Love conquers all but nicotine; 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 through common 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. If so, there is a spousal peer effect on the decision to quit smoking. We use data containing retrospective information of Dutch partnered individuals about their age of onset of smoking and their age of quitting smoking. We estimate mixed proportional hazard models of starting rates and quit rates of smoking in which we allow unobserved heterogeneity to be correlated across partners. Using a timing of events approach we determine whether the quitting-to-smoke decision of one partner has a causal effect on the quitting-to-smoke decision of the other partner. We find no evidence of substantial spousal peer effects in the decision to quit smoking. 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. Targeted anti-smoking policies such as workplace smoking bans may affect smoking behavior of the workers involved. If spousal peer effects are important, focusing on the directly affected worker will underestimate the benefits of the intervention. Similarly the effectiveness of treatments to help addicted smokers quit smoking may be underestimated if spousal peer effects are ignored.

There are several ways in which 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 each-other. If there is such a partner-caused accumulation of information, then the decision of one partner to quit smoking might affect the decision of 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. Nevertheless, 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 on the one hand the subjects of a peer effects investigation and on the other hand the peers who potentially provide the mechanism for causal effects on these subjects. 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 on 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 model mixed proportional hazard models of starting rates and quit rates of smoking for both partners. This enables us to take account of observable as well as unobservable factors that might affect the dynamics in smoking. We allow unobservable determinants of smoking behavior to be correlated between partners. We assume that this correlation is due to assortative matching. Peer effects are established by investigating whether the quit decision of one of the partners increase the quit rate of the other partner. Using a timing of events approach we determine whether the quitting-to-smoke decision of one partner has a causal effect on the quitting-to-smoke decision of the other partner. As in other timing of events studies, identification of the peer effects come from the functional form assumption of the mixed proportional hazards and from the sequential nature of the quitting decisions. We discuss this in more detail in Section 4.

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

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

for males and females in couples. 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. After accounting for this, we find no evidence of substantial peer effects in the decision to quit smoking.

Our contribution to the existing literature on spousal peer effects in quitting-to-smoke 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 (Van Ours (2006)). 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 study transitions in 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 provide a natural way to study the determinants of the dynamics in tobacco use 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 age the respondents quit smoking. Therefore, we can identify quit behavior and prevent our results from being contaminated by failed or mis-specified quitting that might occur in panel data studies. 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 on the decision to quit smoking.

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 of the empirical method used in this study. In section 5 parameter estimates are presented. Section 6 concludes.

2 Previous studies on spousal peer effects in smoking

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. Previous studies have usually examined peer effects in smoking behavior either at the neighborhood, at the school level or at the level of colleges.² In the latter case random assignment of roommates is exploited to account for potential selectivity in the interaction between individuals. Usually in peer effect studies, random variation in peer groups is needed to distinguish correlation from causation. We study spousal peer effects in quitting smoking where it is clear that there is a non-random assignment to peers. In fact, it is the opposite. Partnership formation 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) use the presence of workplace smoking bans as an instrumental variable for smoking of the partner. 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 level of education. 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. However, the authors acknowledge that their results need to be evaluated with caution. In the instrumental variable estimates spousal peer effects double in magnitude compared to the OLS estimates.³

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. They 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

²Peer effects studies based on school, school-class or school-year find different results. Lundborg (2006), Gaviria and Raphael (2001), Kawaguchi (2004), Powell et al. (2005) and Fletcher (2010) find significant peer effects in smoking while Clark and Youenn (2007) finds small peer effects and Ali and Dwyer (2009) conclude that school-level peer effects are not long-lasting whereas the effect of close friends persists. Card and Giuliano (2013) using networks of friends finds no peer effects. Eisenberg et al. (2014) using college room mates find little evidence of smoking peer effects.

³This is contrary to the expectation related of positive assortative matching. As the authors indicate they are "somewhat skeptical about the fact that the estimated coefficient rises."

on this correlation, smoking behavior of partners is statistically independent.

Canta and Dubois (2015) model the smoking decision of spouses as a non-cooperative game by eliminating the possibility of bargaining. They use a two-wave panel data set to investigate the implications of their model on the spousal peer effects. They find strong spousal peer effects. 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.

McGeary (2015) uses a fixed effects model and data from the Health and Retirement Study (HRS) finding spousal peer effects on the decision to quit smoking. Khwaja et al. (2006) also uses HRS data and Arellano-Bond estimates to find that spousal peer effects exist.

Previous studies on the peer effects of smoking predominantly deal with peer effects during adolescence and without making a clear distinction between starting and quitting. 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 peer effects. Since the period of observation is generally not very long, two kinds of problems may occur. First, it is hard to identify quitting behavior. Most studies rely on the observation that a respondent report no smoking behavior in a single year to identify 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 spousal peer effects on the decision to quit smoking taking account of smoking dynamics i.e. separating starting and quitting.

3 Data and Stylized Facts

3.1 Data

CentERdata collects information about individuals in the Netherlands through an internet-based panel consisting of around 2000 households. 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, partly retrospective information about 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 do not 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.⁴

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 probability 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 25 shown in panel (a) indicates that those who did not start smoking at age

⁴Further information on the data set is given in web-Appendix 2. The complete set of variables which are used throughout this study, their descriptions and sample statistics are given in web-Appendix 3.

25 are very unlikely to do so later on in life. Apparently, individuals mature out of smoking initiation 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 never smoke. This is also clear from the slope of the cumulative starting probability, which becomes virtually zero after age 25. Figure 2 shows 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 to 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 1 presents the 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 (37% of the males and 28% of the females), those who start and do not quit using tobacco (38% of the males and 34% of the females) and those who do not start using tobacco (25% of the males and 38% of the females). In our sample, 62% of the females and 75% of the males ever smoked. The figures in Table 1 show that there is correlation between partners' smoking behavior. In almost 50 % of the couples both partners follow the same starting-quit behavior. We also see that the percentage of couples in which only the male has ever smoked is considerably higher ($13+11=24\%$) than the percentage of couples in which only the female ever smoked ($4+7=11\%$).

Figure 3 presents the scatter plot of the calendars years in which partnered smokers quit smoking. 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 the calendar time gap between the two quit decisions is small. In 44% of the couples in which both partners quit smoking the male quits first while in 45%

of these couples the female quits first, leaving 11% of the couples in which both partners quit in the same calendar year.

4 Empirical Model

4.1 Tobacco use dynamics ignoring assortative matching

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 smoking from age 11 onwards.

The starting rates 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

$$\theta_j^s(t | x_j, u_j) = \lambda_j^s(t) \exp(x_j' \beta_j + u_j) \quad (1)$$

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, duration dependence is equivalent to age dependence. Unobserved heterogeneity in the starting rates controls for differences in unobserved susceptibility of individuals to start smoking. Duration (age) dependence is specified in a fully flexible way by means of a step function $\lambda_j^s(t) = \exp(\sum_k \lambda_{jk}^s I_k(t))$, where k ($= 1, \dots, 11$) 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

$$f_f^s(t_j | x_j, u_j) = \theta_j^s(t | x_j, u_j) \exp\left(-\int_0^{t_j} \theta_j^s(s | x_j, u_j) ds\right) \quad (2)$$

Individuals who do not start using tobacco until the time of the survey are considered to have right-censored durations of non-use. The inflow nature of the data guarantees that there are no left censored individuals.

Quit rates are also modeled using a 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 ($j = m$) conditional on observed characteristics z and unobserved characteristics v is defined as

$$\theta_j^q(\tau | z_j, I_p^q(\tau), I_p^s(t), v) = \lambda_j^q(\tau) \exp(z_j' \gamma_j + \phi_j I_p^s(t) + \delta_j I_p^q(\tau) + v_j) \quad (3)$$

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.⁵ 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. A graphical illustration 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

$$\lambda_j^q(\tau) = \exp(\sum_m \lambda_{jm}^q I_m(t)) \quad (4)$$

where m ($= 1, \dots, M$) 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 since 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

⁵If 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.

using tobacco, there are no left censored individuals.

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

$$f_j^{sq}(t_j, \tau_j | I_p^q(\tau), I_p^s(t), x_j, z_j) = \int_{v_j} \int_{u_j} f_j^s(t_j | x_j, u_j) f_j^q(\tau_j | z_j, I_p^q(\tau), I_p^s(t), v_j) dG_j(u_j, v_j) \quad (5)$$

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. The associated probabilities denoted as $\Pr(u_{1j}, v_{1j}) = p_{1,j}$, $\Pr(u_{1j}, v_{2j}) = p_{2,j}$ and $\Pr(u_{2j}) = p_{3,j}$ are assumed to follow a logistic distribution, $p_{i,j} = \frac{\exp(\alpha_{i,j})}{\sum_{i=1}^3 \exp(\alpha_{i,j})}$, where the $\alpha_{3,j}$ are normalized to zero. 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. The third group has a zero starting rate, therefore the quit rate does not exist at all.

4.2 Tobacco use dynamics accounting for assortative matching

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.⁶

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 hazard specification of the smoking dynamics using the “timing of events” approach (Abbring and van den Berg (2003)).⁷ 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

⁶Using 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.

⁷See for an example of a study on peer effects in the context of a duration model Drepper and Effraimidis (2015).

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.⁸ 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

$$f_{fm}^{sq}(t_f, \tau_f, t_m, \tau_m, | x_f, z_f, x_m, z_m) = \int_{v_f} \int_{u_f} \int_{v_m} \int_{u_m} f_m^s(t_m | x_m, u_m) f_m^q(\tau_m | z_m, I_p^q(\tau), I_p^s(t), v_m) f_f^s(t_f | x_f, u_f) f_f^q(\tau_f | z_f, I_p^q(\tau), I_p^s(t), v_f) dG(u_f, v_f; u_m, v_m) \quad (6)$$

where $G(u_f, v_f; u_m, v_m)$ is the a mixing distribution with nine points of support.⁹ This is akin 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.¹⁰ 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

⁸Abbring 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.

⁹The distribution of these points of supports is given in web-Appendix 1.

¹⁰It 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.

and a peer effect. By allowing for correlation of unobserved characteristics across partnered individuals and using a timing of events approach, we take potential assortative matching into account.

5 Parameter Estimates

5.1 Baseline Estimates

The parameter estimates of the mixed proportional hazard models of starting rates and quit rates of tobacco use are given in Table 2. The first two columns present estimates of the independent MPH models (equation (5)). 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.¹¹ The parameter estimate of *Partner quits* is positive and significant indicating that males whose partner quits smoking are more likely to quit smoking themselves. Not many of the observed characteristics have a significant effect on the quit rates but it is clear that younger cohorts are more likely to quit than older cohorts. Also individuals who start smoking later on in life are more likely to quit. Furthermore, we find unobserved heterogeneity in the quit rates of males. Panel b of the first column presents the results for starting rates of tobacco use for males. Again, not many of the observable characteristics have a significant effect. However, it is clear that higher educated individuals are less likely to start smoking.¹² It is well-known that education has a negative effect on the prevalence of smoking. Our parameter estimates suggest that this is because higher educated individuals are less likely to start smoking. Once they do, they do not behave differently from less educated individuals. The probability parameters (α_1, α_2) indicate that 40% of males have 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 have a positive starting rate and a zero quit rate. Finally, 21% of males have a zero starting rate of tobacco use, i.e. they will never start smoking. Panel (a) of the second column presents the results for quit rates of females

¹¹The model is restricted in the sense that the unobserved components of smoking dynamics of females and males are assumed to be independent.

¹²As before, we note that educational attainment is an indicator of ability as many individuals will not have finished their education before they started smoking.

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 for females. In this case, the probability parameters (α_1, α_2) indicate that 29% of females have 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 have a positive starting rate and a zero quit rate. Finally, 38% of females have a zero starting rate of tobacco use.

Columns 3 and 4 of Table 2 present the results of the mixed proportional hazard models where assortative matching is taken into account by allowing for correlation between partner's unobserved heterogeneity affecting starting and quit rates of tobacco use (equation (6)). In both columns, the parameter estimates of partner's quit behavior are found to be negative but insignificantly different from zero. A comparison of 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 that the magnitude becomes small and insignificant, it is also the case that the sign flips. Apparently the partner effect found in the independent model is due to correlation in unobserved heterogeneity. Once this correlation is accounted for no spousal peer effect remains.

A likelihood ratio test shows that the correlation between unobserved heterogeneity is highly significant.¹³ 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 panel c of Table 2. 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 couples in which the male is a smoker but not the female are more likely 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.

¹³The LR test statistic is 130.2; the critical value for 4 degree of freedom at a 1% significance level is 13.2.

One of the interesting results in Table 2 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 smokes are less likely to quit smoking, compared to those whose partner is a non-smoker. The same holds for females. 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)). The fact that smokers are less likely to quit if their partner also smokes could be caused by a spousal peer effect in the sense that a smoker becomes less likely to quit smoking if he or she matches with another smoker. However, it could also be the result of assortative matching on smoking, i.e. the two partners were reluctant to quit smoking before they met and this made match formation easier but the match formation itself did not affect their quit behavior. Because there is no variation in the timing of events, we cannot make a distinction between assortative matching and a peer effect that occurred at the start of the match.

5.2 Sensitivity Analysis

In order to investigate the robustness of our baseline findings, we perform an extensive sensitivity analysis of which the relevant parameter estimates are presented in Table 3. 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 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.¹⁴

Many women stop smoking during pregnancies. Based on American data, Colman et al. (2003) conclude that 30-40% of smoking women quit smoking during pregnancy. However, most women who quit smoking during pregnancy relapse after giving birth. According to

¹⁴We 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.

Colman et al. (2003) 50% of quitters start smoking again within six months after giving birth, and 75% start smoking within one year after giving birth. Similarly, summarizing earlier studies on pregnancy quitting and relapsing, Notley et al. (2015) report that 45% of pregnant smokers quit smoking with 70-85% relapsing within one year after giving birth. Pregnancy seems to lead a lot of temporary smoking quits. Panel (b) shows how spousal peer effects are influenced by the inclusion of pregnancies as explanatory variable in the quit rates.¹⁵ Although pregnancies themselves have a positive effect on the quit rates of both males and females, the estimated spousal peer effects hardly differ from the baseline specification.

So far, in the estimations we assume that there is no partner effect if both partners quit in the same year. Panel (c) presents the results of a joint estimate when allowing for possible peer effects for partners who quit in the same year. This hardly affects our main parameter estimate. Panel (d) restricts the partner effect to couples who partner before quit behavior takes place. There are only a few observations where quitting occurs before partnership formation, and the no-partner-effect result remains. Panel (e) 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 reported to have quit smoking one year before the survey might smoke 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 (f) shows that baseline results do not change if we control for survey years.

It is possible that the effect of quit behavior of one partner prevails only shortly after quitting, 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 $\kappa = 5$ or 10. Panels (g) and (h) present the result of these estimations, indicating that no causal effect result remains after controlling for possible changes in the partner effect.

¹⁵Clark and Etilé (2006) also find a pregnancy effect on women's smoking (at a 10% significance level) but not on men's smoking.

Finally, panel (i) 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 general smoking bans that were introduced in the Netherlands over our sample period and a time trend 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.

To illustrate the magnitude of the other parameter estimates we performed a simulation analysis. In these simulations we calculate the cumulative probability to start smoking (by age) and the cumulative probability to quit smoking (by duration of smoking). For this, we use the parameter estimates from columns 3 and 4 of Table 2. We first calculate these probabilities for a reference person who has low education, low social status, no declared religion, living in a highly urbanized area, and born before 1945. Moreover, for quitting decision the reference person started smoking at age 15 and has a non-smoking partner. Then we calculated the cumulative probabilities to illustrate the effect of specific personal characteristics. The results of the simulations are presented in Table 4. Of the male reference persons 35% have started smoking by age 15 and 83% by age 25. For the female reference person this is 23% by age 15 and 73% by age 25. About 30% of the reference person smokers will have stopped smoking 15 years after having started. Table 4 also shows that having higher educations decreases the cumulative probability of starting to smoke by around 10 %-point for males and females. Younger cohorts of females are much more likely to start smoking at all ages. A smoker with a smoking partner is 15%-point less likely to quit compared to a smoker with a non-smoker partner. Finally starting to smoke at the age of 25 instead of 15 increases the likelihood of quitting within 15 years by almost 10%-point.

6 Conclusions

If two partnered individuals smoke, the decision of one of them to quit smoking may lead the other to quit smoking as well. Such spousal peer effects may exist because one partner tries to convince the other to quit. Or, one partner can learn from the health effects of the quitting experience of the other. An observed association in quitting behaviors of partners does not necessarily mean that this is due to a spousal peer effect. Individuals form partnerships through an assortative matching process. Their preferences and attitudes, including smoking behavior are likely to be similar. An observed association between the quitting decision of two-smokers partners may reflect assortative matching rather than a peer effect.

Spousal peer effects on quit-smoking behavior are interesting from a policy point of view because if they exist, the effects of specific anti-smoking policies may be underestimated. Targeted anti-smoking policies such as workplace smoking bans for example, may affect smoking behavior of the workers involved. If spousal peer effects are important, focusing on the directly affected worker will underestimate the benefits of the intervention. Similarly, the effectiveness of treatments to help addicted smokers quit smoking may be underestimated if spousal peer effects are ignored.

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. We 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 affects 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. 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. We find no evidence of strong spousal peer effects in the decision to quit smoking. This implies that anti-smoking policies that would affect one partner do not spillover to the other partner. Our results are quite surprising. In a partnered relationship and with important health-damaging behavior like smoking one would expect spousal peer effects to occur. Apparently, love conquers a lot and perhaps all except for nicotine addiction.

CONFLICT OF INTEREST

The authors have no conflict of interest

References

- Abbring, J. H. (2002). Stayers versus defecting movers: a note on the identification of defective duration models. *Economics Letters* 74, 327-331.
- Abbring, J. H. and J. J. Heckman (2007). *Econometric evaluation of social programs, part III: Distributional treatment effects, dynamic treatment effects, dynamic discrete choice, and general equilibrium policy evaluation*, Chapter 72, pp. 5145–5303. Handbook of Econometrics. Elsevier.
- Abbring, J. H. and G. J. van den Berg (2003). The nonparametric identification of treatment effects in duration models. *Econometrica* 71, 1491–1517.
- Abrevaya, J. and H. Tang (2011). Body mass index in families: spousal correlation, endogeneity, and intergenerational transmission. *Empirical Economics* 41, 841–864.
- Ali, M. M. and D. S. Dwyer (2009). Estimating peer effects in adolescent smoking behavior: a longitudinal analysis. *Journal of Adolescent Health* 45, 402–408.
- Angrist, J. D. (2014). The perils of peer effects. *Labour Economics* 30, 98–108.
- Canta, C. and P. Dubois (2015). Smoking within the household: Spousal peer effects and childrens health implications. *BE Journal of Economic Analysis and Policy* 15, 1939–1973.
- Card, D. and L. Giuliano (2013). Peer effects and multiple equilibria in the risky behavior of friends. *Review of Economics and Statistics* 95, 1130–1149.
- Clark, A. E. and F. Etilé (2006). Don’t give up on me baby: Spousal correlation in smoking behavior. *Journal of Health Economics* 25, 958–978.
- Clark, A. E. and L. Youenn (2007). “It wasn’t me, it was them!” Social influence in risky behavior by adolescents. *Journal of Health Economics* 26, 763–784.
- Colman, G., M. Grossman, and T. Joyce (2003). The effect of cigarette excise taxes on smoking before, during and after pregnancy. *Journal of Health Economics* 22, 1053–1072.
- Cutler, D. M. and E. L. Glaeser (2010). *Research Findings in the Economics of Aging*, Chapter Social Interactions and Smoking, pp. 123–141. University of Chicago Press.
- Drepper, B. and G. Effraimidis (2015). Social interaction effects in duration models. Mimeo.
- Eisenberg, D., E. Golberstein, and J. L. Whitlock (2014). Peer effects on risky behaviors: new evidence from college roommate assignments. *Journal of Health Economics* 33, 126–138.
- Fletcher, J. M. (2010). Social interactions and smoking: evidence using multiple student cohorts, instrumental variables, and school fixed effects. *Health Economics* 19, 466–484.
- Freund, J. (1961). A bivariate extension of the exponential distribution. *Journal of the American Statistical Association* 56, 971–977.
- Gaviria, A. and S. Raphael (2001). School-based peer effects and juvenile behavior. *Review of Economics and Statistics* 83, 257–268.

- Heckman, J. J. and B. Singer (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica* 52, 271–320.
- Humbad, M. N., M. B. Donnellan, W. G. Iacono, M. McGue, and S. A. Burt (2010). Is spousal similarity for personality a matter of convergence or selection? *Personality and Individual Differences* 49, 827–830.
- Kawaguchi, D. (2004). Peer effects on substance use among American teenagers. *Journal of Population Economics* 17, 351–367.
- Khwaja, A., F. Sloan, and S. Chung (2006). The effects of spousal health on the decision to smoke: Evidence on consumption externalities, altruism and learning within the household. *Journal of Risk and Uncertainty* 32(1), 17–35.
- Leonard, K. E. and P. Mudar (2003). Peer and partner drinking and the transition to marriage: A longitudinal examination of selection and influence processes. *Psychology of Addictive Behaviors* 17, 115–125.
- Lundborg, P. (2006). Having the wrong friends? Peer effects in adolescent substance use. *Journal of Health Economics* 25, 214–233.
- Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60(3), 531.
- McGeary, K. A. (2015). Spousal effects in smoking cessation: Matching, learning, or bargaining? *Eastern Economic Journal* 41, 40–50.
- Notley, C., A. Blyth, J. Craig, A. Edwards, and R. Holland (2015). Postpartum smoking relapse - a thematic synthesis of qualitative studies. *Addiction* 110, 1712–1723.
- Powdthavee, N. (2009). I can’t smile without you: Spousal correlation in life satisfaction. *Journal of Economic Psychology* 30, 675–689.
- 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, 950–968.
- Sacerdote, B. (2011). *Peer effects in education: how might they work, how big are they and how much do we know thus far?*, Volume 3 of *Handbook of the Economics of Education*, Chapter 4, pp. 249–277. Elsevier.
- Van Ours, J. C. (2006). Dynamics in the use of drugs. *Health Economics* 15(12), 1283–1294.

Table 1: 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	9	4	28
	Starting but no Quitting	9	18	7	34
	No starting	13	11	14	38
Total		37	38	25	100

Table 2: Parameter estimates of starting rates and quit rates of tobacco use for males and females in couples.

	Independent				Correlated			
	Males		Females		Males		Females	
	(1)		(2)		(3)		(4)	
<i>a. Quit rates:</i>								
Time-varying								
Partner quits	0.74	(0.24)**	0.61	(0.26)**	-0.10	(0.19)	-0.15	(0.23)
Time-invariant								
Both smokers	-0.52	(0.18)**	-0.34	(0.29)	-0.81	(0.17)**	-0.69	(0.30)**
Starting age	0.89	(0.24)**	0.50	(0.31)	0.80	(0.24)**	0.27	(0.33)
Intermediate	0.04	(0.29)	0.14	(0.26)	-0.05	(0.23)	0.28	(0.23)
Higher	0.13	(0.32)	-0.01	(0.27)	0.11	(0.26)	0.15	(0.24)
High social status	-0.02	(0.26)	-0.03	(0.32)	-0.06	(0.22)	-0.03	(0.27)
Moderate social status	0.08	(0.28)	0.29	(0.31)	0.06	(0.24)	0.17	(0.28)
Low/very low social status	-0.05	(0.36)	0.09	(0.35)	-0.23	(0.31)	0.23	(0.32)
Catholic	-0.09	(0.22)	-0.03	(0.26)	-0.08	(0.19)	-0.09	(0.22)
Protestant	-0.02	(0.22)	0.16	(0.29)	0.00	(0.18)	0.21	(0.25)
Others	0.08	(0.53)	0.21	(0.57)	0.01	(0.45)	0.50	(0.68)
Urban	0.06	(0.32)	0.22	(0.39)	0.05	(0.27)	0.17	(0.34)
Moderately urban	0.18	(0.29)	0.20	(0.34)	0.19	(0.23)	0.22	(0.3)
Rural	0.06	(0.29)	0.35	(0.36)	-0.04	(0.24)	0.30	(0.31)
Very rural	0.24	(0.26)	0.46	(0.37)	0.18	(0.23)	0.39	(0.32)
Cohort55	0.52	(0.23)**	0.69	(0.33)**	0.44	(0.2)**	0.61	(0.29)**
Cohort65	0.85	(0.25)**	1.10	(0.36)**	0.61	(0.21)**	1.02	(0.31)**
Cohort75	1.41	(0.29)**	1.52	(0.44)**	1.23	(0.24)**	1.37	(0.37)**
Cohort75+	1.88	(0.54)**	2.29	(0.62)**	1.67	(0.42)**	1.88	(0.46)**
v_1	-5.51	(0.79)**	-5.39	(0.95)**	-5.10	(0.71)**	-4.85	(0.90)**
v_2	-∞		-∞		-∞		-∞	

Table 2 continued

	Independent				Correlated			
	Males		Females		Males		Females	
	(1)		(2)		(3)		(4)	
<i>b.Starting rates:</i>								
Intermediate	-0.19	(0.14)	-0.15	(0.13)	-0.24	(0.14)	-0.15	(0.13)
Higher	-0.39	(0.16)**	-0.33	(0.14)**	-0.35	(0.16)**	-0.33	(0.14)**
High social status	0.14	(0.16)	-0.08	(0.17)	0.18	(0.16)	-0.08	(0.18)
Moderate social status	0.26	(0.17)	-0.22	(0.19)	0.21	(0.18)	-0.22	(0.19)
Low/very low social status	0.19	(0.19)	-0.27	(0.19)	0.16	(0.19)	-0.27	(0.20)
Catholic	-0.04	(0.12)	-0.09	(0.13)	-0.02	(0.13)	-0.09	(0.13)
Protestant	-0.14	(0.13)	-0.16	(0.14)	-0.09	(0.13)	-0.16	(0.14)
Others	0.09	(0.24)	0.06	(0.23)	0.16	(0.24)	0.06	(0.25)
Urban	-0.10	(0.18)	-0.31	(0.19)	-0.07	(0.18)	-0.31	(0.20)
Moderate urban	-0.13	(0.16)	-0.10	(0.18)	-0.11	(0.16)	-0.10	(0.19)
Rural	0.07	(0.16)	-0.18	(0.17)	0.06	(0.16)	-0.18	(0.18)
Very rural	0.08	(0.16)	-0.15	(0.18)	0.19	(0.16)	-0.15	(0.18)
Cohort55	0.02	(0.15)	0.58	(0.20)**	0.05	(0.14)	0.59	(0.21)**
Cohort65	0.10	(0.16)	1.13	(0.18)**	0.15	(0.15)	1.13	(0.20)**
Cohort75	-0.67	(0.17)**	0.75	(0.20)**	-0.35	(0.18)	0.75	(0.21)**
Cohort75+	-0.29	(0.21)	1.50	(0.22)**	0.07	(0.20)	1.50	(0.23)**
u_1	-3.46	(0.33)**	-4.98	(0.50)**	-3.55	(0.33)**	-4.98	(0.55)**
u_2	$-\infty$		$-\infty$		$-\infty$		$-\infty$	
α_1	0.76	(0.14)**	-0.25	(0.09)**	0.89		(0.14)**	
α_2	0.70	(0.15)**	-0.12	(0.08)	$-\infty$			
α_3					-1.18		(0.22)**	
α_4					-1.88		(0.88)**	
α_5					0.36		(0.14)**	
α_6					-0.72		(0.18)**	
α_7					0.06		(0.15)	
α_8					-0.18		(0.16)	
-LoglikeLihood	6452.3				6387.2			
<i>c.Distribution of unobserved heterogeneity (%):</i>								

Based on 812 observations; all estimates contain duration dependence parameters in the quit rates and age dependence parameters in the starting rates; standard errors in parentheses. * and ** are for statistical significance at 10% and 5%, respectively. The numbers in panel c show the percentage of couples in each category of the unobserved heterogeneity groups. For example, 31% 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 3: Parameter estimates quit rates; sensitivity analysis

	Independent				Correlated			
	Males		Females		Males		Females	
	(1)		(2)		(3)		(4)	
a. Imposing perfect correlation								
Partner quits (δ)					-0.09	(0.19)	-0.23	(0.21)
-Loglikelihood							6434.1	
b. Including Pregnancies								
Partner quits (δ)	0.70	(0.24)**	0.63	(0.27)**	-0.14	(0.18)	-0.20	(0.20)
Pregnancy	0.43	(0.20)*	0.41	(0.19)**	0.31	(0.17)*	0.04	(0.19)
-Loglikelihood			6449.8				6387.4	
c. Same year quits								
Partner quits (δ)	0.92	(0.21)**	0.73	(0.25)**	-0.16	(0.17)	-0.08	(0.21)
-Loglikelihood			6448.2				6389.6	
d. Timing of the partnership								
Partner quits (δ)	0.64	(0.25)**	0.60	(0.26)**	-0.19	(0.19)	-0.20	(0.22)
-Loglikelihood			6458.5				6390.1	
e. Quit at least 2 years ago								
Partner quits (δ)	0.66	(0.24)**	0.60	(0.27)**	-0.16	(0.19)	-0.31	(0.20)
-Loglikelihood			6411.8				6368.8	
f. Controlling for survey years								
Partner quits (δ)	0.74	(0.28)**	0.64	(0.28)**	-0.07	(0.18)	-0.16	(0.22)
Year 2001	-0.03	(0.18)	0.20	(0.22)	-0.10	(0.20)	0.17	(0.18)
Year 2003	-0.18	(0.20)	0.13	(0.26)	-0.14	(0.17)	0.09	(0.21)
Year 2005	-0.20	(0.23)	-0.01	(0.24)	-0.11	(0.19)	0.01	(0.22)
Year 2007	-0.10	(0.21)	0.15	(0.25)	-0.13	(0.17)	0.24	(0.23)
-Loglikelihood			6448.4				6380.2	
g. $\kappa=5$								
Partner quits (δ)	0.67	(0.18)**	0.72	(0.27)**	0.04	(0.25)	0.18	(0.26)
Partner quits and 5 years (δ_1)	0.15	(0.35)	-0.11	(0.38)	-0.23	(0.31)	-0.54	(0.31)*
-Loglikelihood			6450.7				6386.6	
h. $\kappa=10$								
Partner quits (δ)	0.67	(0.25)**	0.57	(0.22)**	-0.12	(0.20)	-0.05	(0.23)
Partner quits and 10 years (δ_1)	0.27	(0.31)	0.39	(0.39)	0.06	(0.21)	-0.15	(0.27)
-Loglikelihood			6449.9				6388.4	
i. Smokers only								
Partner quits (δ)	0.73	(0.25)**	0.67	(0.28)**	-0.04	(0.20)	-0.17	(0.23)
-Loglikelihood			4088.1				4038.6	

The set-up of the model is the same as in Table 2 but only the relevant parameter estimates are reported; standard errors are 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 i.

Table 4: Simulated cumulative probabilities to start and quit smoking (in %)

	Males			Females		
a. Cumulative probability to start by age	15	20	25	15	20	25
1. Reference person	35	72	83	23	54	73
2. High educated	26	60	73	20	44	61
3. Cohort 75+	37	75	86	36	81	93
b. Cumulative probability to quit after duration (years)	5	10	15	5	10	15
1. Reference person	9	18	28	10	19	30
2. Partner smokes	4	8	15	5	9	14
3. Started smoking age 25	12	25	38	14	27	40
3. High educated	10	21	32	9	18	27
4. Cohort 75+	15	31	46	19	38	58

Reference person: Low education, social status low or very low, no religion, highly urbanized, cohort born before 1945. For quitting decision: started smoking at age 15; non-smoking partner. Simulations based on the parameter estimates of the correlated model presented in Table 2.

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

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 dots show the same figure for males whose partner does not quit smoking.

Figure 4: Representation of the partner effect

Fig1a.png

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Fig1b.png

Fig2a.png

Fig2b.png

Fig3.png

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