** (0.0270)	0.191*** (0.0470)
Age	-0.042*** (0.0077)	-0.042*** (0.0086)	-0.0413*** (0.0084)	-0.084*** (0.0226)	-0.082*** (0.0234)
(Age)2	0.001** (0.0005)	0.001* (0.0005)	0.001* (0.0056)	0.001 (0.0017)	0.001 (0.0018)
Gender (1: man, 0: woman)	0.014 (0.0162)	0.006 (0.0204)	0.018 (0.0223)	0.042 (0.0517)	0.054 (0.0617)
BMI	-0.0001 (0.0026)	-6.16e-05 (0.0029)	-0.001 (0.0029)	-0.001 (0.0082)	-0.004 (0.0092)
Number of children under 15	-0.029*** (0.0097)	-0.028*** (0.0116)	-0.024** (0.0121)	-0.095*** (0.0301)	-0.072* (0.0325)
Mother's education higher than HS	0.024 (0.0226)	0.046* (0.0273)	0.033 (0.0293)	0.085 (0.0609)	0.106 (0.0741)
Father's Education higher than HS	0.052** (0.0233)	0.087*** (0.0346)	0.081*** (0.0342)	0.163*** (0.0076)	0.241*** (0.0846)
Mother's BMI	0.0004 (0.0022)	0.004 (0.0030)	0.002 (0.0034)	0.001 (0.0065)	0.005 (0.0086)
Father's BMI	0.002 (0.0028)	0.006* (0.0040)	0.006* (0.0038)	0.006 (0.0076)	0.016 (0.0086)
Income	-3.15e-06*** (1.03e-06)	-2.13e-06* (1.23e-06)	-2.01e-06* (1.19e-06)	1.07e-05*** (3.60e-06)	-7.73e-06** (3.94e-06)
Constant	0.494*** (0.0960)	0.244* (0.1550)	0.217 (0.1535)	-0.765*** (0.2756)	-1.489 (0.4411)
Observations	4897	4897	4897	4897	4897
Sargan	.	1.717	0.002	.	.
	.	(P val. 0.4237)	(P val. 0.9676)	.	.