The impact of job loss on family dissolution[1]

by

Denise Doiron and Silvia Mendolia
School of Economics,
Australian School of Business Building
University of New South Wales,
Sydney, NSW 2052 Australia

Abstract

The impact of involuntary job displacements on the probability of divorce is analysed using discrete duration models. The analysis uses the sample of couples from the British Household Panel Survey and distinguishes between types of displacements. Results show that couples in which the husband experiences a job loss are more likely to divorce. Redundancies have the smallest and most short-lived effects relative to dismissals and temporary job endings. This is consistent with the interpretation of redundancies as capturing negative income shocks while other types of job loss also convey new information about potential future earnings and match quality.

JEL Codes: J12, J60, J63

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[1] Corresponding author. Postal address: School of Economics, ASB Building, University of New South Wales, Sydney, NSW, Australia 2052. Email address: silvia.mendolia@student.unsw.edu.au.

1. Introduction[1]

The aim of this paper is to analyse the relationship between labour market outcomes and family well-being. Specifically, we focus on the impact of job losses on family dissolution. The involuntary termination of employment usually leads to lower earnings and the stress created by the negative income shock can increase the probability of family dissolution. Moreover, a job displacement may signal individual traits that impact negatively on future earnings or on the quality of the match more generally. Again this suggests a positive relationship between family dissolution and job displacement. While policies aimed at reducing the earnings' shock from job losses may alleviate stress on the couple in the case of the former effect, they will have less impact if the latter effect is the dominant one.

In recent decades, family and marriage characteristics have dramatically changed; divorce rates have risen and marriage rates fallen. Fertility has declined, longevity increased and cohabitation has emerged as an important institution, often as a substitute for marriage. Economic models that explain why people marry and remain together have been developed in an attempt to explain these changes (Ermisch, 2003). The economic approach to marriage is based on the assumption that couples marry and stay married when the net gains from marriage are greater than those from remaining single. According to the traditional models of household economics, starting from Gary Becker's *Treatise on Family*, these gains result mostly from gender specialization (especially when raising children) and sector-specific investments in human capital (Becker, 1974 and Becker 1975).

Fundamental changes in the technology of household production and of birth control and increased female labour market participation have altered the returns to household specialization and, according to the traditional model, reduced the opportunity cost of marriage. More general models of household production have shifted attention away from specialization and the division of labour, to the benefits of joint consumption and a positive match between husbands' and wives' preferences (Lundberg, 2005 and Lam, 1988).

In this framework, the analysis of the relationship between job loss and family dissolution is particularly appropriate. Given the increased complexity of the marriage relationship, individuals are likely to spend more time searching for a good match on the marriage market (Gould and Paserman, 2003). We also expect partners to re-evaluate the benefits from an existing marriage more frequently. A husband's involuntary job loss can lead to such a re-examination of the partnership as it can affect both the contemporaneous value of the marriage (compared to its alternatives) and signal the likelihood of undesirable traits and lower future earnings.

To fix ideas, consider a stylised model of marriage and divorce involving an initial match quality that is known at the time of marriage and the evolution of this match quality over time. Partners stay together if the match quality (including future expected benefits of the partnership) is high relative to outside options. The dynamic process underlying match quality will depend on various factors including choices made by the partners (e.g. having children) and state dependence whereby the match quality is causally affected by the duration of the match to date. Match quality will also depend on the occurrence of various shocks some of them having only contemporaneous effects while others generate more persistent impacts. A job loss can cause a contemporaneous shock in the loss of earnings and an increased stress on the union. It can also cause a more persistent effect if the earnings loss is long lasting or if the future expected match quality is revised. The latter will occur when the job loss is seen as a signal of lower future match benefits. This framework underlies the empirical approach adopted in the paper.

It is important to understand the reason for the termination of the employment spell in order to evaluate what information this event may convey regarding the partner's suitability. An involuntary and exogenous displacement (e.g. due to a plant closure) causes an income shock, but does not convey new information about the partner's characteristics. On the other hand, a "person-specific" dismissal is likely to be caused at least in part by the individual's characteristics and behaviour. Papers studying the effects of layoffs on future earnings and probabilities of employment support these hypotheses. Job losses from plant closures (Gibbons and Katz, 1991; Doiron, 1995) or redundancies (Arulampalam, 2001) have a smaller effect on future earnings than other types of involuntary displacements.[2]

In this paper, data from the British Household Panel Survey (BHPS) are used to analyse the effects of involuntary job losses experienced by the husband on the probability of marital dissolution. We take into account the length and history of the union and we estimate discrete time duration models. Individual and family characteristics are included and random, unobserved, time-invariant and match-specific effects are modelled. The reasons for the termination of the employment spell are used to distinguish between different types of job losses: dismissals, redundancies and temporary job endings. While dismissals are more likely to be related to individual traits, redundancies are based on the employer's characteristics and environment and are interpreted as representing effects of earnings shocks only.

Our treatment of redundancies as uninformative about individual traits is based on the legal definition of redundancy. The British legislation is quite explicit that the term redundancy should not refer to a dismissal caused by an individual worker's behaviour. (We discuss the definition of redundancies more extensively in the data section.) Also, the distinction between types of displacements is supported by a recent study of the BHPS. Arulampalam (2001) finds that redundancies overall have less of a scarring effect; specifically, she finds that the earnings loss due to redundancies is about one half of that due to other displacements and 81% of men made redundant found jobs without any spell of non-employment. In another study of the BHPS, Borland et al (2000) also compare the earnings loss of workers based on the reasons for the termination of the employment spell. They argue that the institutional system often blurs the distinction between the different categories and separate displaced workers from industries with decreasing employment in order to further control for the possibility of endogenous variations in job losses[3].

This interpretation of redundancies and the contrast with dismissals leads to several implications in the empirical results; for example, we expect dismissals to have more severe and longer lasting impacts on divorce probabilities. This is in fact what is found in the data. Also various specifications are estimated as sensitivity analysis. Using information on the workforce growth rate by industry, we separate redundancies occurring in declining and growing industries; job displacements due to redundancies in declining industries are less likely to represent signals of unfavourable individual traits. Similar reasoning leads to the separate treatment of job losses during recessionary years.

There are very few papers looking at the effects of job losses on marital dissolution and to our knowledge only two of them take into account the reason for displacement. Furthermore these two papers find conflicting results. Charles and Stephens (2004) analyse US data and find that unlike layoffs, displacements due to plant closures have no significant effect on divorce[4]. On the other hand, Eliason (2004) finds that factory closures in Sweden do lead to an increase in dissolutions. Our paper provides new evidence on this topic based on new data and models.

Our empirical framework is closer to that of Charles and Stephens (2004) in the sense that we estimate duration models that account for marital longevity[5]. However there are also substantial differences between the approaches in the two papers. Our models are based on a proportional hazards framework and the resulting estimates are easier to interpret. We also estimate a variety of specifications of the baseline hazard and look at selection into the stock and flow samples. Finally, cohabitations are included in the analysis.

We find that the probability of divorce increases following a husband's job loss and the results are stronger and longer lasting for dismissals compared to redundancies. In the main model, a redundancy experienced by the husband increases the probability of family dissolution by about 50% one year later and 16% two years later (the latter is not significantly different from zero). The impact of dismissals is much higher: around 150% one year later and 100% two years later. Effects of temporary job endings are generally located between the two. These results are consistent with our original interpretation: dismissals have a larger signalling content than redundancies. Random effects specifications yield similar results, an indication that our model of the baseline hazard is sufficiently general to capture the correlation in unobservables across time.

Redundancies have stronger effects in negative economic climates (declining industries) while dismissals matter more in good conditions (non-recessionary years and growing industries), another sign that the former displacements capture mostly earnings shocks. A comparison of the effects of job loss in the stock and flow samples also show marked differences across the types of dissolution: while the coefficients on dismissals and temporary job endings are multiplied fourfold in the flow sample (with idiosyncratically short marriages), for redundancies, the coefficient drops close to zero in that sample[6].

Turning to other results, there is strong evidence of duration dependence in marital stability. In general, the longer people have been married, the smaller the probability of family dissolution. This result is reversed for the intermediate durations (7 to 14 years of marriage) where the probability of divorce is either flat or slightly positive depending on the specification. The wife's employment status and nonlabour income have no effect on the probability of divorce while the husband's nonlabour income reduces the likelihood of dissolution. Education has a non-monotonic impact in that the highest probability of divorce is found for the lower high school graduates; this is true for both the husband's and wife's education. The number of children has no effect when the overall sample is used but it has different and significant effects when distinguishing between stock and flow samples.

The paper is organized as follows. The following Section provides an overview of the existing literature. Section 3 includes a description of the data construction and descriptive statistics. Section 4 discusses the econometric model and Section 5 presents the empirical results. Finally Section 6 contains concluding comments.

2. Overview of existing literature

We begin the section with a brief discussion of economic models of marriage and marital stability. Although we focus on economic models, it is clear that economic considerations form but part of the picture and as stated by Weiss and Willis (1997): “A successful theory which is capable of explaining the data on marriage and divorce must incorporate ideas from sociology, biology and other fields”. Nonetheless, economic factors have been shown to play a significant role in the decisions to form and dissolve households.

Becker’s seminal work (1973, 1974) forms the first economic framework of marriage and divorce. Two individuals marry when there is a positive surplus from their union relative to the two remaining single. As long as they are married, the two individuals maximise a joint expected utility function, whose arguments are the income or labour earnings received by each spouse (see Weiss 2000 and Charles and Stephens, 2004 for more details). The couple divorces when the joint expected utility of being married is less than the sum of the individual expected utilities from divorce. The expected utility of divorce includes the probability of remarriage as well as the costs of divorce and the expected utility of remaining married includes the future option of divorce.

Two general causes for marital instability and divorce are present in this model. First, although the search for a partner is costly, meetings do occur on a random basis. As a consequence, a union may become unacceptable if one of the two partners meets a person who would be superior to the current match. Second, people enter a marriage based on expectations about the match-quality which depends on the traits of the other spouse. These characteristics may change over time unexpectedly and cause the spouses to reconsider their initial decision (see Weiss and Willis, 1997 and Boheim and Ermish, 2001). Thus “surprises”, such as unexpectedly high or low income, may affect marriage dissolution. According to Becker, Landes and Michael (1977), “the majority of divorces results from uncertainty and unfavourable outcomes”.

A job loss may be considered as an economic “surprise” impacting negatively on the partner’s future expected earnings. It could also be a signal of characteristics (heretofore unknown) of the partner that affect his/her suitability as a mate such as reliability or sense of responsibility. Eliason (2004) underlines that the traits needed to keep a job are partly the same as the traits that make a partner desirable. Hence a job loss may reveal new information about the match quality and lead to marital dissolution.

An alternative theory of divorce is the family stress theory, the ABC-X model, first elaborated by Hill (1949) and later by McCubbin and Patterson (1982)[7]. In this model, A is a stressor event, B the family's coping resources, C the family's perception of the event and X the crisis. The stressor event will have an impact both on the family's coping resources and on the family's perception and can result in a crisis or a resolution. A job displacement can be considered as a stressor event. It may cause financial and psychological stress and have broad implications on health and social networks for both the person experiencing the job loss and the other members of the family. For example job loss is found to be correlated with alcohol abuse (Catalano et al, 1993) and domestic violence (Kyriacou at al, 1999).

Game theoretic models of family bargaining offer alternatives to unitary models. Household members are assumed to maximize altruistic utility functions subject to resource and technology constraints. In the "divorce threat models" bargaining power depends on the expected utility outside of marriage (Manser and Brown, 1980 and McElroy and Horney, 1981). In contrast, Lundberg and Pollak (1996) propose a "separate spheres" model, assuming that both partners behave noncooperatively and treat divorce as an outside option.

In a recent study, Matouschek and Rasul (2004) develop stylised models of marriage as an exclusive contract. At the beginning of the first period each man is matched with one woman and each couple receives a signal about the future gains from being together. After observing the signal, each couple then decides whether to break up, cohabit or get married. If the couple decides to get married each partner immediately realizes an exogenous "marriage bonus", that represents the extra utility gained from publicly demonstrating their commitment to each other. In some variations of this approach, couples are involved in an infinitely repeated prisoner's dilemma in which the partners decide simultaneously whether to cooperate or not. Marriage is a commitment device that fosters cooperation.

In all these models, job displacement plays a natural role in explaining marriage dissolution. Furthermore, several channels of transmission are expected. A job loss can be a stressor event, a signal of altered future earnings or more generally future match quality, an indication of shifts in household bargaining powers, the values of the outside option, and the degree of commitment to the marriage.

We now turn to empirical studies analysing the effects of job losses. There is a well-established body of work showing the effects of job displacement on re-employment probabilities and future earnings. Displaced workers tend to experience reduced employment possibilities, increased job instability, as well as lower earnings' profiles (Ruhm, 1991; Jacobsen, Lalonde and Sullivan, 1993; and Chan and Stevens, 2001). A growing number of studies consider the effects of job loss on the behaviour of other members of the family. For example Stephens (2001) analyses family consumption changes after the husband's job loss; also Ercolani and Jenkins (1999) and Stephens (2004) focus on wives' labour supply changes in response to the husband's job loss[8].

Changes in family labour supply and consumption form only part of the impact of job loss and the reduction in earnings. Recent work shows substantial impacts of unemployment on mental and physical health and well-being generally. There is a large empirical psychological literature[9] investigating the impact of unemployment on the incidence of low life satisfaction, depression, low self-esteem, unhappiness, and even suicide. The negative income shock is but one source of these effects as employment is also a provider of social relationships, one's identity in society and individual self esteem (Winkelmann and Winkelmann, 1998). For example, a British study by Clark and Oswald (1994) shows that unemployed people have much lower levels of mental well being than those in work and Sullivan and von Watcher (2006) find a significant relationship between job loss and mortality[10].

The effect of job displacements on decisions regarding fertility and marriage forms yet another dimension of the impact of job loss. These non-pecuniary adjustments cannot be regarded as being of secondary importance; divorce is ranked as the second most stressful of life events following death of a family member (Miller and Rahe, 1997). Nevertheless, there is but limited research on this aspect of the costs of job displacements; furthermore, to date these papers provide inconsistent evidence.

Jensen and Smith (1990) analyse Danish panel data and find significant effects of job losses on divorce but only for contemporaneous spells of unemployment. Job losses occurring one or two years earlier have no impact. These findings raise concerns that reverse causality may be driving findings of significant effects of job losses when the timing of events is not accounted for. Information regarding the length of the union is not used in this study.

Weiss and Willis (1997) use US data from the National Longitudinal Study of the High School Class of 1972 to study the effects of earnings shocks on the probability of divorce. Shocks or "surprises" are defined as the difference between realized and predicted earnings estimated from earnings regressions. They show that a positive surprise to a husband's earnings lowers the probability of marriage dissolution, while a positive shock in a wife's earnings raises the chance of divorce. These results are robust to the inclusion of several controls for match quality. More recent studies use direct measures of earnings' shocks. For example, based on the German Socio-economic panel data, Kraft (2001) analyses the impact of unemployment on married couples' decision to separate. The husband's unemployment is found to increase the risk of separation in the following year and this impact increases with the duration of unemployment.

Using the Panel Study of Income Dynamics, Charles and Stephens (2004) find an increase in the probability of divorce following a spouse's job displacement in the first three years. In the last part of this paper, they compare different job losses and find a significant increase only for layoffs and not for plant closures. As Charles and Stephens (2004) state "This suggests that information conveyed about a partner's non-economic suitability as a mate due to a job loss may be more important than the financial losses in precipitating a divorce." In contrast, Eliason (2004) finds a significant negative impact on the marriage's stability in the long term (up to 13 years after the displacement) caused by the husband's or the wife's job displacement due to a factory closure in Sweden.

Lastly, in an independent study to ours, Blekesaune (2008) finds a significant increase in the probability of family dissolution after any form of unemployment (experienced by husbands or wives). The paper is based on the BHPS and panel data techniques (random effects models) are used to control for unobserved heterogeneity. One major difference with our analysis is that Blekesaune does not distinguish between different causes of unemployment.

3. Data construction and descriptive statistics

The analysis uses data collected in the first 14 waves of the British Household Panel Survey (BHPS), which is a nationally representative sample recruited in September 1991. The survey contained approximately 10,000 persons (5,500 households) when it was constituted[11]. The BHPS is an indefinite life panel survey and the longitudinal sample consists of members of original households and their natural descendants. If the original members split off from their household to form a new family, all the adult members (older than 16) of the new households are included in the survey and interviewed.

In order to analyse the possible impact of job loss on family dissolution, we firstly construct a sample of all married or cohabitating couples in the BHPS. A dataset, containing consolidated marital, cohabitation and fertility histories for the 29,065 adults, interviewed at least once during the survey is available together with the original data (see Pronzato, 2007). This dataset provides the starting and end date of each union. If the union is a marriage, one or both partners can die, they can get divorced, separated or stay together. If the union is cohabitation, the partners can split, get married or they can continue cohabitating. In this analysis, we do not distinguish between marriages and cohabitations. If the two partners cohabitate before marriage, we consider the cohabitation starting date as the union starting date. If there is a separation before the divorce, the date of separation is considered as the union end date[12].

A divorce binary variable is defined to equal 1 when the end date from the family data set indicates a separation, a divorce or a split (for cohabitating partners) and when this is the last time the couple is observed being together in the survey. Usually, this can be easily confirmed by subsequent observations in consecutives waves. A very small number of individuals[13] disappear from the survey for one or more interviews when still married or cohabitating and re-appear with a different marital status (divorced or separated). For these couples, we assume they separate in the first year that they are not observed in the survey[14]. If a union ends, the partners are subsequently dropped from the analysis sample. Also, couples in which the man is younger than 16 or older than 65 years are dropped[15].

The analysis sample includes second and later marriages. Also we include both flow and stock samples. The flow sample consists of marriages starting in1991 or later while the stock sample includes unions in existence at the start of the survey period. Separate models are estimated for these two groups as part of the sensitivity analysis. Families formed before the beginning of the survey can have idiosyncratically higher levels of durability and represent better matches. A finding that job losses increase the probability of divorce *even* in families which are idiosyncratically stable forms a conservative lower bound for the population at large.

Information on labour market behaviour and periods of unemployment is collected in different sources within the BHPS. At each interview, the individual is asked about his/her current employment situation[16], and whether he/she did any paid work or was away from a job in the week prior to the interview. Retrospective information about labour force behaviour and all employment spells over the previous year is also collected. G. Paull has compiled a special data set containing labour forces spells (defined in terms of spell state, start date and end date) for each individual after leaving fulltime education until the time of the interview (Halpin, 1997, Paull, 1997 and Paul 2002). This data set is complete for the first 11 waves of the BHPS and reconciles multiple sources of information on employment spells.

The reason for the termination of an employment spell is not included in the Paull data set and was derived from the job history files. When providing the reason for leaving a job, individuals can choose among the following alternatives: promoted, left for better job, made redundant, dismissed or sacked, temporary job ended, took retirement, stopped for health reasons, left to have a baby, children/home care, care of other person, and other reasons. In this paper we focus on involuntary displacements and consider only dismissals, redundancies and temporary job endings as job losses. Also, only job losses experienced by the male partner are considered.

All involuntary job losses are expected to lead to negative shocks on earnings but dismissals are more likely to incorporate individual traits and act as signals for the future match quality. Temporary jobs are similar to dismissals in the sense that there may be an individual-specific reason for the non-renewal of the contract; but it is also possible that the end date of the job was fixed in advance (with no chance of renewal) in which case there is no signalling effect contained in the termination of the employment spell (although there may be in the acceptance of such jobs). The British redundancy law allows three reasons for redundancy: total cessation of the employer's business (whether permanently or temporarily), cessation of business at the employee's workplace and reduction in the number of workers required to do a particular job. Moreover, the employment law clearly specifies that, in a redundancy situation, the employer should select workers fairly and should consider any alternatives to redundancy (this includes offering alternative work). Workers are eligible for redundancy payments after two years of tenure on the job.

Despite its legal definition, redundancy can be used more generally as a term for involuntary separation and respondents may be willing to report redundancies in cases of dismissals[17]. This will blur the distinction between dismissals and redundancies and inflate the effect of redundancies on marital dissolution. We follow Borland et al (2000) and construct a more stringent definition of redundancy using information on the industry of the job just ended. Specifically, data on industry-specific workforce growth rates is collected from published UK government statistics and a three years moving average growth rate for each industry is constructed. In some models, redundancies from jobs in industries with declining employment are treated separately in the analysis. Finally we include interaction terms of redundancies with calendar year dummies for 2000-2001. These years correspond to recessionary conditions in the labour market. Redundancies during those years are less likely to be influenced by individual-specific characteristics and to indicate new information regarding the husband's traits.

Table 1 lists the explanatory variables (other than job displacements) used in the empirical model. The choice of regressors follows the literature and includes human capital indicators, income, children, and similarities between partners. These variables measure variations in the utility of staying in the marriage, the value of the outside option, bargaining powers, and the quality of the match. Income is measured as household non labour income and includes pensions and other benefits, government transfers and investment income. The use of yearly income helps smooth out effects of unusually high income receipt in any 1 month. Empirically, both yearly and monthly incomes produce very similar results. Nonlabour income for the wife and husband is included separately[18].

Other variables included are: highest educational qualification attained (Degree, HND/A level, CSE/O level, No qualification), number of children, a binary indicator of the wife's employment status and two match quality characteristics. The economic literature related to marriage and divorce underlines the importance of "good matches". Couples are characterised by their "match quality" at the start of the relationship and this is an important predictor of the future stability of their union. Factors such as similar life experiences and goals can affect the intensity of the initial connection and help determine the probability of a long term marriage. We include information about differences in age of the partners and similarities in educational attainment to capture variations in match quality across couples.

The final sample contains 7,517 couples and 45,322 observations. Figure 1 displays the percentage rate of divorce/separation for couples who are in the analysis sample. From these raw numbers, we can see that on average about 2% of unions are dissolved by divorce or separation each year and the incidence of dissolutions trends slightly downwards over the length of the union. (Note that the average duration of unions increases over time even in the unbalanced sample.) In total, 653 dissolutions are observed in the sample.

Figure 1 here

Table 2 presents the number of job losses by year in the analysis sample. In total, there are 2,057 displacements consisting of 1275 redundancies, 205 dismissals and 577 temporary job endings. If a husband experiences more than one type of job loss in any year, this information is used in the analysis[19]. Generally, the incidence of displacements decreases over the 14 waves as the average age of the sample rises. Exceptions occur around the recession of 2000-01 especially for redundancies. In any one year, the incidence of job displacement for any of these causes is around 4 to 5%. This shows the importance of large samples when studying this topic.

Figure 2 presents the distribution of length of marriages/cohabitations in the sample, by job loss experience. From the raw figures we see that marriages with no job loss experiences are shorter on average. This result is consistent with Charles and Stephens (2004).This would seem to contradict the theoretical predictions discussed above. However, these figures do not take into account other characteristics in particular the match quality. Shorter marriages may have failed because of relatively bad match quality and since these observations do not remain in the sample of couples, they are less likely to appear in the sample that has experienced displacements. This illustrates the importance of controlling for characteristics of the union (observed and unobserved) and in particular, state dependence in the effect of marital duration.

Figure 2 here

Table 3 presents sample means of demographic and socio-economic variables among couples with and without job loss experience. The sample of couples where husbands do not experience any job loss is on average older (both partners) and better educated (both partners). Also, the household nonlabour income is higher and the number of children lower. All this corresponds with a stereotypical view of those households where partners are relatively successful in the labour market and hold more secure jobs. Also indicators of good match quality are slightly higher. The table includes the divorce rate by characteristic for the two samples. In general, couples with a job loss experience also have higher divorce rates. The highest divorce rates are found for partners who got married at a very young age and have middle to low educational qualifications.

4. Estimation methods[20]

We estimate a discrete time proportional hazards model, to investigate the effect of job loss on the probability of a marital dissolution at time t, given that the partnership has survived until t-1. A discrete time representation of the continuous time Cox proportional hazards model can be written as:

$$h_i(t) = \Pr[T_i = t \mid T_i \geq t, x_i(t)] = 1 - \exp[-\exp\{x_i(t)'\beta_i(t) + \gamma(t)\}]$$

where t denotes time in the union, $h_i(t)$ is the hazard at time t for couple i (the dependence on x and estimation parameters is suppressed), $x_i(t)$ is a vector of covariates that vary across unions i and with time t, $\beta_i(t)$ is a vector of coefficients (the subscript i is added to allow for unobserved match-specific effects), and T_i is a discrete random variable representing the time at which the union ends. $\gamma(t)$ is the log of the integral of the underlying continous time baseline hazard between t and t+1. Variables and parameters are assumed constant between t and t+1 for all t. The form of the hazard as an extreme value distribution is implied by the proportional hazards specification.

The sample log-likelihood function of the observed duration data can be simplified by defining a dummy variable a_{it} equal to 1 if $t = T_i$ and the marriage is non-censored (a divorce is observed at time t) and $a_{it} = 0$ otherwise (the marriage continues on to t+1 or is censored at time t). The log-likelihood function can be written as:

$$\ln L = \sum_{i=1}^{N} \sum_{t=\tau_i}^{T} [a_{it} \ln(h_i(t)) + (1 - a_{it}) \ln(1 - h_i(t))]$$

where N denotes the number of couples in the sample, T is the maximum marital duration observed in the sample, and τ_i equals 1 for the flow sample and the duration of the i^{th} union in 1991 for the stock sample (constructed using the starting date of the union). The main issues in specifying this model revolve around the form of the dependence of $h_i(t)$ on t, in particular the form of the baseline hazard and any other coefficients that should depend on the time in the relationship; and the dependence of $h_i(t)$ on i, in particular the presence and form of couple-specific, time-invariant and unobserved effects.

In the simplest model, the hazard depends on duration only through the variation in the covariates and there is no couple-specific time-invariant unobserved effect. The log likelihood becomes:

$$\ln L = \sum_{i=1}^{N} \sum_{t=\tau_i}^{T} [a_{it} \ln(h_i(t)) + (1 - a_{it}) \ln(1 - h_i(t))]$$

The log-likelihood differs from common binary choice models (logits and probits) only in the distribution of the error. In this case, the baseline hazard is invariant and is estimated by the constant term γ. The presence of unobserved match quality and the evolution of relationships over time suggest that these are overly restrictive assumptions.

The assumption of a constant baseline hazard is relaxed and various specifications for the dependence on duration are estimated. We make the common assumption that the only duration dependent parameters are those characterizing the baseline hazard. It is well known that ignoring unobserved match-specific and time-invariant heterogeneity will cause the overestimation of negative duration dependence since it then becomes the only form of correlation over time in the model (other than that present in the covariates). We estimate models with random effects to control for unobserved heterogeneity. With single spell data, it is not possible to control for general correlations between the match-specific unobserved effects and the covariates; we follow the literature and maintain the assumption of random unobserved match-specific effects independent of the covariates. The unobserved heterogeneity is assumed to be multiplicative in the hazard rate specification and normally-distributed. Specifically, the hazard takes the form:

$$h_i(t) = 1 - \exp[-\exp\{x_i(t)'\beta(t) + \gamma(t) + \ln(\varepsilon_i)\}]$$

where ε_i is a normally distributed random variable with unit mean and constant variance σ^2. Independence between ε_i and $x_i(t)$ (and the censoring date) is a maintained assumption[21]. See Wooldridge (2002) pp. 700-714 for more details on this and on the assumptions regarding the types of covariates that can be included (i.e. external covariates).

Generally, flow samples are drawn from a population of short spells since their duration is limited by the survey period (in our case 1991-2003). On the other hand, long spells are overly represented in stock samples since spells that began and ended before the first interview are excluded. This is the problem of length-biased sampling. In our analysis sample, these two subsamples are fairly evenly divided: the stock sample contains 22046 observations (with 232 divorces and 899 job displacements) while the flow sample numbers 23276 (with 421 dissolutions and 1158 job losses). In order to check that the specification of the hazard (in particular the baseline hazard and the unobserved heterogeneity) is sufficiently general to represent the non-random selection between stock and flow samples, we estimate separate models for the subsamples and compare results.

The independence assumption which must be maintained with random effects has implications for the measurement of the impact of the job displacement variables. Specifically, in models with unobserved time-invariant random effects, any signal contained in a job loss variable must be independent of the initial unobserved match value. One can easily imagine violations of this assumption. A strong marriage may be harder to influence; hence the signalling effect of a dismissal may be lower for these couples. Sensitivity analysis with a wide variety of specifications (especially that of the baseline hazard) is needed to check for the importance of this assumption.

Furthermore, since this study focuses on the effects of job displacements on the duration of marriage, the distinction between duration dependence (the shape of the baseline hazard) and unobserved heterogeneity is secondary. In other words, the specification of a flexible baseline hazard capturing both duration dependence and unobserved heterogeneity would work just as well for our purposes. Separating out unobserved heterogeneity does not change the effects of the covariates on the mean duration. It is useful however as an indication of how well the baseline hazard is specified. Given the restrictive assumptions needed on the form of the unobserved heterogeneity, it is useful to consider models without this component. Consequently, we estimate and present specifications with and without unobserved heterogeneity and look at the robustness of results on job displacements.

It is helpful to relate the econometric framework to a stylized marriage model where individuals decide to stay married as long as the value of the match surpasses the outside option. Let q_{0i} denote the match quality at the time of marriage for couple i; q_{0i} captures the partners' knowledge of their and their partner's personality traits as well as their expectations regarding the future. The match quality will evolve over time depending on choices (e.g. the decision to have children) and shocks (e.g. involuntary job losses). Let q_{ti} represent the match quality at time t, then we can write $q_{ti} = f(q_{0i}, q_{1i}, ..., q_{t-1i}, e_{ti})$ where e_{ti} represents the innovation to match quality at time t. Similarly, the outside option to the partnership, say z_{ti}, evolves over time depending on observable and unobservable factors. A divorce will occur when $q_{ti} - z_{ti} < 0$. The probability of divorce at time t for existing marriages -the hazard rate- is then a function of match quality relative to outside options and this in turn is dependent on the initial values and the innovations over time.

In the econometric framework explained above, the baseline hazard captures the evolution of the match quality over time (relative to outside options) that is systematic across couples. The time-invariant unobserved random effects capture the distribution of initial match quality (relative to outside options) across couples and the x variables measure the effects of couple and time specific observables on the match quality relative to outside options.

Since the data are annual and the exact timing of events during the year is unknown for most variables, our specification of the hazard links the probability of dissolution during a time period t with control variables measured at t-1. This will alleviate any reverse causality between divorce and explanatory variables in particular the job loss variables. We also include additionnal lagged observations of job losses. This can be motivated as follows. Consider a person-specific dismissal. This event implies a negative shock in earnings and a reduction in the value of the marriage. It also may signal a shift in the perceived characteristics of the partner and a further reduction in the value of the marriage. If this effect is only felt for a short time then including the one-period lagged dismissal is sufficient. If the job loss implies a permanent drop in earnings or a permanent revision in the value of the match then the job loss will permanently alter the probability of divorce. This means that all past job losses should also be included in the specification of the divorce probability. Effects of job losses that fade relatively quickly would require the inclusion of a few lags only. We experiment with various specifications of the lagged job loss variables. Finally assuming that redundancies are exogenous and do not convey signals regarding the partner's traits, we expect effects from longer lags in these displacements to be small relative to other forms of displacements as they represent dependence caused by earnings losses only.

The interpretation given to variations in the job loss variables is related to the potential endogeneity of these regressors. As seen above, reverse causality (the increased likelihood of a job loss due to the imminent breakdown of the partnership) can be reduced by taking into account the relative timing of the events. A second source of endogeneity, the omission of common important variables is in some sense a component of the model. In this case we consider the possibility that the probability of job loss and divorce could be correlated due to a common trait of the individual or match not observed in the data. In the context of our duration model, any variation across couples in unobserved traits that are time invariant or that evolve systematically over the length of the marriage will be controlled for by the couple-specific effects and the baseline hazard. There remains the possibility of an unobserved, match-specific and time-varying trait which is correlated with the job displacement.

In other words, a particular worker could be chosen for dismissal because he has a (previously unknown or unimportant) character trait which is then signalled by the displacement and leads to a revision of match quality and perhaps divorce. In this case, the effect of the job loss should be attributed at least in part to the signal rather than the job loss itself. This is what we believe to be the case for dismissals and temporary job endings and this is how we interpret their impacts. As seen below, the evidence for redundancies is quite different and points to less if any signalling role. To conclude, we also estimate models excluding job losses other than redundancies in order to see if the impact of redundancies remains stable after the omission of the likely endogenous job losses.

5. Results

After much experimentation with various specifications, our main model consists of a set of regressors that include two lags in the job loss variables, no unobserved heterogeneity, and a piece-wise linear log baseline hazard with three segments: years of marriage <7, 7≤ years of marriage ≤14, and 14< years of marriage. For comparison, we also present results of models that include a third lag in the job loss variables and unobserved heterogeneity. The main model is parsimonious and fits the observed data well. Figure 3 shows the raw smoothed incidence of divorce along with the predicted value obtained from the main model. As can be seen, the model performs very well except for the durations greater than 40 years where the number of observations is small.

Figure 3 here

To simplify the analysis we use a piece-wise linear specification in the log of the baseline hazard rather than the baseline hazard. (As seen in figure 3 this models fits the data well.) It does make the interpretation of the coefficients on the duration variables less straightforward but since these are not the main variables of interest we keep this specification. Experiments with other models of the baseline and inclusion of additional log linear segments do not improve significantly upon the chosen specification.[22] Also, as shown below the addition of unobserved heterogeneity has hardly any effect on the coefficients of the model. This is consistent with the baseline hazard capturing most of the correlation in the probability of divorce across time for individual couples.

The tables of results report coefficients and their standard errors. An element from the coefficient vector β, say β^k, represents the effect of a small change in x^k on the log hazard of a divorce if x^k is a continuous covariate; i.e. $\beta^k=\partial \ln(h(t))/\partial x^k$. For a categorical variable say x^j, β^j represents the shift in the log hazard: $\beta^j=\ln(h(t|x^j=1))-\ln(h(t|x^j=0))$. Results are also presented in the relative risk format ($\exp(\beta)$); these represent proportional changes in the hazard due to the change of x^j from 0 to 1 or the addition of 1 unit to x^k. For specifications with unobserved heterogeneity, the unobserved component is set at the mean value, that is $\varepsilon_i=1$. Standard errors are clustered by couple and are robust to correlation across time for the same household.

Table 4 presents models with 2 lags in the job loss variables. In the left-most column of results, the model includes one job loss variable representing the incidence of (at least) one involuntary displacement: either a dismissal, redundancy or temporary job ending. The effect is large; the probability of divorce almost doubles the following year. The average probability of divorce in any one year is around 2% hence a job loss would raise this to almost 4% on average for the sample. The effect persists and two years later the probability of divorce is still 90% higher. These are significant at conventional levels.

The middle column shows the effects on dissolution of job losses separately for the different types of displacement. Losing one's job due to a dismissal has the highest effect on divorce: the probability is increased by 150% one year later and 100% two years later. These are individually significant. A job loss due to redundancy has the smallest effect: 50% increase one year later and 16% two years later. The latter is not statistically significant. The effects of temporary job endings are in between the two. These results are consistent with the interpretations discussed above; that is, dismissals have a larger signalling content regarding the future match quality. Redundancies represent mostly negative earnings shocks and hence the effects are smaller and more short-lived. Both dismissals and redundancies have effects that taper off with time. The effect of temporary job endings does not decline in the second year but when 3 lags are used the effect tapers off over time and is insignificant for the third lag (these results are discussed below).

In all regressions, we find strong evidence of duration dependence in marital stability. In general, the longer partners have been together, the smaller the divorce hazard. This result is consistent with the traditional marriage model: the longer people have been married (or cohabitating), the more time they have had to familiarize themselves with their partners' characteristics and the more time they have had to evolve strategies for dealing with any problems. However, this negative duration effect does not hold for the intermediate years (7 to 14). Specifically, the log baseline hazard shows a steep decline for the first 7 years followed by a slightly increasing segment for the durations between 7 and 14 years and a gently declining hazard for durations longer than 14. This matches the observed data well as seen in Figure 3.

The right-most columns present results of a model similar to the main model except for the addition of unobserved heterogeneity or "frailty" in the form of a normally distributed random effect. A test that the unobserved effect is constant leads to the rejection of the null at conventional levels of significance (the p-value on the standard deviation of the random effect equals 0.047). Nevertheless the effects of this specification change on the estimated coefficients are minimal. Coefficients are affected at the second decimal point only and there are no sign reversals. None of the conclusions regarding the job loss variables are affected. It is interesting that the major effect on the baseline hazard is to make the first segment slightly flatter. This is not surprising since the unobserved heterogeneity now captures some of the negative duration dependence.

Turning to results of the main model with respect to other variables, we find that varying education levels causes significant effects on divorce probabilities but only in the middle of the education distribution. A lower high school qualification (CSE O level) raises the probability of divorce by 40% compared to the highest educational level which is that of a university degree. This is found for both men and women. The similarity of education across the two partners does not matter. This is consistent with overall results by Charles and Stephens (2004) in US data.

The wife's employment status and level of nonlabour income have no significant effects while the husband's nonlabour income shifts the hazard down significantly. Greater levels of monetary well-being may reduce stresses experienced by the relationship. It is interesting that in the British data we find no significant effects of the number of children on the probability of divorce. Charles and Stephens found a negative effect of children on the probability of divorce in US data. A large difference in age at the time of marriage increases the probability of divorce significantly by 35%. This could be an indication of poor match quality.

Table 5 presents coefficients on the job loss variables and the baseline hazard for specifications in which the number of lags on the displacement variables is varied. (Other regressors are the same as in the main model.) When only one lag is included, the job loss variables are individually and jointly significantly different from zero and quantitatively, they are not very dissimilar from the corresponding results in the main model. When 3 lags are included, results change substantially. In this case the sample size is reduced to 27,665 and only one coefficient is individually significant. Furthermore joint tests cannot reject the null that all 3 coefficients on the job loss variables lagged 3 times are zero. A joint test on the coefficients of the job loss variables lagged twice also does not lead to rejection of the null. It may be that the loss of sample observations and the presence of correlations across the lagged job loss variables prevent the measurement of existing persistent effects. In any case, long term dynamic effects of job loss cannot be detected in these models.

Charles and Stephens (2004) also found that the effects of job displacements were short run. In their specification, displacements in the previous 3 years were grouped and these had significant positive effects on the probability of divorce. There was no evidence of effects for those job losses that occurred in the previous 4 to 5 years. For job losses that occurred more than 5 years ago, a negative effect was found in the case of layoffs but no effects were detected for displacements due to plant closures. They interpret the long term effects from layoffs as an indication that the marriages involved survived a crisis and came out with a strengthened relationship. They also argue that the lack of effects in the medium term following a displacement can be perceived as evidence that the effects they do find (either from plant closures or layoffs) cannot be due to an omitted (time-invariant) variable. In the context of our paper, the omission of a time-invariant effect also cannot explain the effects of job displacements since results from the random effects model are virtually the same as those of the main model.

Table 6 presents 2 models in which the effect of job displacements is allowed to vary depending on the state of the economy or industry (these models include all other regressors added in the main model and listed in Table 3). A job loss that occurs during a recession will contain less of a signal about individual performance. If this is a significant component of the impact of the job loss, we expect to see a reduction of the effect during recessionary years. The top panel of Table 6 presents the coefficients on the job loss variables separately for the years 2000-01. Displacements in t-1 or t-2 are grouped to increase the incidence of job losses in the two recession years. Only temporary job endings are significant in 2000-01. Still the coefficient on redundancies doubles (the earning shock is higher in recessions) while that of dismissals is reduced by a factor of 4 (the signalling effect decreases).

The bottom panel of Table 6 shows coefficients on job loss variables separated by industry group. Specifically a three year moving average workforce growth rate is constructed for every industry. These data are sourced from published UK government statistics. Industries are grouped based on whether this growth rate is negative or positive and displacements from jobs in industries with declining employment are treated separately from those located in growing industries. (More details are available from the authors.) A displacement in a declining industry will generally not include the same signalling content as an involuntary job loss in a growing industry simply based on the probability of the event occurring.

We present results for models with one lag only (to increase sample size) and with displacements occurring with either one or two lags (to increase the number of displacements). The results for redundancies are again markedly different than for other job losses. The impact of redundancies is substantially greater and is only significantly different from zero in the declining industries. These results are consistent with the hypothesis that redundancies capture mostly the effects of negative earnings' or psychological shocks and these can be worse in declining industries given the difficulty of finding new and equivalent employment. For the other job losses the effects are substantially smaller in the declining industries or statistically indistinguishable in the 2 industry groups. With one lag, the effects of dismissals and temporary job endings are larger and only significantly different from zero in the growing industries (where the signalling effect is stronger). When 2 lags are allowed, dismissals and temporary job endings have significant effects in both sectors; however the effects are not statistically different from each other based on Wald tests[23].

Table 7 presents estimation results for a model in which all coefficients except for the baseline hazard are allowed to shift depending on whether the couple is part of the stock or flow sample[24]. As explained previously, we expect idiosyncratically long (short) matches to form part of the stock (flow) sample. For the stock sample, all coefficients on the job loss variables are similar although none of them are individually significantly different from zero[25]. The effects of dismissals and temporary job endings are greater for the flow sample, but only for temporary job endings is the difference significantly different from zero at conventional levels. A test of the null that the coefficients on the job loss variables are jointly zero in the flow sample shows that these variables are jointly highly significant ($\chi^2(3)$= 64.49 and p-value=0.000). For redundancies, the coefficient on the interaction is negative but insignificant. Again the effects differ markedly across job type and are consistent with the hypothesis that dismissals and temporary job endings contain a signalling effect which impacts more on the younger sample. Interestingly we recover the effect of children on durations found in the US data but only for the flow sample. The number of children is seen to increase the probability of divorce in the longer matches.

Table 8 presents results from the main model, the model with random effects and the model with separate effects for stock and flow sample for the specification which only includes redundancies as job losses. The purpose of this table is to see to what extent the effects of redundancies are driven by correlations with the other (potentially endogenous) displacements. The results are similar to those of the main model: redundancies significantly increase the risk of family dissolution one year after the job loss. The magnitude of the effect is slightly higher than previous findings (65% compared to 50%), an indication of a positive correlation across the three types of job losses. Other coefficients are consistent with the findings of the main model.

6. Conclusion

In this paper we have examined the effects of involuntary job loss on partnership dissolution, a topic that is particularly relevant in the current economic climate. Data from the British Household Panel Survey are used in the study. We distinguish between different types of job changes (dismissal, redundancy and temporary job ended) and we analyze their impacts on the probability of divorce in the year following the job displacement. In general job losses raise the probability of divorce and these effects are stronger for dismissals or temporary job endings.

The evidence presented in the various specifications support the hypothesis that job losses that are dependent on the worker's characteristics contain signals of future match quality and hence have a more important impact on the probability of match dissolution. Redundancies that are dependent on the employer's characteristics represent mainly earnings or psychological shocks and are smaller, shorter-term and have more influence in bad economic situations when the earnings shock is expected to be more serious. The effects of redundancies are statistically significant in the main model but are often insignificant on other specifications. In this sense, our results support those of Charles and Stephens (2004).

This analysis could be expanded in several directions. The incorporation of the wife's job loss is an obvious and interesting extension. Also, the role of social supports could be incorporated by distinguishing the impact of job loss in high unemployment areas. Finally, the role of expectations on job changes can be investigated using information on the worker's opinion regarding his job security. Individuals who expect to lose their jobs may be paid compensating wage differentials and these may partially protect the families from high distress and other negative outcomes. On the other hand, they may make the negative earnings' shock more severe.

The finding of significant effects of job losses on the probability of divorce has important consequences for the modelling of the impacts of displacements on families generally. Studies of the effect of job loss on family consumption or labour supply that only consider couples who remain married will produce biased results since the couples who remain together are those who had to face the fewest adjustments as a consequence of the loss of employment. Excluding divorced couples is likely to lead to an underestimate of the impact of job displacements.

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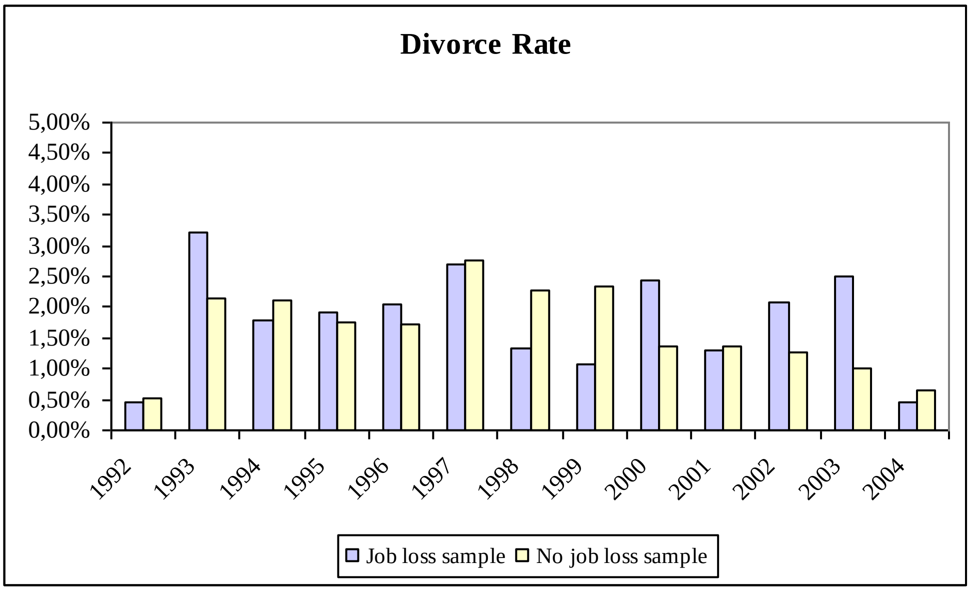
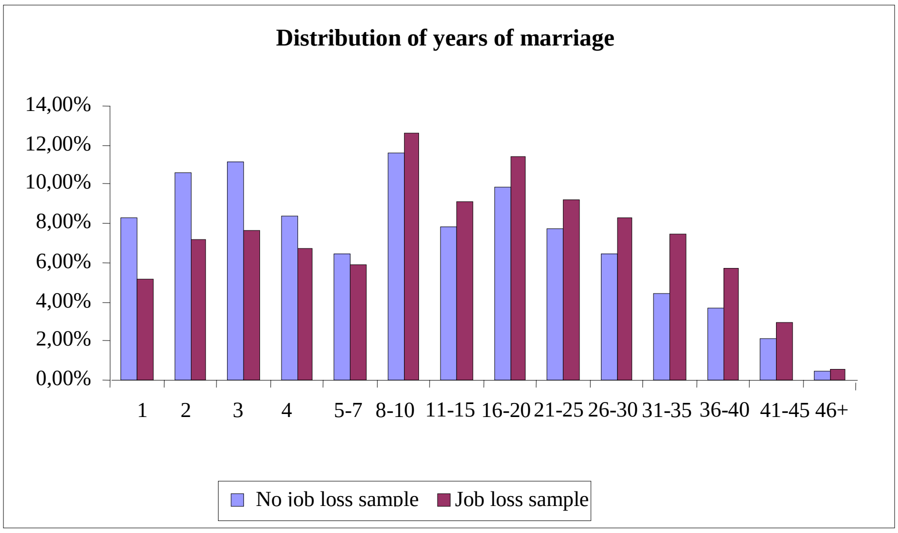
Figure 1 – Divorce rate by year, analysis sample



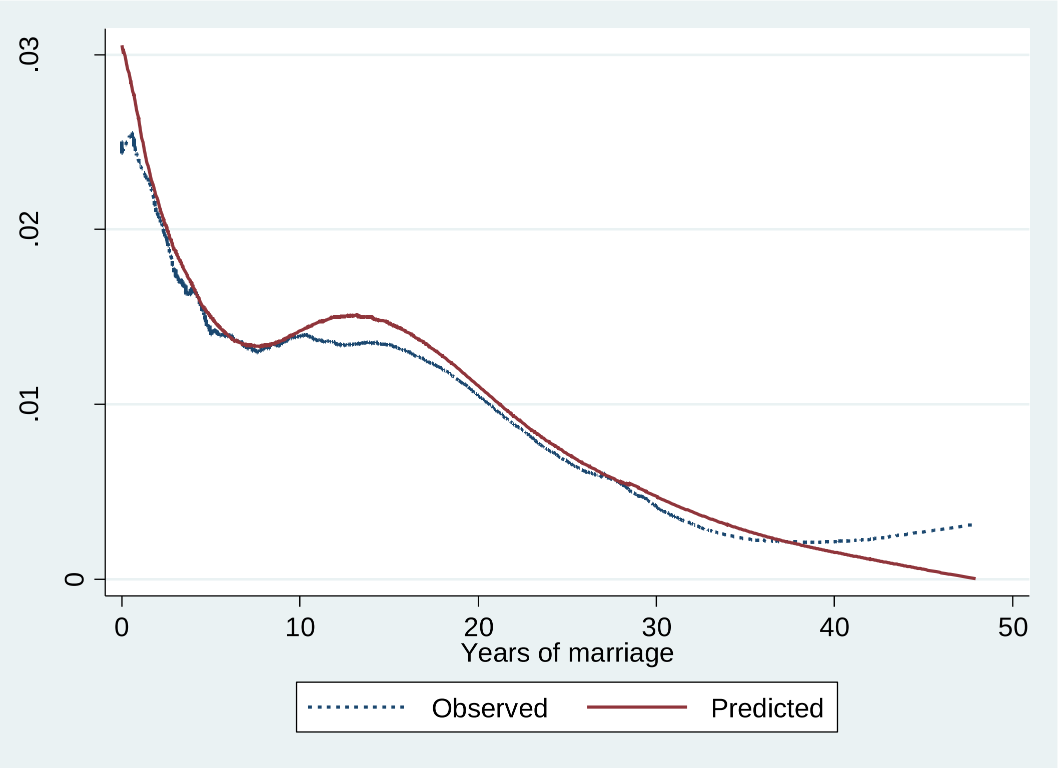
The sample contains 45,322 observations involving 7,517 couples. Divorces include separations.

Figure 2 – Distribution of years of marriage, analysis sample



The sample contains 45,322 observations involving 7,517 couples. Marriage includes cohabitation.

Figure 3 – Observed and predicted probability of divorce by duration of marriage



The predicted probability of divorce is generated from the main model and corresponds to the estimates presented in Table 3. In both cases, locally weighted regression smoothing is done using running-line least squares.

Table 1. Variable definition - additional regressors.

Duration of marriage	Expressed in years
Difference in age	1 if the difference in age >= 8 years
Similarity in education	1 if partners have the same highest qualification
Education: Degree	1 if the highest academic qualification is a university degree. This is the omitted category.
HND/A	1 if the highest academic qualification is HND (including teaching qualification, nursing or other higher qualification) or GCE A level (upper high school graduate)
O/CSE	1 if the highest academic qualification is GCE O level or CSE (lower high school graduate).
No qualification	1 is highest qualification is less than high school
Husband’s non labour income	In ‘0,000 £ (base year=2005).
Wife’s non labour income	In ‘0,000 £ (base year=2005).
Number of children	Number of dependent children in the household
Wife’s employment	1 if the wife is in paid employment or self employed

Table 2. Involuntary job displacements by year and type

Year	Dismissals			Redundancies			Temporary job endings		
	No.	% of total	% of couples	No.	% of total	% of couples	No.	% of total	% of couples
1991	18	8.8	0.68	129	10.1	4.91	39	6.8	1.48
1992	6	2.9	0.24	108	8.5	4.29	25	4.3	0.99
1993	14	6.8	0.58	113	8.9	4.67	38	6.6	1.57
1994	19	9.3	0.76	95	7.5	3.82	47	8.2	1.89
1995	10	4.9	0.42	68	5.3	2.83	35	6.1	1.46
1996	19	9.3	0.74	69	5.4	2.7	37	6.4	1.45
1997	16	7.8	0.66	82	6.4	2.89	38	6.6	1.34
1998	17	8.3	0.61	63	4.9	2.27	48	8.3	1.73
1999	19	9.3	0.63	78	6.1	2.57	40	6.9	1.32
2000	21	10.2	0.58	98	7.7	2.72	69	12.0	1.91
2001	27	13.2	0.53	208	16.3	4.07	99	17.2	1.94
2002	13	6.3	0.30	75	5.9	1.73	35	6.1	1.24
2003	4	2.0	0.09	50	3.9	1.12	15	2.6	0.81
2004	2	1.0	0.05	39	3.1	1.01	12	2.1	0.34
Total	205	100.0	0.45	1275	100.0	2.81	577	100.0	1.27

The sample size is 45,322. See the main text for definitions of the types of displacements. % of couples is the proportion of job losses relative to the number of couples in the analysis sample in the year in question. For the total, the % of couples refers to the proportion of displacements in the total number of observations.

Table 3. Means of socio-economic variables and divorce rates by job loss samples

	Job loss sample		No job loss sample	
	Sample mean	Divorce rate (%)	Sample mean	Divorce rate (%)
Men - Education				
High degree*	0.11	1.52	0.15	1.31
HND/A level	0.42	1.71	0.42	1.85
CSE/O level	0.22	2.35	0.21	1.86
No qualification	0.25	1.15	0.22	0.90
- Age at marriage				
14-19	0.08	3.20	0.05	2.74
20-25	0.38	1.70	0.32	1.65
26-30	0.22	1.49	0.20	1.62
31-35	0.13	1.58	0.12	1.38
36-45	0.12	1.08	0.15	1.02
>45	0.07	1.30	0.16	0.41
Mean age in years	28.00		32.00	
Women - Education				
High degree*	0.13	1.04	0.16	1.52
HND/A level	0.24	1.92	0.28	1.35
CSE/O level	0.32	2.04	0.29	1.61
No qualification	0.31	0.93	0.27	0.77
- Age at marriage				
14-19	0.22	2.53	0.15	2.33
20-25	0.38	1.64	0.33	1.63
26-30	0.16	0.97	0.15	1.37
31-35	0.08	2.08	0.11	1.03
36-45	0.10	1.14	0.13	0.78
>45	0.06	0.78	0.13	0.32
Mean age in years	26.00		30.00	
- Work status				
In paid employment or self employed	0.67	1.57	0.67	1.34
Unemployed, retired, family care, other*	0.33	1.84	0.33	1.33
Household non labour income				
0-1,000	0.35	1.55	0.35	1.72
1,001-5,000	0.41	1.68	0.38	1.35
>5,000	0.24	1.83	0.27	0.95
Mean income in £ (base year=2005)	3723.23		4327.32	
Number of children	0.91		0.84	
Couples with children	0.47	1.97	0.44	1.45
Couples without children	0.53	1.37	0.56	1.31
Partners have same education levels				
Yes	0.41	1.65	0.44	1.30
No	0.59	1.65	0.56	1.39
Difference in partners' age >= 8 years				
Yes	0.10	1.99	0.09	1.72
No	0.90	1.62	0.91	1.30

The number of observations is 11498 for the job loss sample and 33824 for the no job loss sample. * denotes an omitted group in regressions. See Table 1 and the main text for more details on the variables. For age, income and number of children, only the continuous variable is included in the estimation models.

Table 4 – Hazard models of the probability of dissolution. Sample size = 33460. (Standard errors)

Variables		**Any job loss**		**Main model**		**Random effects**	
		Coef	**Exp(coef)**	**Coef**	**Exp(coef)**	**Coef**	**Exp(coef)**
Job Loss:	Any job loss t-1	0.664***	1.942				
		(0.172)					
	Redundancy t-1			0.398*	1.489	0.393*	1.481
				(0.226)		(0.230)	
	Temp job end t-1			0.667**	1.949	0.725***	2.064
				(0.272)		(0.278)	
	Dismissal t-1			0.951**	2.587	0.982***	2.670
				(0.413)		(0.372)	
	Any job loss t-2	0.631***	1.880				
		(0.164)					
	Redundancy t-2			0.147	1.159	0.149	1.161
				(0.235)		(0.236)	
	Temp job end t-2			0.794**	2.213	0.825***	2.281
				(0.252)		(0.256)	
	Dismissal t-2			0.715*	2.044	0.745**	2.106
				(0.416)		(0.368)	
Education:	Husband – HND/A	0.114	1.121	0.106	1.112	0.113	1.119
		(0.160)		(0.159)		(0.168)	
	Husband – CSE O	0.323*	1.382	0.301*	1.351	0.349*	1.417
		(0.171)		(0.171)		(0.180)	
	Husband – No qual	-0.139	0.870	-0.132	0.876	-0.119	0.888
		(0.197)		(0.196)		(0.206)	
	Wife – HND/A	0.214	1.238	0.234	1.264	0.215	1.240
		(0.172)		(0.173)		(0.181)	
	Wife – CSE O	0.316*	1.371	0.343*	1.410	0.326*	1.385
		(0.182)		(0.182)		(0.189)	
	Wife – No qual	-0.094	0.911	-0.051	0.951	-0.072	0.931
		(0.220)		(0.221)		(0.226)	
Nonlabour	Wife	0.220	1.246	0.236	1.266	0.250	1.284
income:		(1.067)		(1.051)		(1.458)	
	Husband	-4.601***	0.010	-4.543***	0.011	-4.483***	0.011
		(1.489)		(1.487)		(1.632)	
Wife employed		-0.155	0.856	-0.134	0.875	-0.111	0.895
		(0.107)		(0.108)		(0.113)	
Number of children		0.016	1.016	0.021	1.021	0.015	1.015
		(0.046)		(0.046)		(0.049)	
Match	Age Diff > 8 yrs	0.306**	1.358	0.311**	1.365	0.248	1.282
quality:		(0.141)		(0.141)		(0.152)	
	Same educ level	-0.096	0.909	-0.089	0.915	-0.085	0.918
		(0.097)		(0.097)		(0.101)	
Baseline	Yrs marriage <7	-0.147***	0.864	-0.144***	0.866	-0.120***	0.887
hazard:		(0.031)		(0.031)		(0.031)	
	7≥ Yrs marriage ≤14	0.076***	1.079	0.073**	1.076	0.078***	1.081
		(0.029)		(0.028)		(0.029)	
	Yrs marriage >14	-0.080***	0.923	-0.078***	0.925	-0.082***	0.921
		(0.015)		(0.014)		(0.016)	
LogLikelihood value		-2314.60		-2310.69		-2289.85	
σ-st dev of the random effect						0.915 (0.047)	

Standard errors are robust to correlation across time for the same households. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and *** at 1%. The model is a proportional hazard with a piecewise linear log baseline hazard with breaks at 7 and 14 years. The random effects model assumes a Normal distribution for the match-specific effects.

Table 5. Sensitivity analysis - number of lags. Selected results. (Standard errors)

Variables	One lag included				Three lags included			
	Any job loss		Job loss by type		Any job loss		Job loss by type	
	Coef	Exp(coef)	Coef	Exp(coef)	Coef	Exp(coef)	Coef	Exp(coef)
Job Loss:								
Any job loss t-1	0.598***	1.818			0.539**	1.714		
	(0.149)				(0.214)			
Redundancy t-1			0.331*	1.392			0.194	1.215
			(0.202)				(0.299)	
Temp job end t-1			0.601**	1.823			0.953***	2.594
			(0.244)				(0.297)	
Dismissal t-1			1.059***	2.883			0.464	1.591
			(0.296)				(0.592)	
Any job loss t-2					0.454**	1.574		
					(0.211)			
Redundancy t-2							0.279	1.322
							(0.264)	
Temp job end t-2							0.493	1.636
							(0.345)	
Dismissal t-2							0.410	1.506
							(0.674)	
Any job loss t-3					0.332	1.393		
					(0.207)			
Redundancy t-3							0.189	1.208
							(0.261)	
Temp job end t-3							0.430	1.537
							(0.343)	
Dismissal t-3							-0.094	0.910
							(0.667)	
Baseline hazard:								
Yrs marriage <7	-0.144***	0.866	-0.143***	0.867	-0.161***	0.851	-0.162***	0.851
	(0.024)		(0.024)		(0.042)		(0.042)	
7≥ Yrs marriage ≤14	0.072***	1.075	0.072***	1.074	0.084***	1.088	0.082***	1.086
	(0.027)		(0.027)		(0.032)		(0.032)	
Yrs marriage >14	-0.083***	0.920	-0.083***	0.920	-0.072***	0.930	-0.071***	0.932
	(0.014)		(0.014)		(0.015)		(0.015)	
Number of observations	40080		40080		27665		27665	
LogLikelihood	-2862.43		-2859.88		-1744.13		-1740.78	
Wald test of H_0: all t-3 coeffs=0							$\chi^2(3)$=2.27 p-value=0.519	
Wald test of H_0: all t-2 coeffs=0							$\chi^2(3)$=3.62 p-value=0.305	
Wald test of H_0: all t-1 coeffs=0			$\chi^2(3)$=24.15 p-value=0.000				$\chi^2(3)$=11.54 p-value=0.009	

Standard errors are robust to correlation across time for the same households. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and *** at 1%. The model is a proportional hazard with a piecewise linear log baseline hazard with breaks at 7 and 14 years. Other regressors include: employment status of the wife, education category of the husband and the wife, number of children, match quality variables (difference in age and education levels), and nonlabour income of the husband and wife.

Table 6. Sensitivity analysis – variation across industry group and recessionary years.

a. Job loss interacted with recessionary years dummy:				
	Non recessionary years		**2000-01**	
	Coef	**Exp(coef)**	**Coef**	**Exp(coef)**
Job loss in either t-1 or t-2 (sample size 33460)				
Dismissal t-1 or t-2	1.356***	3.879	0.341	1.406
	(0.262)		(0.735)	
Temp job end t-1 or t-2	0.782***	2.187	1.086***	2.962
	(0.245)		(0.335)	
Redundancy t-1 or t-2	0.225	1.253	0.446	1.562
	(0.215)		(0.303)	
LogLikelihood	-2310.23			
Wald test of H_0: no diff. across years	$\chi^2(3)$= 2.34 (p-value= 0.504)			
b. Job loss interacted with industry group:				
	Growing industry group		**Declining industry group**	
	Coef	**Exp(coef)**	**Coef**	**Exp(coef)**
Job loss in t-1 only (sample size 40080)				
Dismissal t-1	1.043***	2.840	0.860	2.360
	(0.358)		(0.587)	
Temp job end t-1	0.789***	2.202	0.318	1.375
	(0.277)		(0.502)	
Redundancy t-1	0.247	1.280	0.553**	1.740
	(0.288)		(0.294)	
LogLikelihood	-2858.2642			
Wald test of H_0: no diff. across ind.	$\chi^2(3)$= 1.13 (p-value=0.77)			
Job loss in either t-1 or t-2 (sample size 33460)				
Dismissal t-1 or t-2	0.936***	2.549	1.111**	3.040
	(0.307)		(0.474)	
Temp job end t-1 or t-2	1.047***	2.850	0.733**	2.850
	(0.220)		(0.357)	
Redundancy t-1 or t-2	0.052	1.054	0.610**	1.840
	(0.255)		(0.257)	
LogLikelihood	-2303.83			
Wald test of H_0: no diff. across inds	$\chi^2(3)$= 2.71 (p-value= 0.44)			

Standard errors (in parentheses) are robust to correlation across time for the same households. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and *** at 1%. Models with industry group interactions also include interactions with a missing industry dummy. In all models, other independent variables are the same as those listed for the main model. When including a second lag, job losses are grouped across the 2 lags to increase the number of displacements. The number of job losses in the years 2000-01 with one lag is small, in particular the effect of dismissals cannot be estimated. These results are not presented. See the main text for more details and for the definition of the industry groups.

Table 7. Sensitivity analysis – variation across stock and flow samples. Sample size = 33460

Variables	Stock sample (married before 1991)		Flow sample (married on or after 1991) Differences from stock sample	
	Coef	**(st err)**	**Coef**	**(st err)**
Job Loss:				
Dismissal t-1 or t-2	0.376	(0.584)	0.946	(0.653)
Temp job end t-1 or t-2	0.291	(0.419)	0.798*	(0.483)
Redundancy t-1 or t-2	0.389	(0.259)	-0.257	(0.359)
Education:				
Husband – HND/A	0.357	(0.250)	-0.356	(0.326)
Husband – CSE O	0.237	(0.275)	0.117	(0.351)
Husband – No qual	0.266	(0.292)	-0.752*	(0.403)
Wife – HND/A	-0.111	(0.261)	0.505	(0.348)
Wife – CSE O	-0.002	(0.273)	0.472	(0.367)
Wife – No qual	-0.379	(0.325)	0.472	(0.442)
Nonlabour income:				
Wife	1.307	(2.315)	-0.554	(2.456)
Husband	-2.237	(1.729)	-5.144*	(2.985)
Wife employed	0.133	(0.173)	-0.440**	(0.223)
Number of children	0.145*	(0.075)	-0.244**	(0.096)
Match quality:				
Age Diff > 8 yrs	0.361*	(0.215)	-0.192	(0.292)
Same educ level	0.086	(0.147)	-0.336*	(0.198)
Baseline hazard:				
Yrs marriage <7	-0.211***	(0.035)		
7≥ Yrs marriage ≤14	-0.020	(0.031)		
Yrs marriage >14	-0.069***	(0.016)		
Constant	-3.048***	(0.399)	-0.368	(0.441)
Number of observations	18279		15181	
LogLikelihood	-2282.23			
Wald test of H_0: no differences across samples	$\chi^2(16)$= 60.77 (p-value= 0.000)			

A single model is estimated across both samples and interactions with a flow sample dummy are included for all variables except the marriage durations. Interactions on the baseline segments were all highly insignificant and were excluded. Job losses across two lags are grouped to reduce the number of coefficients. Please see the main text for more details. Standard errors (in parentheses) are robust to correlation across time for the same households. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and *** at 1%.

Table 8. Hazard models excluding job losses other than redundancies.

Variables	Main model		Random effects		Separate stock and flow samples			
					Stock sample		Flow sample	
							(diff. from stock)	
	Coef	Exp(coef)	Coef	Exp(coef)	Coef	Exp(coef)	Coef	Exp(coef)
Job Loss:								
Redundancy t-1	0.501**	1.65	0.491**	1.633				
	(0.222)		(0.230)					
Redundancy t-2	0.297	1.345	0.277	1.320				
	(0.226)		(0.232)					
Redundancy t-1 or t-2					0.408	1.504	-0.057	0.944
					(0.255)		(0.346)	
Education:								
Husband – HND/A	0.120	1.128	0.117	1.124	0.356	1.428	-0.334	0.716
	(0.160)		(0.167)		(0.250)		(0.327)	
Husband – CSE O	0.336*	1.399	0.369*	1.446	0.237	1.268	0.155	1.167
	(0.171)		(0.179)		(0.274)		(0.352)	
Husband – No qual	-0.131	0.877	-0.126	0.881	0.265	1.303	-0.756*	0.469
	(0.197)		(0.206)		(0.291)		(0.405)	
Wife – HND/A	0.208	1.231	0.197	1.217	-0.115	0.891	0.489	1.631
	(0.171)		(0.181)		(0.261)		(0.347)	
Wife – CSE O	0.319*	1.375	0.310*	1.364	-0.003	0.996	0.471	1.602
	(0.181)		(0.188)		(0.272)		(0.366)	
Wife – No qual	-0.084	0.919	-0.092	0.912	-0.376	0.686	0.437	1.548
	(0.219)		(0.225)		(0.325)		(0.442)	
Nonlabour income:								
Wife	0.300	1.350	0.301	1.352	1.359	3.892	-0.525	0.591
	(0.973)		(1.409)		(2.293)		(2.403)	(1.421)
Husband	-4.696***	0.009	-4.620***	0.009	-2.226	0.108	-5.341*	0.005
	(1.470)		(1.623)		(1.732)		(2.922)	
Wife employed	-0.171	0.843	-0.148	0.863	0.133	1.142	-0.511	0.599
	(0.107)		(0.112)		(0.172)		(0.221)	
Number of children	0.018	1.020	0.014	1.014	0.148	1.159	-0.251***	0.778
	(0.046)		(0.050)		(0.074)		(0.096)	
Match quality:								
Age Diff > 8 yrs	0.310*	1.364	0.251*	1.286	0.360*	1.433	-0.176	0.838
	(0.140)		(0.151)		(0.214)		(0.291)	
Same educ level	-0.096	0.908	-0.089	0.914	0.084	1.087	-0.322	0.724
	(0.096)		(0.101)		(0.146)		(0.197)	
Baseline hazard:								
Yrs marriage <7	-0.150***	0.861	-0.125***	0.882	-0.221***	0.802		
	(0.031)		(0.030)		(0.034)			
7≥ Yrs marriage ≤14	0.073**	1.076	0.076**	1.080	-0.021	0.979		
	(0.028)		(0.028)		(0.031)			
Yrs marriage >14	-0.080***	0.923	-0.083***	0.920	-0.068	0.933		
	(0.014)		(0.015)		(0.016)			
LogLikelihood	-2329.0415		-2307.4718		-2302.4884			
Wald test of H_0: no diff. across samples					$\chi^2(14)$= 29.43 (p-value= 0.0212)			

Standard errors are robust to correlation across time for the same households. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and *** at 1%.

[1] We thank participants of the 2007 Australian Labour Market Research workshop and the 2008 Australian Conference of Economists for their suggestions and comments. The BHPS data was provided by the Economic and Social Research Council's Data-Archive at the University of Essex and is used with permission. The usual disclaimer applies.

[2] The related issues of endogeneity in the job loss and the identification of causal effects on divorce are discussed below.

[3] Several studies of the effects of job displacements on earnings have used plant closures as exogenous displacements (see for example Gibbons and Katz, 1991 for the US and Doiron, 1995 for Canada). In these studies, the use of large cross section surveys meant that rare events such as plant closures could be treated separately. Information on plant closures is not available in the BHPS.

[4] The number of observations with displacements due to plant closures is not provided but the estimation results (some substantial quantitative effects with large standard errors) suggest that perhaps the number of such job losses is too small to yield sufficient precision in the estimates.

[5] Eliason uses propensity score matching to compare two samples of married individuals with one sample consisting of persons who have experienced a plant closure during the year 1987. Length of marriage is used as a matching variable but this variable only distinguishes between unions of less than 3 years.

[6] Separate estimations for stock and flow samples essentially halve the sample size and individual coefficients are more imprecise. Please see below for details.

[7] See also Eliason (2004) for a more detailed explanation of this model.

[8] A related strand of the literature considers the impact of earnings' shocks generally on family consumption and production. See for example Browning and Crossley (2001) and Cullen and Gruber (2000).

[9] See Darity and Goldsmith (1996) for a review.

[10] Studies have also found negative impacts of unemployment on the well-being of spouses and children. Most of these papers are also found in other fields of study such as psychology and social sciences (see Strom, 2003; Voydanoff, 1990 and Kalil and Ziol-Guest, 2007).

[11] Additional samples of 1,500 households in each of Scotland and Wales were added in 1999, and in 2001 a sample of 2,000 households was added in Northern Ireland, making the panel suitable for UK-wide research. These samples are included in our analysis.

[12] We would ideally like to know the date at which individuals felt their marriage end, regardless of the legal date of divorce or separation but this is not easily defined.

[13] Around 25 couples.

[14] A sensitivity analysis is conducted by constructing a binary variable for couples who disappear from the survey and re-appear with a different marital status. This variable is introduced in our main models and does not affect the sign and significance of job loss variables. Results are available on request.

[15] Those couples where the man reaches 65 during the survey period are dropped at the time the man reaches 65 and treated as right-censored.

[16] The proposed alternatives are: self employed, in-paid employment (full time or part time), unemployed, retired from paid work, on maternity leave, looking after family or home, full time student/at school, long term sick or disabled, on a government training scheme, something else.

[17] See Borland et al. (2000) and Taylor and Booth (1996).

[18] Previous research suggests that spousal labour income may be endogenous to job displacement so the wife's labour income is not part of the main model.

[19] There is a limited incidence of repeated job loss of the same type in the same year mostly involving temporary job endings. Specifically, out of all observations with either a dismissal or redundancy (1480 couple - year), 106 or 7% have more than one occurrence of the job loss. Not surprisingly, the number is a lot higher for temporary job endings (21%). Sensitivity analysis is conducted with the addition of dummies for the observations with multiple occurrences and results are very similar to those reported below. Details are available from the authors.

[20] For more information on this material see Jenkins (1995) and Wooldridge (2002).

[21] Correlations between time-invariant and couple-specific variables (such as match quality indicators) are allowed as long as the variables are included in the vector of covariates and the correlations are explicitly modelled.

[22] More specifically, baseline hazards with 4 and 5 linear segments were estimated; also alternative break points at 4, 10 to 14, 20, and 30 were used and in all cases the likelihood was not significantly improved. In addition the job loss coefficients were virtually unchanged. Details are available upon request.

[23] Specifically a test of the null that the coefficient on dismissals in growing industries is the same as that in declining industries yields a $\chi^2(1)$ value of 0.09 which corresponds to a p-value of 0.7653. The figures for a similar test on temporary job endings are $\chi^2(1)= 0.54$ and p-value=0.4619.

[24] Interactions with the three baseline hazard coefficients were all highly insignificant and were excluded.

[25] A test of the null that the coefficients of the 3 job losses are jointly zero yields a $\chi^2(3)$ value of 3.76 which corresponds to a p-value of 0.2887.