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by

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JEL Codes: J12, J60, J63

Keywords: job loss, divorce, marriage duration

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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 1991).

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).

The analysis of the relationship between job loss and family dissolution is particularly appropriate in this context. 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 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.

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 of the union and we estimate discrete time duration models. Individual and family characteristics are included and in some specifications, unobserved, time-invariant and match-specific random 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 expected to represent effects of earnings shocks only.

According to the legal definition of redundancy in the UK, this type of job loss should be uninformative about the individual's traits. 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) 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 reduce the potential bias from endogenous variations in job losses[2].

A job loss that contains a signal of the individual's characteristics is more likely to be correlated with unobservable components of match quality and lead to endogeneity bias. Furthermore, this bias is expected to be positive in the sense that it inflates effects of the job loss variables. Much of the empirical analysis conducted in the paper is designed to provide evidence on whether the different types of job loss impact differentially on the probability of divorce. The results all point to the treatment of redundancies as exogenous events in this context.

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[3]. 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[4]. 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 hazard and look at selection into the stock and flow samples. Finally, cohabitations are included in the analysis.

Whether the displacement contains a signal of unfavourable individual traits or simply represents an earnings shock has several implications in the empirical analysis. For example, “person-specific” dismissals are expected to have more severe and longer lasting impacts on divorce probabilities. This is in fact what we find. A redundancy experienced by the husband has positive but insignificant effects on the probability of family dissolution. The impact of dismissals is much higher - an increase of around 154% one year later - and statistically significant. (The average divorce rate for the sample is between 1 and 2% per year.) Effects of temporary job endings are generally located between the two. The addition of lags in the job loss variables does not change these overall results. Random effects specifications also yield similar results, an indication that our model of the baseline hazard is sufficiently flexible to capture the correlation caused by match-specific unobservables across time.

Using information on the workforce growth rate by industry, we separate job losses occurring in declining and growing industries. Displacements in declining industries are less likely to represent signals of unfavourable individual traits. Results differ considerably by type of job loss; redundancies from declining industries have a significant positive effect on the probability of divorce (a 100% increase one year later) while dismissals have a significant effect only in expanding industries (an increase of 161%). Again results are robust to semi parametric random effects specifications. These findings are consistent with the view of redundancies as capturing earnings shocks while dismissals contain signals of a bad match. Earnings shocks are more serious in declining industries given the difficulty of finding new and equivalent employment while unfavourable individual traits are more likely explanations of displacements in tight labour markets.

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 (10 to 20 years of marriage) where the probability of divorce is increasing with time ceteris paribus. The wife’s nonlabour income and age increase the probability of divorce as do large differences in the partner’s ages. Other regressors are generally individually insignificant. This is partly due to specification choices; we concentrate on the effects of job losses and adopt flexible specifications for all other variables.

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 divorce. 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 (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 first elaborated by Hill (1949) and later by McCubbin and Patterson (1982)[5]. A job displacement can be considered as a stressor event and have an impact on the family's coping resources potentially leading to a crisis or a resolution. 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. 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 Lundberg and Pollak (1996), both partners behave noncooperatively and treat divorce as an outside option. Finally, in a recent study, Matouschek and Rasul (2004) develop stylised models of marriage as an exclusive contract. In a repeated games context, marriage can act as 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[6].

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[7] 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[8].

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 the husband's earnings lowers the probability of marriage dissolution, while a positive shock in the 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[9]. 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 household 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[10]. 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[11].

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[12] 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[13]. 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[14].

The analysis sample includes second and later marriages. Also we include both flow and stock samples. The flow sample consists of marriages starting in 1991 or later while the stock sample includes unions in existence at the start of the survey period. Models that distinguish between these samples are estimated 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[15], 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. There are a few reasons for this. In many households men are the primary earners and their job loss will cause the largest earnings shocks hence we are more likely to find impacts through that channel[16]. Secondly, female labour market mobility is much greater and due to a variety of reasons (e.g. child bearing and rearing). Modelling these movements appropriately is complex. In the following we add a control for the wife's employment status hence our results are conditional on the employment profile of the female partner. Our paper is a first step in a broader model of household behaviour that incorporates both male and female job losses.

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. (1999) and treat redundancies differently based on the industry of the job just ended. Specifically, data on industry-specific workforce growth rates are collected from published UK government statistics and a variable measuring a three year moving average growth rate for each industry is constructed. In some estimation models, job displacements are separated depending on whether they refer to jobs in industries with declining or growing employment.

Appendix 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 one month. Empirically, both yearly and monthly incomes produce very similar results. Nonlabour income is included separately for the wife and husband[18].

Other variables included are: age of husband, age of wife, highest educational qualification attained (Degree, HND/A level, CSE/O level, No qualification), number of children in the household, 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. We include information about the difference in age of the partners (a dummy variable equal to one if the difference in age is greater than 8 years) and similarities in educational attainment (a dummy variable equal to one if the partners have the same education category) to capture variations in match quality across couples.

For most models presented below the sample consists of 33463 observations involving 6134 couples. In terms of potential divorces, this sample covers the period 1993 to 2005. The reason for the omission of 1991 and 1992 is as follows. All regressors are measured with a lag to prevent reverse causality and because we do not know the exact timing of the divorce during the year. For example, for someone who experienced a job loss between interviews in 1998 and 1999, we will associate the occurrence of divorce or the continuation of the union between the interviews in 1999 and 2000. Hence, in the main sample, divorces can occur between 1993 and 2005 while the exogenous variables are measured over the period 1992 to 2004. Furthermore, in several models we include a second lag in the observed displacements (this is discussed below) so in these cases, the estimation data include occurrences of job losses over the years 1991 to 2004.

Figure 1 displays the percentage rate of divorce/separation for couples who are in the analysis sample. The sample is divided into 2 groups: those couples who experience at least one job loss over the sample period and those who do not. From these raw numbers, we can see that on average between 1 and 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, 512 dissolutions are observed in the sample.

Insert figure 1 here

Table 1 presents the number of job losses by year in the analysis sample. In total, there are 1,413 displacements consisting of 900 redundancies, 131 dismissals and 382 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 is around 4 to 5%. This shows the importance of large samples when studying the 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) and would seem to contradict the theoretical predictions discussed above. However, these figures do not take into account other characteristics. 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 and in particular, state dependence in the effect of marital duration.

Insert Figure 2 here

Table 2 presents sample means of demographic and socio-economic variables among couples with and without job loss experience. Focussing on differences that are significantly different from zero, we find that the sample of couples where husbands do not experience any job loss over the sample period is slightly older (both partners), better educated (both partners) and the household nonlabour income is higher. This is consistent with a stereotypical view of those households where partners are relatively successful in the labour market and hold more secure jobs. Having the same education level is more common in the sample of couples without any job loss, an indication of better match quality. The table includes the divorce rate by sub-groups for the two samples. In general, couples with a job loss experience also have higher divorce rates but most differences between divorce rates by sub-groups are not significant. The highest divorce rates are found for partners who are young and who have middle to low educational qualifications.

4. Estimation methods

We estimate a discrete time proportional hazards model, to investigate the effect of job loss on the probability of a marital dissolution during time interval (t, t+1), given that the partnership has survived until time t. A discrete time representation of the continuous time proportional hazards model is given by:

$$h_i(t) = \Pr[t < T_i \leq t + 1 | \, T_i \geq t, \beta' X_i(t), \gamma(t), \alpha_i]$$
$$= 1 - \exp[-\exp\{\beta' X_i(t) + \gamma(t) + \alpha_i\}] \quad (1)$$

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 potentially vary across unions and time, β is a vector of coefficients common across time and unions, 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 continuous time baseline hazard between t and t+1. Variables and parameters are assumed constant between t and t+1 for all t. We have made the usual assumption of common effects of the covariates across unions; unobserved individual heterogeneity in the hazard model takes the form of intercept shifts through the vector α which is further specified below. Finally, the complementary log-log form of the hazard is implied by the underlying continuous time proportional hazards specification.

To take into account censoring, the sample log-likelihood function of the observed duration data is written with the aid of a dummy variable c_{it} equal to 1 if $t < T_i \leq t + 1$ and the marriage is non-censored (a divorce is observed during the time interval (t, t+1)) and $c_{it} = 0$ otherwise (the marriage continues on to the next interval or is censored). The log-likelihood function can be written as:

$$\ln L = \sum_{i=1}^{N} \sum_{t=\tau_i}^{T} [c_{it} \, \ln(h_i\,(t)) + (1 - c_{it}\,) \ln(1 - h_i\,(t))] \quad (2)$$

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 1992 for the stock sample (constructed using the starting date of the union). Independence between T_i and c_{it} conditional on $X_i(t)$ is a maintained assumption[20] (see Wooldridge, 2002, page 708).

The main issues in specifying this model revolve around the form of the baseline hazard and the presence and form of couple-specific, time-invariant and unobserved effects denoted as α in (1). These components of the model represent the systematic evolution of relationships over time (over and above that captured by the covariates) and the presence of unobserved match quality respectively. We adopt a flexible baseline that takes the form of a set of dummies $\gamma(\tilde{t})$ equal to 1 if the observation is in time interval $\tilde{t}$ and 0 otherwise. Ideally a full set of dummy variables (one for each year covered in the sample) would be used. However due to small number of observations, we group dummies over the following year intervals: $(0-1, 2-4, 5-6, 7-10, 11-15, 16-20, 21-25, 26-30, 30+)$. As seen below the individual dummies are mostly insignificant with this many categories (they are usually jointly significant), but since we do not care about the individual coefficients we do not group them into coarser durations. An overly restrictive baseline hazard will not fully take into account correlations in unobservables across time and lead to inefficient estimates. As discussed next, we check for this with alternative approaches.

In the simplest models presented below, there are no couple-specific time-invariant unobserved effects. 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). However, 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. Separating out unobserved heterogeneity from duration dependence does not change the effects of the covariates on the mean duration (see Wooldridge, 2002, page 706). In other words, the specification of a flexible baseline hazard capturing both duration dependence and unobserved heterogeneity works just as well for our purposes. Nevertheless, models with flexible couple-specific time-invariant effects are useful as a specification check and we use the robustness of our results as an indication of how well the baseline hazard is specified.

In the models with time-invariant unobserved heterogeneity, random effects independent of the covariates and the censoring times are assumed[21]. In the most flexible specifications, we use a semi-parametric distribution based on the work of Heckman and Singer (1984) and Meyer (1990)[22]. Specifically the unobserved heterogeneity is assumed to be multiplicative in the hazard rate specification:

$$h_i(t) = 1 - \exp[-\exp\{x_i(t)'\beta(t) + \gamma(t) + \ln(\varepsilon_i)\}] \tag{3}$$

where ε_i has a discrete distribution with a small number of mass points. The models with unobserved heterogeneity shown below are estimated under the assumption of 2 mass points (a model with 3 mass points is also estimated as a robustness check). An alternative model with normally distributed random effects is also estimated and the results are qualitatively and quantitatively very similar to those using the discrete distribution. More details are provided below.

Generally, flow samples are drawn from a population of short spells since their duration is limited by the survey period (in our case 1991-2005). 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 18279 observations (with 222 divorces and 697 job losses) while the flow sample numbers 15184 (with 290 dissolutions and 716 job losses). In order to check that the specification of the hazard (in particular the baseline hazard) is sufficiently general to represent the non-random selection between stock and flow samples, we estimate models that distinguish between the subsamples. Results are summarized below.

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 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 explanatory variables measure the effects of couple and time specific observables on the match quality relative to outside options.

As mentioned above our specification of the hazard links the probability of dissolution during a time period t with control variables measured at t-1. We also include additional 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. Note that if, as expected, redundancies do not convey signals regarding the partner's traits, the impacts from longer lags in these displacements should be small relative to other forms of displacements as they represent effects caused by earnings losses only.

Taking into account the relative timing of the events does not necessarily control for all sources of endogeneity of the job losses with respect to the probability of divorce. The issue arises because of imperfect measurement of the match quality at the time of the job loss. 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 occurrence of a job displacement. Consider a particular worker who is chosen for dismissal because he has a particular character trait. If this character trait is correlated with an unobserved component of the match quality (e.g. the trait matters more because the match quality is poor relative to other similar couples and relative to previous values of the match quality for this couple) then we will incorrectly attribute some of the effect of the match quality to the job loss.

The possibility that a job loss captures both an income effect and a signal of an unfavourable character trait does not necessarily lead to a problem for the causal interpretation of the impact of job loss. The problem arises only when this character trait is correlated with omitted factors such as unobserved match quality components. A job loss that doesn't depend on the worker's traits will not pose this problem and our evidence suggests that this is the case for redundancies. As a robustness check, 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 possibly endogenous dismissals and temporary job endings.

5. Results

In the estimation models presented below, the explanatory variables are measured at t-1 for divorce risks at time t except where explicitly indicated. Estimates are presented in the relative risk format ($\exp(\beta)$); for an element of the coefficient vector β, say β^k, these represent proportional changes in the hazard due to the change of X^k from 0 to 1 in the case of a discrete variable or the addition of 1 unit to X^k if X^k is continuous. Standard errors are appropriately transformed. Generally, we present standard errors that are robust and clustered by couple so that inferences are valid in the context of a quasi-maximum likelihood framework where the standard distributional assumptions do not hold. In the models with random effects, we present the usual standard errors. (In practise the robust and clustered standard errors are very similar to the unadjusted ones, an indication that our specification is sufficiently flexible in capturing correlations in durations across time.)

In Table 3 we present results on the job loss variables for a variety of specifications. (Results concerning other regressors are presented below.) 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, a redundancy or a temporary job ending. The effect is large; the probability of divorce increases by 87% the following year. The average probability of divorce in any one year is around 1 to 2% hence a job loss would raise this to about 3% on average for the sample. There is evidence that the effect persists; with two lags, the probability of divorce is increased by 66% the following year and 52% two years later. These are individually and jointly significant at the 1% level.

The middle column shows the effects on dissolution of job losses separately for the different types of displacements. Losing one's job due to a dismissal has the highest effect on divorce: the probability is increased by 154% one year later in the model with one lag. A job loss due to redundancy has the smallest effect (39%) and it is not statistically significant. The effect of temporary job endings is in between the two, and statistically significant. In the model with two lags the coefficients on the redundancy variables are individually and jointly statistically insignificant. Although positive, they are also quantitatively much smaller than those on other job loss variables. For dismissals, only the effect of the first lag is statistically significant and it is comparable to that found in the model that includes one lag only. Both dismissals and redundancies have effects that taper off with time but this is not the case with temporary job endings. For this reason we estimate a model with three lags in the job loss variables[23]. In this case the coefficients on temporary job endings fall as the lag increases and the coefficient on the third lag is individually insignificant with a p-value of 0.841[24]. (Results on the model with three lags are available upon request.) Long term dynamic effects of job loss cannot be detected in these models[25].

The right-most columns correspond to a model where job loss variables are interacted with industry group dummies. Industries are grouped based on whether a three year moving average workforce growth rate is negative or positive and displacements from jobs in industries with declining employment are treated separately from those located in growing industries. We expect that a displacement in a declining industry will not include the same signalling content as an involuntary job loss in a growing industry simply based on the probability of the event occurring.

The results for redundancies are again markedly different than for other job losses. The impact of redundancies is larger and is significant in the declining industries. For the other job losses the effects are also substantially larger and significant but only for the expanding industries (with the exception of the second lag in the temporary job ending variable that is significant in both industry groups). The probability of divorce is doubled for a couple in which the husband experienced a redundancy from a declining industry while the probability is increased by over 160% when the husband experienced a dismissal from an expanding industry.

In Table 4 we present results for semi-parametric models with random effects distributed discretely with two mass points[26]. (Models with normally distributed random effects yield very similar results with coefficients generally differing at the second decimal point. These are available from the authors.) The effects of this specification change on the estimated coefficients are marginal. Without the industry group interactions, the only important change is that the dismissal dummy lagged twice becomes marginally significant. With industry interactions, the temporary job endings variable lagged twice becomes insignificant in declining industries. None of the general conclusions regarding the job loss variables are altered. We can interpret this as an indication that our model of the baseline hazard is flexible enough to capture most of the correlation across time in unobservables.

Overall, the results in Tables 3 and 4 are consistent with the interpretations discussed above; that is, redundancies represent mostly negative earnings shocks and hence the effects are smaller and more short-lived. Dismissals are expected to have a larger signalling content regarding the future match quality and hence a greater impact on the probability of dissolutions. Also since they capture mostly the effects of negative earnings shocks, redundancies have worse effects in declining industries compared to expanding industries given the difficulty of finding new and equivalent employment in these sectors. The fact that dismissals and temporary job endings have more substantial effects in expanding industries is also consistent with a signalling role for these displacements; that is, unfavourable traits are more likely explanations of displacements in tight labour markets.

Results with respect to other regressors for selected specifications are presented in Table 5. We note that these estimates are similar across the columns and are generally insensitive to the specific form used for the job loss variables. There are greater changes when random effects are added to the model but qualitative results are unaffected. We find positive and significant effects from the non labour income of the wife. The wife's age shifts the hazard down while the dummy capturing a difference in age between partners greater than 8 shifts the hazard up. Increasing both partners' age by one year shifts the hazard down (the exponential of the sum of the coefficients is 0.923) an indication of greater marital stability with the age of the partners (note that this is over and above the effects of the duration of the marriage). Shifts in education are insignificant in these models as well as similarity of education across partners[27]. It is interesting that in the British data we find no significant effects of the number of children on the probability of divorce. In contrast, Charles and Stephens (2004) found a negative effect of children on the probability of divorce in US data. The baseline hazard dummies are generally individually insignificant although jointly they are significant at a 5% level in all specification. (We discuss the shape of the baseline hazard further below.)

Given our interpretation of dismissals and temporary job endings as capturing signals of unfavourable traits, the question arises as to the possible endogeneity of these job loss variables. As discussed above, if the trait being signalled is correlated with the match quality and if match quality is imperfectly controlled for, then an endogeneity bias will result. Furthermore, we would expect the bias to be positive in the sense that the strength of a signal of an unfavourable trait is likely to be negatively correlated with match quality and hence increase the likelihood of divorce. In other words the bias would increase the estimated impact of the job loss variables. Since the inclusion of endogenous variables potentially biases all coefficients, we also estimate models where both dismissals and temporary job endings have been omitted. The effects of redundancies are slightly increased quantitatively, an indication of a slight correlation across types of job losses, but none of our overall conclusions regarding the effects of redundancies are affected. (Results are available upon request.)

Figure 3 plots the empirical hazard by year of marriage along with a predicted hazard. The prediction is derived from the model with two lags and interactions with industry types although the graph looks very similar across the various specifications. We see that the fit of the model is quite good throughout the whole distribution of marriage length. Without controlling for sample characteristics, the hazard is seen to decline over marital duration with a slight hump occurring around 7 to 19 years of marriage. (For durations over 30 years, the numbers are too small to detect any trend).

Insert figure 3 here

Figure 4 plots the baseline hazard for the same specification. The hazard is normalised to zero for the reference duration segment (2 to 4 years). (Note that these values correspond to the unadjusted coefficients while the results in the tables are presented in the relative risk format.) The risk of divorce decreases over the first 7 to 10 years of marriage. This is followed by a sharp increase and a flattening out at around 20 years. The risk of divorce declines after 25 years of marriage. Individually, only the coefficient corresponding to the 16 to 20 years duration is significantly different from zero although compared to the lowest risk at 7 to 10 years, the coefficients for the durations 11 to 15, 16 to 20, and 21 to 25 are all individually significant. So is the coefficient for the shortest durations of 0 to 1 years of marriage. The shape of the baseline suggests that controlling for sample characteristics, the hump in the probability of divorce is sharper and occurs later in the duration of the marriage than what is suggested by the unadjusted hazards.

Insert figure 4 here

Additional sensitivity analysis is described briefly in what follows. Detailed results are not presented to save on space but are available upon request. We estimate models that include interactions of displacements with recessionary years (2000-2001) on the grounds that these job losses are less likely to convey any information on the partner's traits. In general, the results support our overall conclusions; however, we have small numbers of events (job losses during recessionary years) and standard errors are large. Similar conclusions are reached with models that include job losses after a marital dissolution as instruments.

Models in which coefficients are allowed to shift depending on whether the couple is part of the stock or flow sample are estimated. As explained previously, we expect idiosyncratically long (short) matches to form part of the stock (flow) sample. Specifically, variables are interacted with a flow sample dummy.[28] The results involving the job loss variables described previously still hold for the stock sample (the reference group) and with one exception, the interactions between the job loss variables and the flow dummy are individually and jointly insignificant. The exception to this is the interaction with the twice lagged temporary job ending that is marginally significant at 10%. In contrast, the interactions involving variables other than the job loss variables are strongly jointly significant. Also, the baseline hazard becomes flatter in these specifications as the flow dummy now captures some of the duration effects. But as far as displacements are concerned, the overall results presented above hold for both stock and flow subsamples.

The final robustness analysis incorporates self-reported satisfaction with one's partner as a direct measure of the match quality. Job displacements that are exogenous will not depend on the match quality of the union. Regressions with job loss as the dependent variable and lagged satisfaction variables as regressors are estimated. Unfortunately the satisfaction information is only available starting in wave F (1996) of the BHPS and the sample size is substantially reduced. Nevertheless, our results support the treatment of redundancies as exogenous in the sense that the satisfaction measures do not help explain the incidence of job loss in the next period in the case of redundancies in any of the models estimated. In contrast, the effects on temporary job endings and dismissals are significant in some specifications. (Results are not shown to save on space but are available upon request.) We are unaware of previous economic studies making use of satisfaction with one's partner in the context of the analysis of divorce risk and we believe this type of information to be a promising avenue of future research.

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 displacements (dismissal, redundancy and temporary job ending) 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 and temporary job endings.

The evidence presented in the various specifications support the hypothesis that job losses that are likely to depend 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 are dependent on the employer's characteristics and represent mainly earnings or psychological shocks. Their impacts 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 a few of the models (for example if they occur in declining industries) but are usually insignificant. In this sense, our results support those of Charles and Stephens (2004).

This analysis could be expanded in several directions. The analysis of the impacts 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/her job security[29]. 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 information on expectations currently available in the BHPS does not allow the separation of voluntary job changes and hence could not be incorporated in this paper.

The finding of significant effects of job losses on the probability of divorce has important consequences for the econometric 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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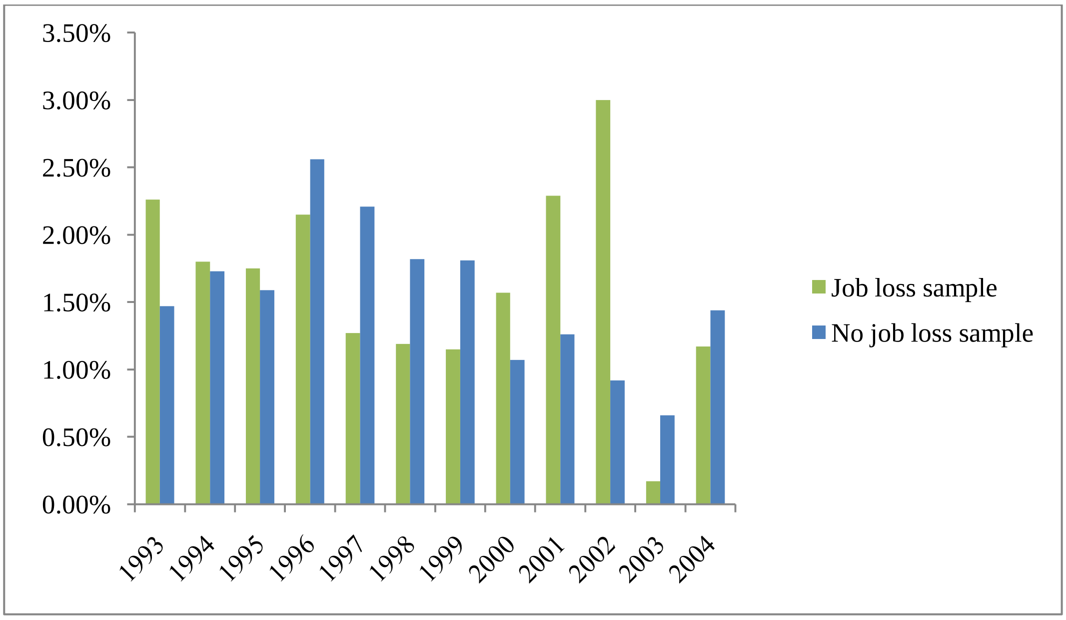
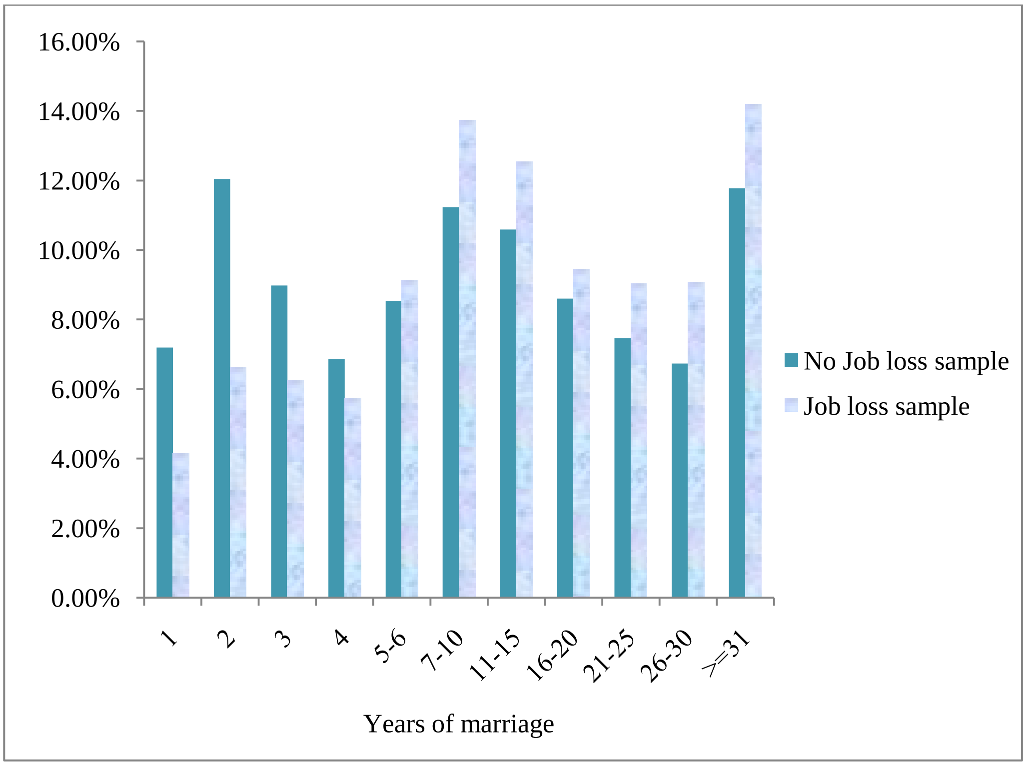
Figure 1 – Divorce rate by year, analysis sample



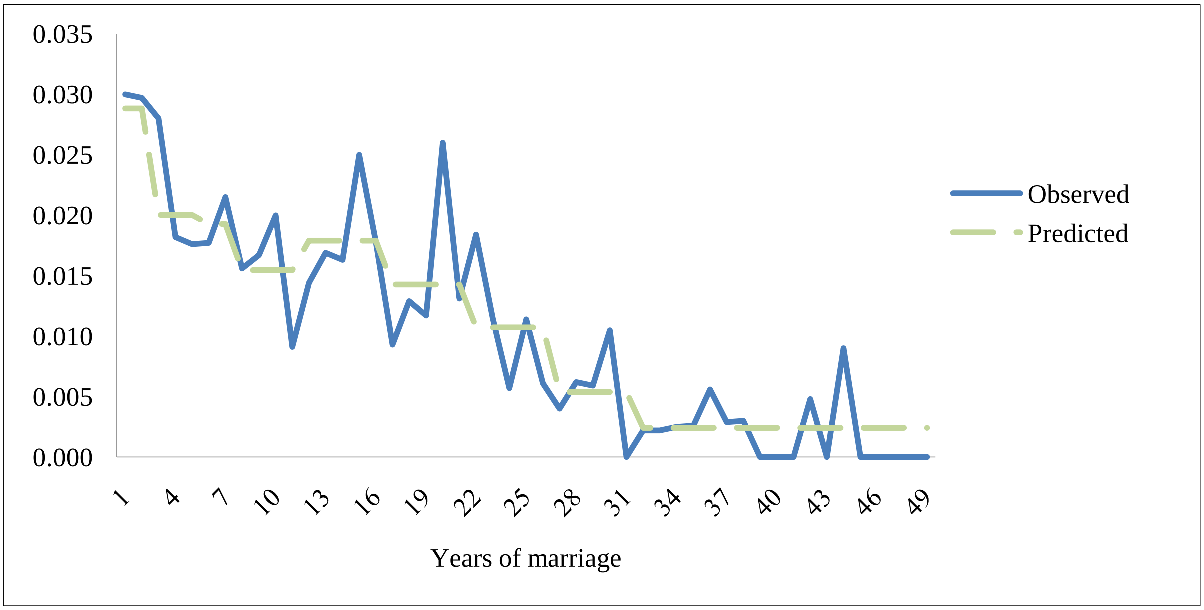
The sample contains 33463 observations involving 6137 couples. Divorce includes separation.

Figure 2 – Distribution of years of marriage, analysis sample



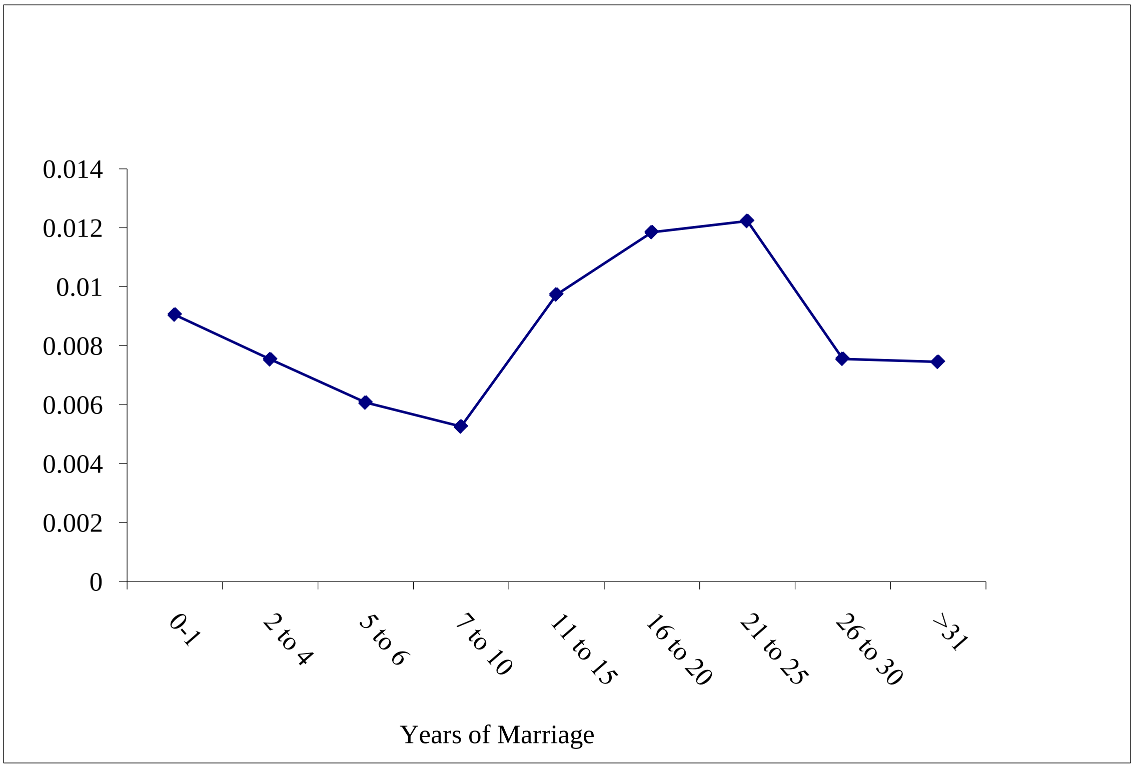
The sample contains 33463 observations involving 6137 couples. Marriage includes cohabitation.

Figure 3 – Observed and predicted hazards by duration of marriage



The predicted probability of divorce is generated from the model presented in the right-most columns of Table 3.

Figure 4 – Baseline hazard



The predicted probability of divorce is generated from the model presented in the right-most columns of Table 3.

Table 1- 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
1992	6	4.58	0.28	88	9.78	4.12	20	5.24	0.94
1993	11	8.40	0.54	99	11.00	4.82	32	8.38	1.56
1994	13	9.92	0.63	80	8.89	3.88	34	8.90	1.65
1995	8	6.11	0.40	57	6.33	2.82	26	6.81	1.29
1996	13	9.92	0.61	61	6.78	2.88	28	7.33	1.32
1997	10	7.63	0.48	54	6.00	2.58	24	6.28	1.15
1998	11	8.40	0.47	43	4.78	1.83	38	9.95	1.62
1999	12	9.16	0.56	56	6.22	2.63	28	7.33	1.32
2000	10	7.63	0.40	67	7.44	2.67	42	10.99	1.68
2001	21	16.03	0.53	166	18.44	4.23	68	17.80	1.73
2002	11	8.40	0.34	52	5.78	1.62	22	5.76	0.68
2003	3	2.29	0.08	45	5.00	1.25	13	3.40	0.36
2004	2	1.53	0.06	32	3.55	0.98	7	1.83	0.22
Total	131	100.0	0.39	900	100.0	2.69	382	100.0	1.14

The sample size is 33463. 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 2 - Means of socio-economic variables and divorce rates by job loss samples. (33463 obs.)

	Job loss sample		No job loss sample	
	Sample mean	Divorce rate	Sample mean	Divorce rate
Men - Education				
High degree*	11.59†	1.78	15.13	1.24
HND/A level	43.21	1.78	42.21	1.48
CSE/O level	21.30	2.32	21.25	2.10
No qualification	23.90†	1.21	21.41	0.96
- Age				
18-30	14.75	3.82	14.15	3.94
31-40	29.12	2.31†	29.17	1.58
41-55	39.27†	1.02	37.69	0.99
56-65	16.86	0.73	18.99	0.38
Mean age in years	43.20†		43.64	
Women - Education				
High degree*	9.41†	1.61	12.87	1.31
HND/A level	32.79†	1.80	36.05	1.64
CSE/O level	34.14†	2.21	30.68	1.69
No qualification	23.65†	1.10	20.40	0.92
- Age				
18-30	20.09	3.56	19.28	3.51
31-40	29.96	2.06	30.42	1.52
41-55	38.85†	1.06	36.42	0.80
56-65	11.09†	0.12	13.90	0.27
Mean age in years	41.06†		41.58	
- Work status				
In paid employment or self employed	67.72	1.60	68.00	1.50
Unemployed, retired, family care, other*	32.28	2.09†	32.00	1.40
Household non labour income				
0-1,000	34.35	1.36	34.80	1.75
1,001-5,000	41.02†	1.87	38.57	1.48
>5,000	24.63†	2.12†	26.63	1.09
Mean income in £ (base year=2005)	3791.50†		4307.17	
Number of children	0.90		0.88	
Couples with children	46.76	2.35†	45.61	1.70
Couples without children	53.24	1.24	54.29	1.27
Partners have same education levels				
Yes	40.67†	1.86	44.23	1.37
No	59.33†	1.54	55.77	1.69
Difference in partners' age >= 8 years				
Yes	8.81	3.12	9.31	2.01
No	91.19	1.63	90.69	1.41

The number of observations is 7276 for the job loss sample and 26187 for the no job loss sample. All figures are percentages unless otherwise indicated. * denotes an omitted group in regressions. † denotes that the difference in the statistics from the job loss and no job loss samples is significantly different from zero based on a two-tailed test and a 5% level of significance. See Appendix 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 3 – Effects of job loss on the probability of dissolution. Sample size = 33463.

	Any job loss		Job loss by type		Job loss by industry group			
					Declining		Expanding	
Variables	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**
a) Models with one lag only								
Any job loss t-1	1.867***	(0.309)						
Redundancy t-1			1.389	(0.316)	2.177**	(0.699)	1.070	(0.352)
Temp job end t-1			2.126***	(0.524)	1.626	(0.828)	2.433***	(0.693)
Dismissal t-1			2.537***	(0.911)	2.049	(1.499)	2.499**	(1.112)
Log pseudolikelihood	-2468.40		-2465.98		-2463.38			
No. of parameters	24		26		31			
b) Models with two lags								
Any job loss t-1	1.664***	(0.283)						
Any job loss t-2	1.522***	(0.242)						
Redundancy t-1			1.350	(0.303)	2.000**	(0.632)	1.093	(0.363)
Redundancy t-2			1.041	(0.242)	0.777	(0.284)	1.311	(0.438)
Temp job end t-1			1.696*	(0.427)	1.191	(0.628)	1.998**	(0.587)
Temp job end t-2			1.834*	(0.444)	2.071*	(0.859)	1.880**	(0.588)
Dismissal t-1			2.151*	(0.885)	1.725	(1.315)	2.614*	(1.330)
Dismissal t-2			1.572	(0.612)	1.749	(1.063)	0.824	(0.549)
Log pseudolikelihood	-2465.23		-2462.34		-2459.07			
No. of parameters	25		29		38			
Wald tests:								
H_0: all job loss coeffs=0	$\chi^2(2)$=20.48 p-value=0.000		$\chi^2(6)$=29.11 p-value=0.000		$\chi^2(6)$=13.91 p-value=0.031		$\chi^2(6)$=18.71 p-value=0.005	
H_0: t-1 job loss coeffs=0			$\chi^2(3)$=9.54 p-value=0.023		$\chi^2(3)$=5.85 p-value=0.119		$\chi^2(3)$=8.88 p-value=0.031	
H_0: t-2 job loss coeffs=0			$\chi^2(3)$=7.94 p-value=0.047		$\chi^2(3)$=5.83 p-value=0.120		$\chi^2(3)$=4.51 p-value=0.212	
H_0: redundancy coeffs=0			$\chi^2(2)$=1.82 p-value=0.403		$\chi^2(2)$=5.06 p-value=0.080		$\chi^2(2)$=0.50 p-value=0.779	

All regressions include the following variables: age of husband, age of wife, husband and wife's education (3 dummies for each partner), wife's employment status (one dummy), husband's nonlabour income, wife's nonlabour income, number of children present in household, dummy for difference in age of partners greater than 8, dummy for similar education level and 8 dummies for duration of marriage. A constant is included. Models that distinguish between industry groups also include missing industry dummies interacted with redundancies (2 dummies) and temporary job endings (1 dummy); these are insignificant in all models. Regressions are cloglog models estimated in Stata. Standard errors are robust and clustered by couple. * indicates that exp(coeff) is significantly different from 1 at 10% level, ** at 5% and *** at 1%.

Table 4 – Effects of job loss on the probability of dissolution - random effects models. Sample size = 33463.

	Job loss by type		Job loss by industry group			
			Declining		Expanding	
Variables	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**
Redundancy t-1	1.353	(0.325)	1.931***	(0.661)	1.127	(0.404)
Redundancy t-2	1.061	(0.256)	1.338	(0.447)	0.772	(0.300)
Temp job end t-1	1.971**	(0.567)	1.300	(0.768)	2.408***	(0.772)
Temp job end t-2	1.811**	(0.486)	2.095	(0.974)	1.866*	(0.602)
Dismissal t-1	2.080*	(0.847)	1.807	(1.499)	2.489*	(1.270)
Dismissal t-2	1.875*	(0.711)	1.966	(1.302)	1.003	(0.580)
Mass pt 1: location, prob.	-1.653, 0.972		-1.671, 0.971			
Mass pt 2: location, prob.	1.970, 0.027		1.904, 0.029			
Log likelihood	-2422.16		-2419.93			
No. of parameters	31		40			

All regressions include the following variables: age of husband, age of wife, husband and wife's education (3 dummies for each partner), wife's employment status (one dummy), husband's nonlabour income, wife's nonlabour income, number of children present in household, dummy for difference in age of partners greater than 8, dummy for similar education level and 8 dummies for duration of marriage. A constant is not included. Models that distinguish between industry groups also include missing industry dummies interacted with redundancies (2 dummies) and temporary job endings (1 dummy); these are insignificant in all models. Models include random effects with discrete distributions containing 2 mass points. All models are estimated with gllamm routines written for Stata. Standard errors are robust and clustered by couple. * indicates that exp(coeff) is significantly different from 1 at 10% level, ** at 5% and *** at 1%.

Table 5 – Hazard models of the probability of dissolution- other regressors. Sample size = 33463.

	One lag		Job loss has two lags		Two lags and industry groups		Two lags, industry groups and random effects	
Variables	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**	**Exp(coef)**	**(st.err.)**
Age:								
Husband	0.975	(0.016)	0.975	(0.016)	0.976	(0.016)	0.976	(0.016)
Wife	0.947***	(0.016)	0.947***	(0.016)	0.947***	(0.016)	0.940***	(0.015)
Education:								
Husband – HND/A	1.119	(0.192)	1.118	(0.192)	1.129	(0.194)	1.166	(0.211)
Husband – CSE O	1.305	(0.239)	1.296	(0.238)	1.307	(0.239)	1.333	(0.260)
Husband – No qual	0.995	(0.205)	0.993	(0.204)	1.005	(0.207)	1.000	(0.226)
Wife – HND/A	1.151	(0.204)	1.160	(0.206)	1.144	(0.203)	1.133	(0.215)
Wife – CSE O	1.257	(0.240)	1.264	(0.242)	1.243	(0.238)	1.172	(0.235)
Wife – No qual	1.176	(0.273)	1.181	(0.274)	1.165	(0.271)	1.054	(0.255)
Nonlabour inc.:								
Husband	1.695	(0.703)	1.688	(0.707)	1.686	(0.703)	1.388	(1.246)
Wife	4.852***	(2.258)	4.818***	(2.250)	4.858***	(2.263)	6.087***	(4.060)
Wife employed	0.895	(0.100)	0.934	(0.110)	0.914	(0.103)	0.934	(0.110)
Number of children	0.920	(0.048)	0.922	(0.048)	0.924	(0.049)	0.913	(0.051)
Match quality:								
Age Diff > 8 yrs	1.470**	(0.283)	1.474**	(0.283)	1.464**	(0.281)	1.606**	(0.352)
Same educ level	0.910	(0.086)	0.908	(0.086)	0.901	(0.086)	0.936	(0.101)
Baseline hazard:								
Year 0 to 1	1.173	(0.179)	1.153	(0.175)	1.172	(0.178)	0.978	(0.170)
Year 5 to 6	0.905	(0.145)	0.908	(0.145)	0.913	(0.146)	1.113	(0.187)
Year 7 to 10	0.812	(0.128)	0.816	(0.129)	0.816	(0.129)	1.037	(0.180)
Year 11 to 15	1.289	(0.203)	1.289	(0.203)	1.287	(0.204)	1.628***	(0.300)
Year 16 to 20	1.446*	(0.278)	1.442*	(0.277)	1.435*	(0.277)	1.791***	(0.399)
Year 21 to 25	1.446	(0.333)	1.447	(0.333)	1.446	(0.333)	1.895	(0.494)
Year 26 to 30	0.978	(0.333)	0.973	(0.331)	0.970	(0.330)	1.111	(0.387)
Year 31 +	0.736	(0.295)	0.732	(0.293)	0.731	(0.293)	0.852	(0.349)
Log pseudolikelihood	-2465.98		-2462.34		-2459.07		-2419.93	
No. of parameters	26		29		38		40	
Wald test of H_0: baseline coeffs=0	$\chi^2(8)$=16.18 p-value=0.040		$\chi^2(8)$= 15.76 p-value=0.046		$\chi^2(8)$=15.73 p-value=0.046		$\chi^2(8)$=15.90 p-value=0.044	

All regressions include a constant (except for the model with random effects) and job loss variables by type of displacement. Results on job loss variables are presented in Table 3; the models can be matched by the value of the pseudolikelihood. Regressions without random effects are cloglog models estimated in Stata; unobserved heterogeneity is modelled as random effects discretely distributed with two mass points and this model is estimated with gllamm routines written for Stata. Standard errors are robust and clustered by couple except for the random effects model. * indicates that exp(coeff) is significantly different from 1 at 10% level, ** at 5% and *** at 1%.

Appendix

Appendix Table 1 - Variable definition - additional regressors.

Husband's age	Years
Wife's age	Years
Difference in age	1 if the difference in age across partners >= 8 years
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 if highest qualification is less than high school
Similarity in education	1 if partners have the same highest qualification
Husband's non labour income	In '000 £ (deflated using 2005 as base year).
Wife's non labour income	In '000 £ (deflated using 2005 as base year).
Number of children	Number of dependent children in the household
Wife's employment	1 if the wife is in paid employment or self employed

[1] We thank participants of the 2007 Australian Labour Market Research workshop and the 2008 Australian Conference of Economists for their suggestions and comments. Special thanks to two anonymous referees and associate editor Deborah Cobb-Clark for valuable comments and suggestions. 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] 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). There is some dispute about the treatment of plant closures as exogenous (Schwerdt, 2007). In any case, information on plant closures is not available in the BHPS.

[3] 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.

[4] 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.

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

[6] 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).

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

[8] 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).

[9] 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.

[10] In our main sample, 14% of observations consist of cohabitations. The modeling of the duration of the union distinguishing by type of union is not straightforward unless one assumes independent shocks (or competing risks) and although an interesting extension, it is left for future work.

[11] 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.

[12] Less than 25 couples.

[13] 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.

[14] 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. We use age 65 as an exogenous censoring device. Due to the presence of mandatory retirement, the role of job displacements for workers older than 65 is likely to be quite different than for younger individuals.

[15] 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.

[16] In our main sample, 72% of households report the husband as the individual with the largest labour income.

[17] See Borland et al. (1999).

[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] This assumption rules out right censoring rules that are correlated with unobservables and makes the use of self-reported disability or early retirement as censoring variables problematic. In our sample, durations are right-censored when they reach the end date of the sample, when the husband's age reaches 65 or due to attrition from the sample.

[21] With single spell data, it is very difficult to allow for correlations between the time-invariant unobserved heterogeneity and the covariates.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 any 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. Again we stress that these results are used more as sensitivity analysis, in particular as a check on the specification of the baseline hazard.

[22] We are grateful to an anonymous referee for suggesting this approach.
[23] Adding a third lag reduces the sample to 27667 observations.
[24] The third lags on the displacement variables are also jointly insignificant; a Wald test yields a $\chi^2(3)$ value of 1.60 which corresponds to a p-value of 0.659.
[25] 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.
[26] We estimate models with three mass points but these did not converge easily; specifically, we had to omit the age variables and restrict the baseline hazard to get convergence. In all cases, the probability of the third mass point was between 0.011 and 0.012 and the results on the job loss variables were similar to those presented in Table 4 except for coefficients on the temporary job endings that became smaller and generally insignificant.
[27] We should add that results on education, nonlabour income and the wife's employment status are sensitive to the treatment of the age variables. This is not surprising given the correlation in these variables. Since we do not care about these variables per se we choose the more flexible specification and include all regressors.
[28] Interactions with the baseline hazard were restricted to due to the short marriages in the flow sample.
[29] This was suggested by an anonymous referee.