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spousal peer effects on the decision to quit smoking

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Abstract

If two partners smoke, their quit behavior may be related through correlation in unobserved individual characteristics and common external shocks. However, there may also be a causal effect whereby the quit behavior of one partner is affected by the quit decision of the other partner. We use data on Dutch partnered individuals to study the relevance of such spousal peer effects. After controlling for common unobserved heterogeneity and common external shocks, we find that such spousal peer effects in the decision to quit smoking do not exist. Apparently, love conquers all but nicotine addiction.

Keywords: smoking cessation, causal partner effects

JEL codes: C31, I10, I18

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1 Introduction

If partnered individuals both smoke, the decision of one partner to quit smoking may induce the other partner to quit smoking as well. From a policy point of view it is interesting to know whether such spousal peer effects exist. If they do, this might affect government policy aiming to reduce the number of smokers. If there are spousal peer effects in the decision to quit smoking, then anti-smoking policies get 'two for the price of one'.

There are several ways how one partner can affect the quit decision of the other. The first is household bargaining. One partner might try to convince the other partner to quit through bargaining, after he or she takes a decision to quit smoking. The reason is not always clear. The partner can do so because he or she wants to protect the other from the adverse effects of smoking. However, it is also likely that he or she thinks that to quit smoking will be hard if the partner persists in smoking. Whatever the reason is, the spouse who decides to quit first can have an interest in the partner to quit smoking as well. The second is learning. Partners can learn from the smoking or the quit decision of each other. If there is such a partner-caused accumulation of information, then the decision of one partner might affect the other. The third is spill-over effects. One partner can consider the quit decision of the other as an incentive to quit smoking himself or herself. Even in the absence of bargaining or learning there can be a spousal peer effect.

From a research point of view it is not easy to establish the existence of spousal peer effects. Individuals become partnered through an assortative matching process. Therefore, they have correlated characteristics and their preferences and attitudes, including smoking behavior are likely to be similar. However, it is also possible that smoking behavior is not an important factor in the matching process that leads two individuals to form a partnership. The strength of the average correlation in smoking behavior between two partners and the magnitude of spousal peer effects are empirical questions.

Studies from different fields of social sciences find that individuals partner through an assortative matching process and therefore share similar personalities and behaviors, similar proclivities and similar risk attitudes (Humbad et al. (2010), Leonard and Mudar (2003), Canta and Dubois (2015), Powdthavee (2009), Abrevaya and Tang (2011)). In addition to assortative matching there may be convergence in behavior due to learning, bargaining or peer effects. Humbad et al. (2010) state that partners are found to show similar personality traits and these similarities are mostly due to selection in the marriage market rather than a convergence between partners. Leonard and Mudar (2003) show that these similarities are not limited to personality traits but can also be found in observable behaviors such as drinking habits. The authors find strong positive correlation between drinking behavior of husbands and wives. Canta and Dubois (2015) find similar results for smoking behavior; there is a significant correlation between cigarette smoking patterns of partners. They show that individuals whose partner smokes are more likely to smoke themselves and individuals of whom the partner does not smoke are less likely to smoke than singles. Economists have shown interest in establishing peer effects for risky behaviors because it has important policy implications but also because of the research challenges in identifying unbiased causal effects. As we discuss in more detail below there are quite a few economic studies on peer effects in smoking although not so many on spousal peer effects.

In the current paper, we study spousal peer effects in the decision to quit smoking. The main issue in studying peer effects is identification. According to Manski (1993) there are at least three problems related to identification of peer effects. First, there is the endogeneity problem. The influence of peers may not be exogenous because the peer may be influenced by the behavior of the individual subject to the peer effect. Second, individuals may self-select into a particular social environment; i.e. there is correlation in behavior through self-selection. Finally, apparent peer effects in behavior may originate from correlation in personal characteristics or behavior. According to Angrist (2014) correlation among peers is a reliable descriptive fact but going from correlation to causality in peer analysis is non-trivial and the risk of inappropriate attribution of causality is high. To establish peer effects a clear distinction is needed between the subjects of a peer effects investigation on the one hand and the peers who potentially provide the mechanism for causal effects on these subjects on the other. Then, mechanical links between own and peer characteristics can be eliminated.

The existence and magnitude of peer effects is of interest, since peer effects may serve to amplify the effects of interventions i.e. there may be "social multipliers". In order to estimate peer effects the researcher must know the appropriate peer-group associated with each individual. For our paper this is not an issue. It is clear who the peer is, it is the partner. Peers are seldom randomly allocated i.e. they are rarely exogenous to individual behavior. Unless random assignment is available assumptions have to be made to establish causality. Sometimes, in peer effect studies in education classroom level data or grade level data are used, assuming that the peers are in the same classroom or grade. This is done in combination with school fixed effects whereby the assumption is that conditional on the school effects allocation of students over classrooms is random, or conditional of school effects allocation of students within the same grade over cohorts is random.[1] Alternatively, instrumental variables are used to correct for selectivity. Smoking bans at the workplace for example will only affect workers directly and not partners in a different workplace or without a job.

To investigate whether or not there are spousal peer effects in the decision to quit smoking, we follow an alternative approach. We study dynamics in smoking behavior, i.e. the process by which individuals start smoking and if they smoke the process by which they quit smoking. We establish the importance of correlation in spousal smoking dynamics using mixed proportional hazard models with fully flexible baseline specification. This enables us to take account of observable as well as unobservable factors that might affect the dynamics in smoking. To the extent that observable and unobservable determinants of smoking behavior are correlated between partners we assume this to be due to assortative matching. We use biannual data obtained in the Netherlands over the period 2001 to 2007. Our data include information on the age of first smoking as well as the year in which respondents quit smoking. Using this basic retrospective information, we model the dynamic of smoking for males and females in couples. The baseline results show that there is a strong positive correlation between quit behavior of the partners. Quit behavior of one partner is associated with an increase in the probability that the other partner quits smoking as well. We distinguish between correlation and causal effects by estimating a simultaneous model of spousal smoking dynamics. We find that the association in quit behavior is driven by correlated unobserved characteristics, i.e. by assortative matching. Once these are accounted for there are no causal peer effects in the decision to quit smoking.

Our contribution to the existing literature on spousal peer effects in quitting-to-smoke

[1] Sacerdote (2011) presents an overview of peer effect studies in education but with some references to other types of peer effect studies.

behavior is threefold. First, dynamics in smoking behavior are complex. Individuals start smoking over a limited age range. If they have not started smoking at age 25 they are very unlikely to start smoking later on. Some individuals smoke for a period of time after which they quit to never return to smoke. We use hazard rate models to study these dynamics in smoking behavior. Hazard rate models allow us to model transition is smoking status, first from non-smoker to smoker and then from smoker to non-smoker, providing a complete picture of the smoking dynamics. Hazard rate models also provide a natural way to analyze the dynamics of tobacco use and to study its determinants both in terms of observed personal characteristics as well as unobserved determinants. Second, we explicitly focus on the quit behavior of partners by using the unique information that our data set has on the exact times when the respondents quit smoking. Therefore, we can accurately identify a quit behavior and prevent our results from being contaminated by failed or mis-specified quitting that might occur in most panel data studies. Moreover, as peer effects on the starting behavior and the quitting behavior can be very different, it is important to separate the two. Third, we estimate simultaneous models of smoking dynamics of two partners. This allows use to distinguish between correlated spousal behavior and spousal peer effects. Thus, we contribute to the small literature on spousal peer effects.

The set up of our paper is as follows. Section 2 provides an overview of previous studies on peer effects in smoking behavior. In section 3 we present our data and stylized facts highlighting the dynamics of tobacco use for females and males in couples. In section 4 we discuss the details behind the empirical method used in this study. In section 5 parameter estimates are presented. Section 6 concludes.

2 Previous studies

There are quite a few peer effect studies on risky health behaviors during adolescence. Some of these studies analyze the broad set of risky health behaviors such as smoking, using cannabis, drinking alcohol or early participation in sexual activity. Some examples are as follows. Lundborg (2006) studies school-class based peer effects in (among others) smoking. He uses Swedish cross-sectional data finding that peer smoking has significant positive effects on the probability of smoking. Clark and Youenn (2007) investigate peer group influence in the consumption of cannabis, alcohol and tobacco by American adolescents. They use the Add Health (National Longitudinal Study of Adolescent Health) survey which allows them to make a distinction between two peer groups, those in the same school year and friends. Identifying friends is possible because participants in the survey were asked to identify a number of their friends which very often were present in the same school. The authors find strong peer effects for alcohol use while for smoking the peer effects are substantially smaller. Card and Giuliano (2013) use US data on networks of friends to study peer effects. The focus of the paper is on interactions in the decision to initiate sexual activity, but part of the paper addresses the issue of peer effects in smoking behavior. For initiation into sexual activity the authors find clear peer effects, whereas for cigarette smoking the results suggest that some of the correlation patterns are due to common unobserved heterogeneity. Eisenberg et al. (2014) use US data on a natural experiment of assigned college roommates to estimate peer effects of among others cigarette smoking. There are significant peer effects for binge drinking but little evidence of effects for cigarette smoking. The authors argue that in college settings binge drinking takes place in social contexts with many peers and therefore is likely to have large peer effects. Also, heavy drinking has a low stigma in college-age populations. When a distinction is made by gender, the authors find a positive though not significant smoking peer effect for men and a negative and significant smoking effect for women. Apparently, women have a negative reaction to being around a smoker; they become less likely to smoke.

There are also several studies that explicitly focus on the peer effects on smoking during adolescence. An early example is Gaviria and Raphael (2001) who use US data to study school-based peer effects of among others cigarette smoking. The authors argue that focusing on schools rather than neighborhood reduces the importance of selectivity because students are less exposed to the family background of their school peers than they are exposed to the family background of peers residing in the same neighborhood. They find significant peer effects for smoking. Kawaguchi (2004) analyzes NLSY (National Longitudinal Survey of Youth) data using subjective perceptions of respondents concerning the share of children at school who smoke cigarettes. The probability that a subject smokes increases with the perceived number of smoking peers. Powell et al. (2005) investigate smoking behavior of US high school students and how this is affected by peers. Cigarette prices and tobacco control policies are allowed to have a direct effect and an indirect effect – through school level peer effects. The authors find significant peer effects and show that cigarette prices and tobacco policies have direct effects as well as indirect effects. Ali and Dwyer (2009) use data from AddHealth to establish peer effects in adolescent smoking behavior. They distinguish two possible types of peers: friends nominated by the respondent and school-level peers, i.e. students in the respondents grade and school. It appears that school-level peer effects are not long-lasting whereas the effect of close friends persists. Fletcher (2010) uses US classroom data to study peer effects in smoking behavior. Using information on students in different grades within the same high school who face a different set of classmates the author identifies significant peer effects in smoking i.e. individual smoking decisions are influenced by classmate smoking decisions.

The study of peer effects usually relates the behavior of an individual to characteristics and behavior of a group of individuals who are the peers of the individual. Our paper differs from this since the peer is the partner. Previous studies have usually examined peer effects either at the neighborhood, at the school level or at the level of colleges. In the latter case random assignment of roommates is exploited to account for potential selectivity in the interaction between individuals. Whereas usually in peer effect studies random variation in peer groups is needed to distinguish correlation from causation, in our study it is clear that there is a non-random assignment to peers. In fact, it is the opposite. Partnership formation is a non-random process, it is the result of assortative matching.

There are only a few studies that investigate the spousal peer effects in smoking, and even less studies on spousal peer effects in quitting smoking. Cutler and Glaeser (2010) distinguish three broad categories of reasons for social interactions in smoking behavior: direct social interactions including approval and stigma, social formation of beliefs, market-mediated spillovers. Direct social interaction may especially occur between a smoker and a non-smoker because of the discomfort caused by secondhand smoke to a nonsmoker. Social learning may occur if smokers convince non-smokers that cigarettes are pleasurable or not harmful. Market-based spillovers may occur through price effects. Cutler and Glaeser (2010) study the influence of one spouse's smoking decisions on the smoking propensity of the other spouse. They use the presence of workplace smoking bans as an instrument for the smoking of one spouse. They also investigate peer group effects whereby the peer group is defined as people within the same metropolitan area and with the same age and education level. They conclude that spousal smoking does have spillovers, but peer group smoking does not. From this they conclude that smoking bans in the workplace have not only reduced smoking of the worker but also the smoking of the worker's spouse.

According to Clark and Etilé (2006) assortative matching on lifestyle preferences will be picked up by correlated individual effects in the male and female smoking equations. Smoking is one of the domains over which sorting takes place in the marriage market. Smoking may be considered as one of the traits that determine marriage assignments; lifestyle variables will be complements in the sense that partners enjoy sharing these activities. Matching on the marriage market corresponds to correlated effects in partners' behaviors. Clark and Etilé (2006) control for this by including correlated individual random effects in both male and female smoking equations. Analyzing British data, their main finding is that all of the correlation in smoking status between partners works through correlation of individual effects. Conditional on this correlation smoking behavior of partners is statistically independent. This implies that it is not sufficient from a policy point of view to target one person per household in terms of health education. Interventions targeting only the female partner – for instance during pregnancy – would not appear to be effective in reducing male smoking.

Canta and Dubois (2015) model the smoking decision of spouses as a non-cooperative game by eliminating the possibility of bargaining. They use a 2-wave panel data set to investigate the implications of their model on the spousal peer effects. Contrary to Clark and Etilé (2006), the authors find that strong spousal peer effects exist. The respondent with a smoking partner seem to enjoy smoking more than those with non-smoking partners. Moreover, comparing singles and partnered individuals, they find that singles enjoy smoking more than partnered individuals with non-smoking partners. Overall, the authors claim that the smoking behavior of one spouse has strong effects on the smoking behavior of the other.

McGeary (2015) investigates the spousal peer effects on the decision to quit smoking using Health and Retirement Study (HRS). The author uses a fixed effects model to identify the peer effects by defining the quitting decision as reporting no tobacco use in a survey while reporting use in a previous one. There is evidence of spousal peer effects. Spouses affect each other's quitting behavior though bargaining. Furthermore, the authors state that females learn from the health stock of their spouses. Khwaja et al. (2006) indirectly analyze if partners learn from the smoking behavior of each other. Using the first 6 waves of HRS data and Arellano-Bond estimates, they find that spousal peer effects through household learning do not exist. They do not investigate the other possible channels of spousal peer effects, i.e. spill-overs or bargaining.

All in all, a detailed review of the previous studies on the peer effects on smoking shows that the vast majority of the studies deal with the peer effects during adolescence and without making a clear distinction between the starting and the quitting behavior. Starting to smoke can occur with a gentle nudge by a third party. However, as smoking is addictive, quitting requires more than a nudge, it requires a much stronger motivation and determination. Therefore, peer effects on quitting to smoke can be very different from peer effects on starting to smoke. Furthermore, most of the studies use panel data techniques to analyze the peer effects. Since the time dimension is generally not very long, this creates two kinds of problems. First, it becomes very hard to identify a quitting behavior. Most studies rely on the observation that a respondent report no smoking behavior in a single year to identify the quitting. Second, depending on the age cohorts in the samples, it becomes hard to identify the starting behavior. Individuals mature out of the risk of initiating smoking in their mid-20s. Therefore, an analysis based on datasets without sufficiently young cohorts cannot capture the dynamics of starting to smoke, which can be very important to capture the unobserved heterogeneity in smoking dynamics. To the best of our knowledge, our study is one of the first to analyze the spousal peer effects on the dynamics of smoking by clearly separating the starting and quitting behaviors.

3 Data and Stylized Facts

3.1 Data

CentERdata collects information about individuals through an internet-based panel consisting of around 2000 households in the Netherlands. The participants in the panel fill in questionnaires on the internet every week. The panel is representative of the overall Dutch population. Most of the information collected is on work, pensions, housing, mortgages, income, assets, loans, health, economic and psychological concepts, and personal characteristics. We use a specific data collection in 2001, 2003, 2005 and 2007 when individuals provided detailed information on their tobacco consumption, for example whether they ever used tobacco and if so at what age that tobacco use started. Furthermore, if the respondent reported ever tobacco use but no use at the time of the survey, the question was posed at what age the individual smoked for the last time. Our data are quasi-longitudinal, i.e. we know from retrospective questions when (at what age) individuals started smoking and when (at what age) they quit smoking. We do not have longitudinal information in the sense that we follow individuals through time. Therefore, we cannot establish for example how preferences change over time or observe variations in the intensity of smoking over time. Time-invariant variables that may affect smoking dynamics are also constructed from retrospective information. Our time-invariant variables refer to educational attainment (which we assume to be an indicator of ability since many of the transitions in smoking behavior occur before individuals complete their education), degree of urbanization (since smoking may be more common in rural areas), age cohort (as over time there are important changes in smoking behavior), social status and religion.[2]

Since we are interested in spousal peer effects in the decision to quit smoking, we restrict our sample to partnered individuals. This gives us a sample of 812 males and 812 females. Figure 1 presents the relationship between age and starting rates of tobacco use. Starting rates – the rate to start using at a particular age conditional on not having started to use up to that age – show a considerable peak at age of 16. There are other but smaller peaks at ages of 18 and 20 for both males and females. The substantial drop in the starting rates after age 23 shown in panel (a) indicates that those who have not used tobacco before are very unlikely to do so later on in life. Apparently individuals mature out of using tobacco in their mid 20s. Panel (b) shows that cumulative starting rates level off at 75% for males and at 60-65% for females after the age of 25. This means, on average, we expect 25% of males and 40-35% of females to be never smoke. This is also clear from the slope of the cumulative starting probability, which becomes virtually zero after age 25. Figure 2 shows

[2]Further information on the data set is given in Appendix 2. The complete set of variables which are used throughout this study, their descriptions and sample statistics are given in Appendix 3.

quit and cumulative quit rates for females and males in couples. Panel (a) shows that in the first couple of years after initiation into tobacco use, the conditional probability of quitting rapidly decreases. Later on, until 12 or 13 years after the start quit rates gradually increase. The cumulative quit rates are found to be very similar for males and females indicating that smoking cessation behavior is not gender-specific.

3.2 Stylized Facts

We are interested in spousal peer effects in quitting-to-smoke behavior. Since the quit behavior can be observed only if the individual starts smoking in the first place, we report some stylized statistics about starting and quit patterns in the sample. Table 7 shows that 61% of females and 75% of males in the sample ever use tobacco. Among these users 46% of females and 45% of males quit smoking. Table 1 shows how these numbers are distributed in couples. Among all the couples in the sample we see that 51% consists of couples in which both female and male start using tobacco. In 25 % of the couples only male starts, in 11% only female starts and finally in 14% of the couples none of the partners starts using tobacco. The asymmetry between female behavior and male behavior disappears in quit behavior. We see that in 16% of the couples the male quits while the female continues smoking. In 17% it is vice versa. In 29% both partners quit whereas in 38% both partners continue smoking.

Table 2 presents the detailed distribution of the couples based on starting and quit behavior. We define 3 groups for both females and males: those who start and quit using tobacco, those who start and do not quit using tobacco and those who do not start using tobacco. The figures in Table 2 basically show that there is correlation between partners' smoking behavior. In almost 50 % of the couples (a+e+i) both partners follow the same starting-quit behavior. We also see that percentage of couples in which the male uses tobacco but not the female (g+h) is considerably higher than the percentage of couple in which only the female uses it (c+f).

Finally, Table 3 shows the distribution of couples based on the timing of the quit behavior. The first row presents the percentage of couples in which only one partner quits smoking. The figures in the table shows that in 32% of the couples male quits before female and in 68% female quits first. By definition the percentage of "quits in the same year" is zero.

The distribution becomes symmetric when we consider couples in which both partners quit smoking. In 44% of these couples the male quits first while in 45% the female quits first. Figure 3 presents the scatter plot of these couples. The figure shows that there are numerous observations where only one partner quits. Moreover, there is a considerable number of observations which are scattered around 45 degree line indicating that quit behaviors of one partners spills over to the other partner since the calendar time gap between two quit behaviors is small.

4 Empirical Model

4.1 Tobacco use dynamics assuming that partner's decision to quit is exogenous

To investigate the determinants of the starting rates and quit rates of smoking, we use mixed proportional hazard models with a flexible baseline hazard specification and Heckman and Singer type unobserved heterogeneity (Heckman and Singer (1984)). The flexible nature of this model enables us to control not only for observed but also for unobserved characteristics that might affect transitions into and out of tobacco use. Following the extensive literature on initiation into tobacco use, we assume that individuals become vulnerable to the risk of tobacco consumption from age 11 onwards.

The hazard function for starting rate for tobacco use at time t ($t = 0$ at age 11) for females ($j = f$) and males ($j = m$) conditional on observed characteristics x and unobserved characteristics u are defined as

$$\theta_j^s(t \mid x_j, u_j) = \lambda_j^s(t) \exp(x_j'\beta_j + u_j) \tag{1}$$

where β_j represent the effects of control variables and $\lambda_j^s(t)$ represents individual duration dependence. Since we assume that everyone becomes vulnerable to the risk of initiation into tobacco use at age of 11, this duration dependence becomes age dependence. u_j denotes unobserved heterogeneity in the starting rates of tobacco use for females and males and controls for differences in unobserved susceptibility of individuals to tobacco use. Duration (age) dependence is specified in a fully flexible way by means of a step function $\lambda_j^s(t) = \exp(\Sigma_k \lambda_{jk}^s I_k(t))$, where k (= 1,..,11) is a subscript for age categories starting from age 12 and $I_k(t)$ are time-varying dummy variables that are one in subsequent categories, 10 of which are for individual ages or age intervals (age 12, ..,18, 19-20,21-23,24-27) and the last interval is for ages above 27 years. Because we estimate a constant term in the analysis, we normalize $\lambda_{j,1}^s = 0$.

The conditional density function of the completed durations until the first use of tobacco can be written as

$$f_f^s(t_j \mid x_j, u_j) = \theta_j^s(t \mid x_j, u_j) \exp(-\int_0^{t_j} \theta_j^s(s \mid x_j, u_j) ds) \tag{2}$$

In order to take account of unobserved component we integrate out the unobserved heterogeneity such that density function for the duration of time until tobacco uptake t conditional on x becomes

$$f_j^s(t_j \mid x_j) = \int_u f_j^s(t \mid x_j, u_j) dG(u_j) \tag{3}$$

where $G(u_j)$ is assumed to be a discrete mixing distribution with 2 points of support u_{j1} and u_{j2}. This reflects the presence of two types of individuals in the hazard rate for tobacco uptake. The associated probabilities are denoted as follows: $\Pr(u_j = u_{j1}) = p_j$ and $\Pr(u_j = u_{j2}) = 1 - p_j$ with $0 \leq p_j \leq 1$, where p_j is modeled using a logit specification, $p_j = \frac{\exp(\alpha_j)}{1+\exp(\alpha_j)}$. Individuals who do not start using tobacco until the time of the survey are considered as right censored. Inflow nature of the data guarantees that there are no left censored individuals.

Quit rates are also modeled using mixed proportional hazard specification. The quit rate of tobacco use at time τ (τ = time elapsed from the first use of tobacco) for females ($j = f$) and males ($f = m$) conditional on observed characteristics z and unobserved characteristics v is defined as

$$\theta_j^q(\tau \mid z_j, I_p^q(\tau), I_p^s(t), v) = \lambda_j^q(\tau) \exp(z_j' \gamma_j + \phi_j I_p^s(t) + \delta_j I_p^q(\tau) + v_j) \tag{4}$$

where q refers to quit rate. $I_p^q(\tau)$ is a time varying indicator variable, $I(\tau > \tau_p)$ where τ_p is the first duration in which the partner quits smoking, which takes a value of 1 after the specific duration in which the partner quits smoking; 0 otherwise.[3] Therefore δ_j is the parameter of interest of our study and it captures the effect of an individual's quit behavior on the quit behavior of the partner, i.e. it represents the spousal peer effect in quitting behavior. $I_p^s(t)$ is a time varying indicator variable which takes a value of 1 if the partner starts smoking. Representation of these two effects is given in Figure 4. $\lambda_j^q(\tau)$ represents the duration dependence which is similar to age dependence in the starting rates. This duration dependence is modeled as

$$\lambda_j^q(\tau) = \exp(\Sigma_m \lambda_{jm}^q I_m(t)) \tag{5}$$

where m (= 1,..,M) is a subscript for duration of use intervals and $I_m(t)$ are time-varying dummy variables that are one in subsequent intervals which are not age intervals any more but year intervals after the first use of tobacco. Individuals who are still using tobacco are right censored in their quitting. Since the quit analysis is performed only on those who start using tobacco, there are no left censored individuals. As in the analysis of the uptake of tobacco, we assume that there are 2 unobserved heterogeneity groups where the probabilities are assumed to follow a logistic distribution.

In order to take account for possible correlation between unobserved components of starting and quit rates of each partner, we specify a joint density function of the durations of non use and durations of use conditional on z and x as

$$f_j^{sq}(t_j, \tau_j \mid I_p^q(\tau), I_p^s(t), x_j, z_j) = \int_{v_j} \int_{u_j} f_j^s(t_j \mid x_j, u_j) f_j^q(\tau_j \mid z_j, I_p^q(\tau), I_p^s(t), v_j) dG_j(u_j, v_j) \tag{6}$$

where $G_j(u_j, v_j)$ is assumed to be a discrete mixing distribution with 3 points of support (u_{1j}, v_{1j}), (u_{1j}, v_{2j}), (u_{2j}); where $v_{2j} = u_{2j} = -\infty$ in order to allow for the possibility that zero starting rates and zero quit rates exist. This specification of the distribution of unobserved component assumes that there are three types of individuals regarding starting and quit smoking. The first group consists of those with a positive starting and positive quit rate. The second group consists of individuals with a positive starting rate but a zero quit rate.

[3] If two partners quit in the same year, we assume that $\tau_p = 0$. In a sensitivity analysis we allow for a mutual influence if quitting occurs in the same year.

The third group has a zero starting rate, therefore the quit rate does not exist at all.

4.2 Tobacco use dynamics when controlling for endogeneity

Separate estimates of tobacco use dynamics for females and males only capture spousal peer effects if there is no correlation in smoking behavior through unobserved characteristics, i.e. one partner's decision to quit smoking is orthogonal to the decision of the other partner. This is unlikely to be the case due to for example assortative matching underlying partnership formation or common external shocks in the household. To account for this an instrumental variable strategy might be followed. However, instrumental variables for spousal smoking decisions are hard to find. Workplace smoking bans could be used as an instrumental variable if one of the partners is affected by these bans while the other partner is not. However, the use of workplace smoking bans requires information that is unavailable to us and as discussed in section 2 the only study that follows this approach (Cutler and Glaeser (2010)) is not without problems. Using pregnancies as instrumental variables for the quitting behavior of females in a model describing quitting behavior of males is not without problems either since pregnancy may also have a direct effect on the quitting behavior of males.[4]

As an alternative, to control for correlated behavior in the decision to quit smoking, we perform a joint maximum likelihood estimation of partners' starting and quit behavior using mixed proportional hazard specifications in which we allow for spousal correlations in unobserved heterogeneity. Peer effect models on smoking are always about whether or not an individual smokes as a consequence of peer behavior. We study spousal peer effects in quitting-to-smoke behavior which has not been studied very often. Whereas peer effect are usually studied as a static phenomenon we study a dynamic process; i.e. we do not study whether or not an individual smokes but whether an individual quits smoking, i.e. makes a transition from being a smoker to being a non-smoker. When analyzing spousal peer effects of quitting to smoke behavior no instrumental variables can be used as there will be no variables that affect the decision of one partner without having a direct effect of the decision of the other partner. Therefore we rely on functional form assumptions – the mixed proportional

[4] Using linear probability models, we found that a pregnancy in the first three, five or ten years of marriage does not have a significant effect on the probability for females to quit smoking in the first five or ten years. Therefore, pregnancies cannot be use as instruments.

hazard specification of the smoking dynamics using the "timing of events" approach (Abbring and van den Berg (2003)).[5] Identification of peer effects does not rely on a conditional independence assumption and it does not rely on exclusion restrictions. Rather, identification comes from the timing of events, in this case the order in which quitting-to-smoke occurs. If there are sufficient situations in which the quitting-to-smoke of males precedes the quitting-to-smoke of females and vice versa, the causal peer effects can be established. Abbring and van den Berg (2003) focus their discussion on the identification of treatment effects in bivariate duration models to the causal effect of one event on another event. Abbring and Heckman (2007) provide an identification proof of the symmetric case in which two events may causally affect each-other. They refer to the work by Freund (1961) who discusses a bivariate exponential model in the context of physical situations such as engine failures in two-engine planes. A key identifying assumption is no-anticipation. According to Abbring and Heckman (2007) the no-anticipation assumption ensures that the system has a unique solution by imposing a recursive structure on the underlying processes. Abbring and van den Berg (2003) note that the no-anticipation assumption does not exclude that forward-looking individuals take possible future events into account.[6] It does not invalidate our analysis if one partner knows that the other partner is interested in quitting in the future because that other partner is of the high-quitting type. The no-anticipation assumption implies that one partner does not know exactly when in the future the other partner will quit.

We specify the following joint density function of the durations of use and non use for females and males conditional on z and x

$$f_{fm}^{sq}(t_f, \tau_f, t_m, \tau_m, \mid x_f, z_f, x_m, z_m) = \int_{v_f} \int_{u_f} \int_{v_m} \int_{u_m} f_m^s(t_m \mid x_m, u_m)$$

$$f_m^q(\tau_m \mid z_m, I_p^q(\tau), I_p^s(t), v_m) f_f^s(t_f \mid x_f, u_f) f_f^q(\tau_f \mid z_f, I_p^q(\tau), I_p^s(t), v_f) dG(u_f, v_f; u_m, v_m) \quad (7)$$

where $G(u_f, v_f; u_m, v_m)$ is the a mixing distribution with nine points of support.[7] This is akin

[5]See for an example of a study on peer effects in the context of a duration model Drepper and Effraimidis (2015).

[6]Abbring and van den Berg (2003) is about the effect of benefit sanctions on the exit rate from unemployment. Unemployed may have an idea about the likelihood that they will be confronted with a benefit sanction in the future. However, as long as they do not know in advance when that benefit sanction will actually be imposed the no-anticipation assumption is not violated.

[7]The distribution of these points of supports is given in Appendix 1.

to allowing the possibility that the three points of support in the starting-quit estimation of males and the three points of support in the starting-quit estimation of females match up in all possible ways. These combinations enable us to have a very detailed and interpretable distribution of unobserved heterogeneity which prevail in starting and quit rates of tobacco use.[8] By modeling the correlation of unobserved characteristics of smoking dynamics we take assortative matching into account. There is positive assortative matching if there is positive correlation between partners in terms of smoking starting rates and smoking quit rates. A spousal peer effect is related to a time-varying change in the behavior of the partner. If one partner quits smoking then this might have an effect on the decision to quit smoking of the other partner. If we do not account for potential assortative matching between partners the estimated effect would represent a combination of correlated unobserved heterogeneity and a peer effect. By allowing for correlation of unobserved characteristics across partnered individuals we take potential assortative matching into account and we measure the causal peer effect using a timing of events approach.

5 Parameter Estimates

5.1 Baseline Estimates

The parameter estimates of mixed proportional hazard models on starting rates and quit rates of tobacco use for both females and males are given in Table 4. Panel (a) of the first column presents the results for quit rates of males in couples for the restricted model where partner's quit behavior is assumed to be exogenous.[9] The parameter estimate of *Partner quits* is positive and significant indicating that those whose partner quits become more likely to quit. This is because a positive estimate indicates an increase in the hazard rate; exit rates from the spell where the spell is years passed after the first use of tobacco until the year in which quit happens.

[8]It should also be noted that if an individual has a positive starting rate of smoking this does not necessarily imply that this individual will always start smoking. The same holds for individuals who have a positive quit rate but may never quit smoking. See Abbring (2002) for a discussion of stayers versus defecting movers.

[9]The model is restricted in the sense that correlation between unobserved components of females and males is assumed to be absent.

Not many of the observed characteristics have a significant effect on the quit rates. The same holds for "shocks" to family life. Pregnancy for example has a significant effect of the quit rates of females (at the 10% level) but not on the quit rates of males.[10] Furthermore, significant estimate for the mass point parameter indicates that there is unobserved heterogeneity in the quit rates of males. Panel b of the first column presents the results for starting rates of tobacco use. The probability parameters (α_1,α_2) indicate that 40% of males has a positive starting rate and a positive quit rate, i.e. they will start using tobacco but will quit at some point. 39% of males has a positive starting rate and a zero quit rate. Finally 21% of males has a zero starting rate of tobacco use, i.e. they will never use tobacco.

Panel (a) of the second column presents the results for quit rates of females in couples for the restricted model. The parameter estimate of *Partner quits* is also found to be positive and significant suggesting that females whose partners quit, quit smoking earlier than females whose partners do not quit. Similar to males, we find significant estimates for the mass point parameters indicating that there is indeed unobserved heterogeneity in the quit rates of females. Panel (b) presents the results for starting rates of tobacco use. In this case, the probability parameters (α_1,α_2) indicate that 29% of females has a positive starting rate and a positive quit rate, i.e. they will start using tobacco but will quit at some point. Furthermore, 33% of females has a positive starting rate and a zero quit rate. Finally, 38% of females has a zero starting rate of tobacco use.

Columns 3 and 4 of Table 4 present the results of mixed proportional hazard models where endogeneity of the partner's quit behavior is taken into account by allowing for correlation between partner's unobserved heterogeneity affecting starting and quit rates of tobacco use. In both columns, parameter estimate of partner's quit behavior is found to be positive but insignificant. Comparing the results in the first two columns with the ones in columns 3 and 4 shows that parameter estimates decrease substantially. The point estimates change from about +0.7 to about -0.1. It is not just the magnitude becomes small and insignificant, it is also the case that the sign flips. This is because a large part of the effect found in the restricted models is due to correlation in unobserved heterogeneity.

A likelihood ratio test comparing the likelihood obtained in joint estimation of restricted

[10] Clark and Etilé (2006) also find a pregnancy effect on women's smoking (at a 10% significance level) but not on men's smoking.

models and the likelihood of the unrestricted model shows that the correlation between unobserved heterogeneity is highly significant.[11] We consider this to be evidence of assortative matching in terms of smoking dynamics. Since we could not identify the parameter α_2, the distribution of unobserved heterogeneity has 8 points of support. The corresponding probabilities are given in Table 5. These probabilities indicate that almost half of the couples consists of partners who are the same types in terms of unobserved heterogeneity affecting the starting rates and quit rates of tobacco use. Furthermore they suggest that it is more likely to find couples in which the male is a smoker but not the female than couples in which only the female is a smoker. Clearly, there is positive but imperfect correlation between the unobserved characteristics of two partners in terms of their smoking behavior.

One of the interesting results in Table 4 is that the parameter estimate of "both smokers" variable is negative and statistically significant. Since the quit rates analysis is performed only on those who start smoking, this variable actually captures the smoking behavior of the partner. The negative parameter estimate indicates that males whose partner starts smoking become less likely to quit smoking, compared to those whose partner is a non-smoker. The same holds for females. Furthermore, the results of the joint model show that this is not due to the correlated unobserved factors. Apparently, those with smoking partners are less likely to quit. A possible explanation is that smoking together is an extra utility source for both-smoker couples. Thus, quitting has a higher marginal cost (Canta and Dubois (2015)). Another reason could be that the cost of smoking is higher when the spouse does not smoke. This can happen if non-smoker spouse, for example, imposes direct or indirect restrictions on the smoker spouse.

5.2 Robustness Checks

In order to investigate the extent of our baseline findings we perform several sensitivity analysis. Table 6 presents the relevant parts of these estimations.

Panel (a) shows the parameter estimates if we impose perfect correlation in unobserved heterogeneity of males and females. This is equivalent to assuming that there are only three points of support in the joint distribution of unobserved heterogeneity. Clearly, the

[11] The LR test statistic is 127.0; the critical value for 4 degree of freedom at a 1% significance level is 13.2.

difference in parameter estimates between the case of perfect correlation (3 points) and fully flexible specification (8 points) are very small. Apparently, the estimated peer effects are not sensitive to the exact specification of the joint distribution of unobserved heterogeneity.[12]

Panel (b) presents the parameter estimate of our variable of interest obtained in a joint estimation of mixed proportional hazard models by taking account of partners who quit in the same year. So far, in the estimations we assume that there is no partner effect if both partners quit in the same year. In order to see the real effects of possible bargaining in the household we need to allow for such effects. The results in panel (b) show that bargaining also does not matter for partners, i.e. quit behavior of neither males nor females is significantly and causally affected by the partner.

Panel (c) restricts the partner effect to couples who get together before quit behavior takes place. Even though there are only a few observations where quitting occurs before partnership is formed, we present these estimates to check the robustness of our baseline results. The no-partner-effect result remains. Panel (d) reports the results of mixed proportional hazard models of couples if we restrict the quit analysis to those who quit at least 2 years before the survey time. We perform this analysis because of possible cases where partners' quit decisions might be temporary. Someone who reports that using tobacco last year for the last time might use it again after the survey year. However our baseline results do not change after restricting the quit analysis to those who quit at least 2 years before the survey time. Panel (e) shows that baseline results do not change if we control for years in which observations appear in the data.

It is also possible that the effect of quit behavior of one partner might prevail only shortly after quitting happens or change its magnitude over time, i.e. the effect might disappear in the course of time. In order to investigate this possibility we introduce a form of duration dependence in the effect of quit behavior of partners. We do so by allowing our parameter of interest, δ_j, to change its value from δ_j to $\delta_j + \delta_{1j}$ at 5 and 10 years after the partner quits. In other words $\delta_j = \delta_j + \delta_{1,\kappa j} I(\tau > \tau_p + \kappa)$ where κ= 5 or 10. Panels (f) and (g) present the result of these estimations, indicating that no causal effect result remains after controlling for possible changes in the partner effect.

[12] We also estimated our model with a joint distribution of unobserved heterogeneity with 4, 5, 6 and 7 points of support finding very similar parameter estimates for the spousal peer effects.

Finally, panel (h) shows parameter estimates if we restricted the analysis to couples of which both partner smoke or have ever been smoking. In terms of smoking dynamics this implies that we select on the basis of an outcome (smoking) which creates a selective sample. As shown, even though our sample size decreases considerably if we focus on two-smoker couples, our parameter estimates of the spousal peer effects are very much the same.

Although not reported in the paper, we also controlled for the effects of tobacco prices, several smoking bans over time and calendar years in order to fully model possible joint shocks to partners' smoking behavior. Our baseline results remain the same. All in all, the results of various sensitivity checks show that the no-spousal-peer-effect result on the quitting to smoke behavior is very robust.

6 Conclusions

If two partnered individuals both smoke, the decision of one of them to quit smoking may lead the other to quit smoking as well. Such spousal peer effects can exist for several reasons. First, one partner can try to convince the other to quit through bargaining. Second, one partner can learn from the smoking experience of the other. Third, there can be other forms of spill over effects between partners. However, an observed association between the smoking and quitting behaviors of partners does not necessarily mean that this is due to any of these mechanisms. Individuals form partnerships through an assortative matching process. Therefore, they have correlated characteristics. Their preferences and attitudes, including smoking behavior are likely to be similar. This means an observed association between the smoking behaviors of two partners can be due to unobserved factors rather than bargaining, learning or spill-over effects, and can reflect only a correlation rather than a causal peer effect.

Spousal peer effects on quit-smoking behavior are interesting from a policy point of view because if they exists anti-smoking policies get 'two for the price of one'. Through peer effects the quitting of one partner works as a social multiplier for the anti-smoking policies. Therefore, it is important to distinguish the causal spousal peer effect from the correlation in spousal behavior due to assortative matching.

We use a unique quasi-longitudinal data set from the Netherlands that provides information for smokers about their age of onset of smoking and for ex-smokers the year in which they quit smoking. This allows us to model smoking dynamics i.e. the rate by which individuals start smoking and for smokers the rate by which they quit smoking. In our modeling we use Mixed Proportional Hazard specifications which allow us to study how transitions in smoker status are affected by duration and by observed and unobserved individual characteristics. For two smoking partners, we study how the quitting behavior of one partner affect the quit rate of the other partner. First, we estimate smoking dynamics for both partners separately assuming that a quit decision of one partner is exogenous to the quit decision of the other partner. If we do this, we find that the quit decision of one partner has a positive effect on the quit rate of the other partner. Then, to account for assortative matching of the partners, we allow unobserved heterogeneity to be correlated between partners. If we do this, the cross-partner effect of the quit decision disappears, i.e. there is no causal spousal peer effect in the decision to quit smoking. We find that similarities in smoking behavior of partners are due to assortative matching in the partnership formation and common household shocks. The behavior of two partners is correlated and there may be cross-partner effects in behavior but this does not concern the decision to quit smoking. Apparently, love conquers a lot and perhaps all except for nicotine addiction.

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Appendix 1: Details on the mixing distribution

The mixing distribution $G(u_f, v_f; u_m, v_m)$ is specified as follows:

$$
\begin{aligned}
&P(u_f = u_{f1}, v_f = v_{f1}; u_m = u_{m1}, v_m = v_{m1}) = p_1 \\
&P(u_f = u_{f1}, v_f = v_{f2}; u_m = u_{m1}, v_m = v_{m1}) = p_2 \\
&P(u_f = u_{f2}; u_m = u_{m1}, v_m = v_{m1}) = p_3 \\
&P(u_f = u_{f1}, v_f = v_{f1}; u_m = u_{m1}, v_m = v_{m2}) = p_4 \\
&P(u_f = u_{f1}, v_f = v_{f2}; u_m = u_{m1}, v_m = v_{m2}) = p_5 \\
&P(u_f = u_{f2}; u_m = u_{m2}) = p_6 \\
&P(u_f = u_{f1}, v_f = v_{f1}; u_m = u_{m2}) = p_7 \\
&P(u_f = u_{f1}, v_f = v_{f2}; u_m = u_{m2}) = p_8 \\
&P(u_f = u_{f2}; u_m = u_{m2}) = p_9
\end{aligned}
$$

where $v_{2f} = u_{2f} = v_{2m} = u_{2m} = -\infty$ in order to allow for the existence of zero starting rates and zero quit rates. The probabilities associated with these 9 support points are assumed to follow logistic distribution, $p_i = \frac{exp(\alpha_i)}{\sum_{i=1}^{9} exp(\alpha_i)}$, where α_9 is normalized to 0. Apparently, there are 9 groups of people who are systematically different from others due to some unobserved factors. Following the order of the probabilities given above; the first group of people consists of couples where both female and male have a positive starting rate and a positive quit rate. The second group consists of couples where female has a positive starting rate, zero quit rate and male has positive starting and quit rates. The third group consists of couples in which female has a zero starting rate, henceforth no quit rate and male as a positive starting and quit rate, and so on. The last group consists of couples where both female and male have a zero starting rate of tobacco use.

Appendix 2: Details on data

The CentERdata DNB Household Survey is an internet based panel survey which was initially launched in 1993. The panel is a representative sample of the Dutch-speaking population in the Netherlands. Participants in this panel were provided with access to internet if they did not have it themselves. The questionnaires of the surveys were completed once a week without the intervention of an interviewer. The specific questions which enabled us to perform our estimations are asked in 2001, 2003, 2005 and 2007 to some 2,000 households participating in the CentER-panel. The surveys with the smoking questions used in our study were filled by a sub-sample of the CentER-panel. Furthermore in our study we use information of individuals who live with a partner in the same household.

The data collected in 2001 is taken as a base data set. Missing observations in this data set are replaced with information in later data, if available. There are a few individuals who appear in later data but not in 2001 data. Furthermore there are observations with conflicting reporting of the first age of smoking and the last age of smoking. For example an individual reported age of 14 as the first age of using tobacco in 2003 and age of 15 in 2005.

For such observations, we consider the first report since we think that memory would be more fresh for the first reporting. The baseline results do not change when we also control for the years in which observations appear. Furthermore baseline results remain the same if we consider the minimum reported age or the maximum reported age as the age of first use of tobacco use for observations with conflicting information in different years. The reason is that the average difference between such conflicting starting or quit age reports is less than 1.2 years. When plotting cumulative starting rates of smoking or cumulative quit rates of smoking there is hardly any difference between rates based on minimum reported ages and maximum reported age. Measurement error of starting age or quit ages do not seem to be important.

Appendix 3: Description of variables

- Ever smoke: Dummy variable if individual reports ever smoking.
- Both smoke: Dummy variable if both partners were ever smoking.
- Quit: Dummy variable if individual reports having quit smoking.
- Age: Age of individual at the time of survey (2007).
- Cohort dummy variables (reference: born before 1945):
  - Cohort55: Born between 1945 and 1954.
  - Cohort65: Born between 1955 and 1964.
  - Cohort75: Born between 1965 and 1974.
  - Cohort75+: Born after 1974.
- Education dummy variables (reference: basic and primary education):
  - Vocational: Secondary general or vocational education.
  - Higher: Academic or vocational high education.
  - Other: Special education.
- Degree of urbanization dummy variables based on population density per km^2 (reference group: Very urban: more than 2500)
  - Urban: 1500-2500
  - Moderately urban: 1000-1500
  - Rural: 500-1000
  - Very rural: below 500
- Social status dummy variables (reference: very high):
  - High: High social class

- Moderate: Moderate social class
- Low: Low social class
- Very low: Very low social class

- Religion dummy variables (reference: no religion):
  - Catholic: Catholic.
  - Protestant: Protestant.
  - Others: Other religion.

Table 7 provides the summary statistics of the variables.

Table 1: Percentage of females and males in couples who ever smoked cigarettes (on the left) and who quit smoking conditional on ever use (on the right), in %.

		Males					
		Starting			Quitting		
		Yes	No	Total	Yes	No	Total
Female	Yes	50	11	61	29	17	46
	No	25	14	39	16	38	54
Total		75	25	100	35	65	100

Table 2: Distribution of females and males in couples based on starting and quitting smoking, in %.

		Male			
		Starting and Quitting	Starting but no Quitting	No starting	Total
Female	Starting and Quitting	15[a]	8[b]	5[c]	27
	Starting but no Quitting	8[d]	19[e]	6[f]	34
	No starting	14[g]	11[h]	14[i]	39
	Total	37	38	25	100

Table 3: Distribution of females and males in couples based on the timing of quitting smoking; conditional on starting smoking, in %.

	Quit in the same year	Male quits first	Female quits first	Total
Only one quits	0	32	68	100
Both Quit	11	44	45	100

Percentage of the individuals among ever smokers who fall into the groups given in the table above are:
At least one quits: 62% (a+b+d/a+b+d+e); Both quit: 30% (a/a+b+d+e); No one quits: 38% (e/a+b+d+e).

Table 4: Parameter estimates of starting rates and quit rates of tobacco use for males and females in couples.

	Independent				Correlated			
	Males (1)		Females (2)		Males (3)		Females (4)	
a. Quit rates:								
Time-varying								
Partner quits	0.76	(2.7)**	0.62	(2.3)**	-0.14	(0.6)	-0.14	(0.6)
Having a child	0.48	(1.2)	0.49	(1.6)*	0.45	(1.7)*	0.04	(0.1)
Pregnancy	0.69	(0.9)	1.23	(1.6)*	0.53	(0.7)	1.25	(1.6)*
Time-invariant								
Both smoke	-0.58	(3.0)**	-0.35	(1.2)	-0.85	(4.8)**	-0.71	(2.3)**
Starting age	0.93	(3.3)**	0.50	(1.5)	0.82	(3.1)**	0.27	(0.8)
Vocational	-0.03	(0.1)	0.11	(0.4)	-0.09	(0.4)	0.28	(1.2)
Higher	0.11	(0.3)	0.00	(0.0)	0.11	(0.4)	0.16	(0.7)
Other	0.28	(0.1)	-0.12	(0.1)	-0.12	(0.1)	0.00	(0.0)
Urban	0.14	(0.4)	0.23	(0.6)	0.10	(0.4)	0.17	(0.5)
Moderately urban	0.21	(0.7)	0.20	(0.6)	0.23	(1.0)	0.22	(0.7)
Rural	0.10	(0.3)	0.39	(1.0)	0.00	(0.0)	0.30	(1.0)
Very rural	0.24	(0.9)	0.45	(1.2)	0.19	(0.8)	0.39	(1.2)
Cohort55	0.54	(2.2)**	0.67	(1.9)**	0.45	(2.2)**	0.60	(2.1)**
Cohort65	0.88	(3.3)**	1.07	(2.9)**	0.63	(2.9)**	1.01	(3.2)**
Cohort75	1.38	(4.7)**	1.49	(3.3)**	1.19	(4.9)**	1.32	(3.6)**
Cohort75+	1.92	(3.5)**	2.21	(3.6)**	1.68	(4.0)**	1.85	(3.9)**
High social class	-0.02	(0.1)	-0.02	(0.1)	-0.06	(0.3)	-0.03	(0.1)
Moderate sc.	0.10	(0.3)	0.33	(1.0)	0.08	(0.3)	0.17	(0.6)
Low sc.	-0.04	(0.1)	0.11	(0.3)	-0.24	(0.8)	0.24	(0.7)
Very low sc.	-0.52	(0.3)	1.37	(1.5)	-0.09	(0.1)	1.79	(2.2)**
Catholic	-0.06	(0.3)	-0.01	(0.0)	-0.05	(0.3)	-0.09	(0.4)
Protestant	0.02	(0.1)	0.15	(0.5)	0.01	(0.0)	0.21	(0.9)
Others	0.13	(0.2)	0.27	(0.4)	0.05	(0.1)	0.51	(0.7)
v_1	-5.61	(6.7)**	-5.38	(5.3)**	-5.16	(7.1)**	-4.82	(5.3)**
v_2	$-\infty$		$-\infty$		$-\infty$		$-\infty$	

Table 4 Continued

	Independent				Correlated			
	Males (1)		Females (2)		Males (3)		Females (4)	
b.Starting rates:								
Vocational	-0.19	(1.4)	-0.15	(1.1)	-0.24	(1.8)*	-0.15	(1.1)
Higher	-0.39	(2.4)**	-0.33	(2.3)**	-0.35	(2.2)**	-0.33	(2.3)**
Other	-0.12	(0.5)	-0.61	(0.6)	-0.12	(0.1)	-0.61	(0.5)
Urban	-0.09	(0.3)	-0.31	(1.6)*	-0.07	(0.4)	-0.31	(1.6)*
Moderately urban	-0.13	(0.6)	-0.10	(0.5)	-0.10	(0.6)	-0.10	(0.5)
Rural	0.07	(0.6)	-0.18	(1.0)	0.07	(0.4)	-0.18	(1.0)
Very rural	0.08	(0.4)	-0.15	(0.8)	0.20	(1.1)	-0.15	(0.8)
Cohort55	0.02	(0.6)	0.58	(2.9)**	0.05	(0.6)	0.58	(2.8)**
Cohort65	0.10	(1.2)	1.13	(6.0)**	0.15	(1.2)	1.13	(5.8)**
Cohort75	-0.62	(4.1)**	0.75	(3.7)**	-0.34	(1.9)**	0.76	(3.7)**
Cohort75+	-0.28	(1.3)	1.50	(6.5)**	0.07	(1.0)	1.50	(6.4)**
High social class	0.15	(1.0)	-0.08	(0.4)	0.18	(1.2)	-0.08	(0.4)
Moderate sc.	0.14	(1.5)	-0.22	(1.1)	0.20	(1.2)	-0.22	(1.1)
Low sc.	0.26	(0.9)	-0.27	(1.4)	0.17	(0.9)	-0.27	(1.4)
Very low sc.	0.35	(0.9)	-0.46	(0.9)	0.24	(0.6)	-0.46	(0.9)
Catholic	-0.04	(0.1)	-0.08	(0.6)	-0.01	(0.1)	-0.08	(0.6)
Protestant	-0.14	(1.0)	-0.16	(1.1)	-0.09	(0.7)	-0.15	(1.1)
Others	0.09	(0.4)	0.06	(0.3)	0.16	(0.6)	0.06	(0.2)
u_1	-3.45	(10.5)**	-4.98	(8.8)**	-3.55	(10.9)**	-4.98	(9.0)**
u_2	$-\infty$		$-\infty$		$-\infty$		$-\infty$	
α_1	0.76	(5.4)**	-0.26	(2.7)**	0.89	(6.6)**		
α_2	0.70	(4.8)**	-0.12	(1.3)	$-\infty$			
α_3					-1.17	(5.6)**		
α_4					-1.85	(2.2)**		
α_5					0.36	(2.4)**		
α_6					-0.72	(4.3)**		
α_7					0.06	(0.1)		
α_8					-0.17	(1.7)*		
-Loglikelihood	6445.9				6382.4			
Observations	812				812			

All estimates contain duration dependence parameters in the quit rates and age dependence parameters in the starting rates; absolute t-statistics in parentheses. * and ** are for statistical significance at 10% and 5%, respectively.

Table 5: Distribution of probabilities, in %.

		Males			
		[+] Starting [+] Quitting	[+] Starting [0] Quitting	[0] Starting	Total
	[+] Starting [+] Quitting	31	0	4	35
Females	[+] Starting [0] Quitting	2	19	6	27
	[0] Starting	14	11	13	38
	Total	47	30	23	100

The numbers above show the percentage of couples in each category of the unobserved heterogeneity groups. For example, 19% of the couples consist of females and males with a positive starting and positive quit rates.
[+] indicates a positive starting or quit rate. [0] indicates a zero starting or quit rate.

Table 6: Parameter estimates of various sensitivity checks

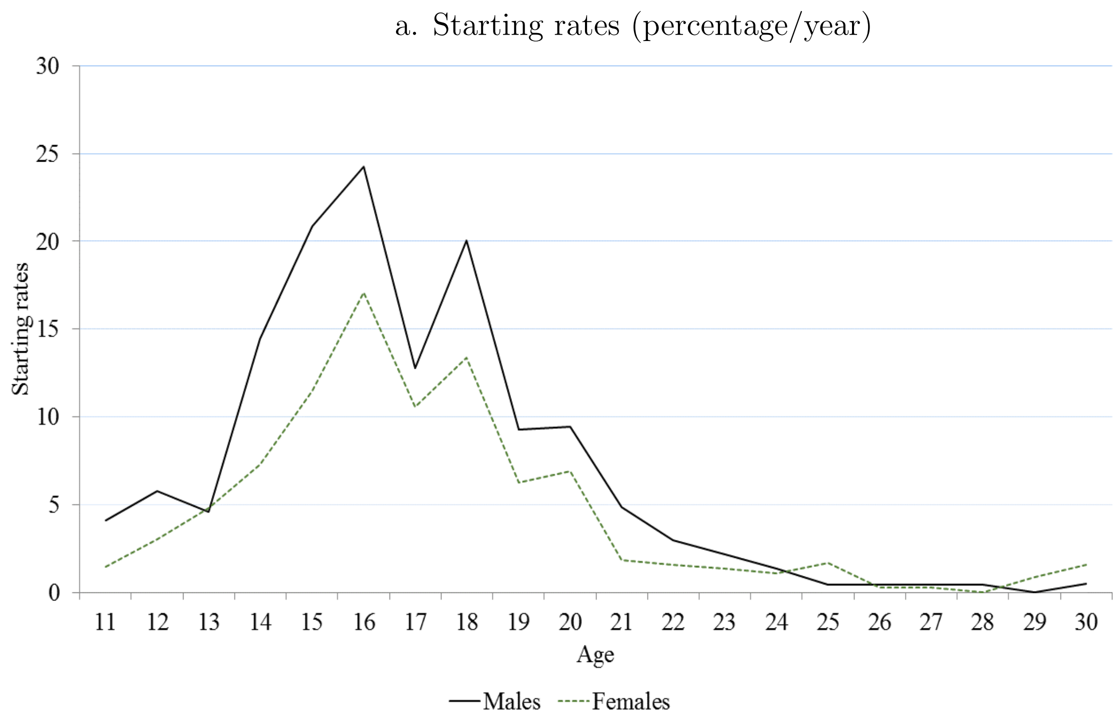
	Independent				Correlated			
	Males		Females		Males		Females	
	(1)		(2)		(3)		(4)	
a.Perfect correlation								
Partner quits (δ)					-0.22	(1.0)	-0.13	(0.6)
-Loglikelihood					6428.2			
b.Same year quits								
Partner quits (δ)	0.70	(2.7)**	0.62	(2.3)**	-0.22	(1.1)	-0.14	(0.6)
-Loglikelihood	6447.4				6381.8			
b.Timing of the partnership								
Partner quits (δ)	0.73	(2.9)**	0.95	(4.3)**	-0.12	(0.6)	0.01	(0.1)
-Loglikelihood	6438.4				6382.6			
b.Quit at least 2 years ago								
Partner quits (δ)	0.72	(2.9)**	0.64	(2.7)**	-0.18	(0.9)	-0.24	(1.2)
-Loglikelihood	6400.9				6363.1			
e.Controlling for survey years								
Partner quits (δ)	0.81	(2.8)**	0.64	(2.2)**	-0.11	(0.6)	-0.08	(0.3)
Year 2001	-0.06	(0.1)	0.24	(1.0)	-0.16	(0.1)	0.21	(1.5)
Year 2003	-0.20	(0.6)	0.12	(0.5)	-0.02	(0.6)	0.07	(0.5)
Year 2005	-0.25	(0.6)	-0.03	(0.1)	-0.12	(0.2)	0.01	(0.1)
Year 2007	-0.08	(0.7)	0.15	(0.3)	-0.10	(0.9)	0.29	(1.0)
-Loglikelihood	6442.7				6375.7			
f. κ=5								
Partner quits (δ)	0.66	(2.4)**	0.72	(2.7)**	0.04	(0.2)	0.12	(0.4)
Partner quits and 5 years (δ_1)	0.15	(0.5)	-0.11	(0.3)	-0.23	(0.7)	-0.57	(1.7)*
-Loglikelihood	6449.9				6385.4			
g. κ=10								
Partner quits (δ)	0.57	(2.4)**	0.66	(2.6)**	-0.12	(0.5)	-0.05	(0.2)
Partner quits and 10 years (δ_1)	0.38	(0.9)	0.27	(0.5)	0.06	(0.3)	-0.14	(0.5)
-Loglikelihood	6448.5				6387.1			
h. Smokers only								
Partner quits (δ)	0.76	(2.8)**	0.66	(2.3)**	-0.09	(0.4)	-0.12	(0.5)
-Loglikelihood	4078.6				4031.6			

Absolute t-statistics in parentheses. * and ** are for statistical significance at 10% and 5%, respectively.
Number of observations is 812 in panels a-h and 419 in panel h.

Table 7: Summary statistics of variables

		Females				Males			
		Mean	St.Dev.	Min	Max	Mean	St.Dev.	Min	Max
Prevalence	Ever smoker	0.61	0.49	0	1	0.75	0.43	0	1
	Quitting	0.46	0.45	0	1	0.45	0.48	0	1
Age	Age	49.47	14.13	23	90	51.92	14.45	21	87
	Cohort45	0.19	0.40	0	1	0.25	0.44	0	1
	Cohort55	0.21	0.41	0	1	0.22	0.41	0	1
	Cohort65	0.24	0.43	0	1	0.22	0.42	0	1
	Cohort75	0.24	0.42	0	1	0.23	0.42	0	1
	Cohort75+	0.12	0.33	0	1	0.08	0.27	0	1
Education	Lower	0.39	0.49	0	1	0.30	0.46	0	1
	Vocational	0.34	0.47	0	1	0.34	0.47	0	1
	Higher	0.27	0.44	0	1	0.35	0.48	0	1
	Other	0.01	0.09	0	1	0.01	0.11	0	1
Urbanization	Very urban	0.13	0.34	0	1	0.13	0.34	0	1
	Urban	0.24	0.43	0	1	0.24	0.43	0	1
	Moderately urban	0.23	0.42	0	1	0.23	0.42	0	1
	Rural	0.23	0.42	0	1	0.23	0.42	0	1
	Very rural	0.18	0.38	0	1	0.17	0.38	0	1
Social status	Very low social class	0.21	0.41	0	1	0.20	0.40	0	1
	High sc.	0.32	0.47	0	1	0.32	0.47	0	1
	Moderate sc.	0.25	0.43	0	1	0.25	0.43	0	1
	Low sc.	0.21	0.41	0	1	0.21	0.41	0	1
	Very low sc.	0.01	0.11	0	1	0.01	0.11	0	1
Religion	No Religion	0.32	0.47	0	1	0.35	0.48	0	1
	Catholic	0.29	0.45	0	1	0.26	0.44	0	1
	Protestant	0.24	0.43	0	1	0.23	0.42	0	1
	Others	0.15	0.36	0	1	0.15	0.36	0	1
Other	Child	0.54	0.50	0	1	0.54	0.50	0	1

Figure 1: Smoking dynamics: starting rates and cumulative starting probabilities of partnered individuals



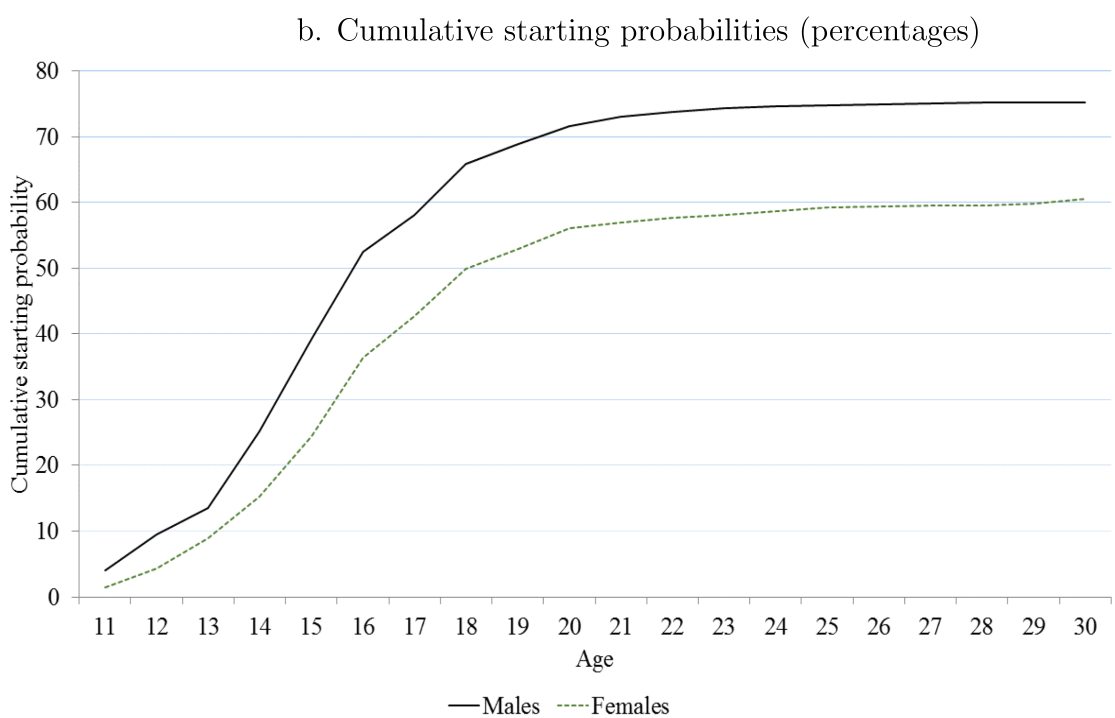
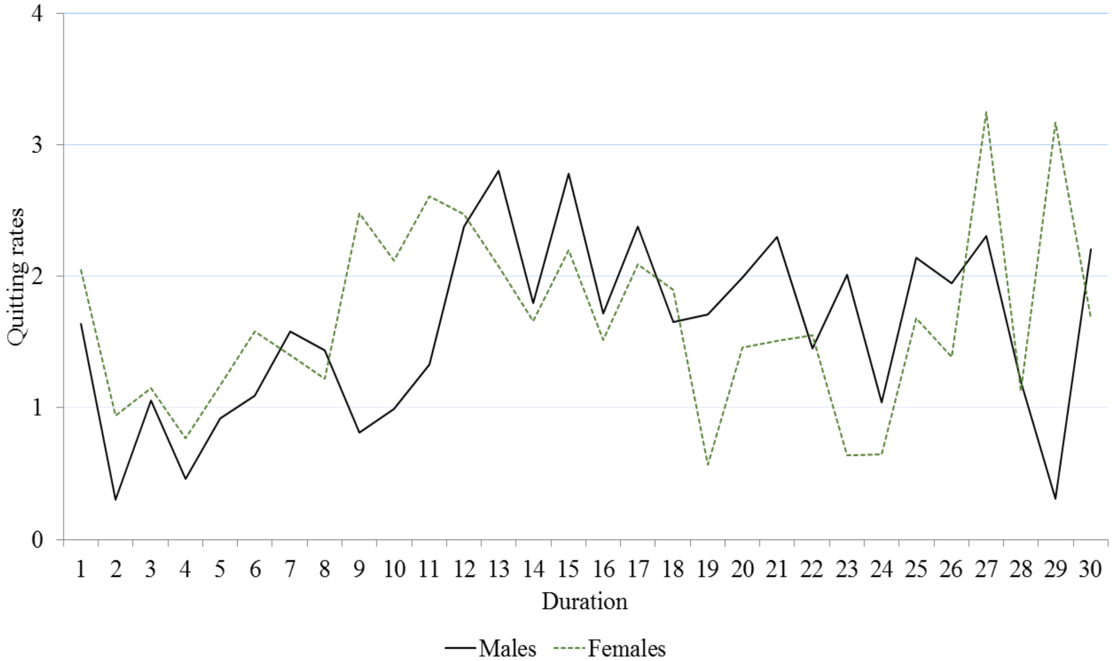


Figure 2: Smoking dynamics: quit rates and cumulative quit probabilities partnered individuals

a. Quit rates (percentage/year)



b. Cumulative quit probabilities (percentages)

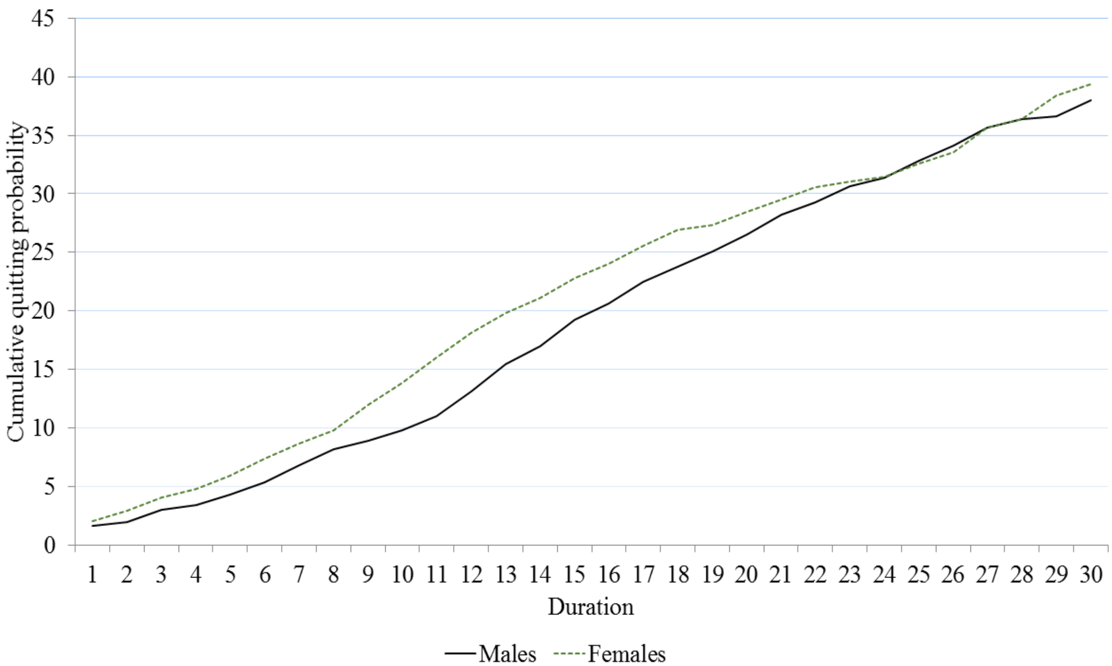
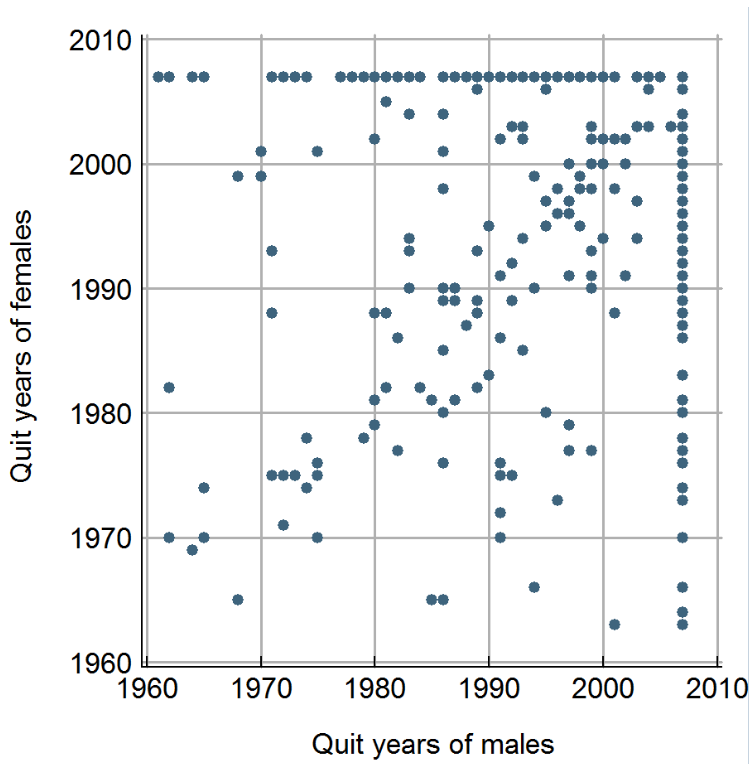
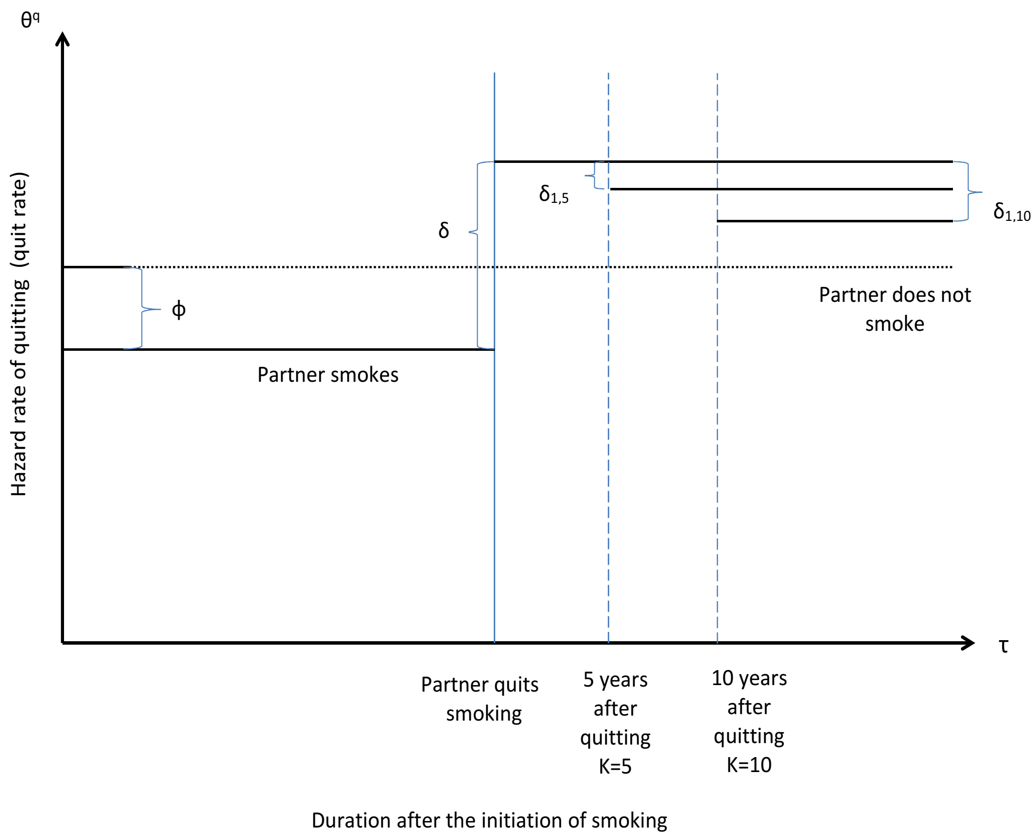


Figure 3: Scatter plot of years of quitting for females and males in couples, conditional on ever smoking.



Each dot represents a couple in the sample. There are several dots which are aligned on a vertical line or a horizontal line in year 2007. These are for couples in which only one spouse quits smoking. In other words, the dots aligned on the vertical line shows the quit years of females in couples in which male does not quit smoking. The horizontally lined dotes show the same figure for males whose partner does not quit smoking.

Figure 4: Representation of the partner effect



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