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The impact of job change on family mental health

1. Introduction

The principal aim of this paper is to understand if a relationship between job loss and family well being exists. There is little research evidence to date on this issue. Even though many relevant contributions analyze the impact of unemployment on individual health, few studies directly address job loss causal effect on mental health, as well as cross effect on family distress.

The economic literature has traditionally considered the impact of earning shocks on family well-being, focusing on the consumption or production side. Nevertheless, the analysis of relationship between unemployment and mental health is essential for many reasons. First of all, this allows to consider the issue of "personal" costs of unemployment, developing estimates of how job loss (or unemployment) affects the lives of the unemployed themselves and their families. A growing literature showed that short run economic shocks, such as job loss, can have persistent effects. Displaced workers tend to experience reduced employment possibilities, increased job instability, as well as lower earning profiles. Significant research on unemployment focuses on the distinction between voluntary and involuntary unemployment (see Clark and Owald, 1994) and this difference has a strong impact when considering well being effects. Korpi (1997) also underlines the potential significance of the relationship between unemployment and mental health for the debate on unemployment hysteresis: lower mental health and lower well being may lead to discouragement, inability to acquire new skills and may then reduce the effectiveness of job search or the productivity of unemployed people who find new jobs.

Second, the relationship between unemployment and mental health is not limited to the individual level and unemployment may have "social" costs, in terms of psychological well being.

Modern macroeconomics considers a social welfare function, defined on inflation and unemployment. Di Tella et al (2001) show that citizens care about these two variables and that self reported well being is altered with unemployment and inflation rates. Joblessness affect reported life satisfaction even after controlling for the personal characteristics of the respondents, country fixed effects, year effects, time trends and lagged dependent variables. Moreover, unemployment depresses reported well being more than does inflation.

Job loss leads to lower income and this may generate negative mental health effects. Nevertheless, it is essential to clarify whether income actually is the main transmission channel of job loss adverse effects.

Substantial efforts have been made in the past to quantify non pecuniary costs of unemployment (see Darity and Goldsmith, 1996 and Winkelman and Winkelman, 1998) and these studies show a significant negative association between unemployment and psychological well being.

Nevertheless, few studies directly address the causal effects, using exogenous job loss, and when panel data have been used, data sets were small or based on a sub-population (see Korpi, 1997). Moreover, there is very little research to date on negative effects of unemployment on family mental well being.

This paper analyses both causal effect of job loss on mental health and cross effect on partner's psychological well being. Using all the 14 waves of the British Household Panel Study, I analyse the impact of exogenous job loss on individual and partner's mental health.

I use an indicator of psychological distress derived from the General Health Questionnaire and I correct for possible endogeneity, linking all the job losses with the reasons for terminating an employment spell. Furthermore, I add the information about the industry workforce growth rate and I identify redundancies in declining industries, as an indicator of exogenous job loss. Lastly, I control for a large set of individual and family characteristics and I try to model individual heterogeneity.

The main results show that the probability of poor mental health increases following a man's redundancy for both the two partners, even controlling for past mental health. Increasing the number of job changes has a negative impact on mental health. Changes for better job or promotion, as well as retirement, reduce the probability of poor mental health. These results persist even when controlling for income.

The rest of this paper is organized as follows. Section 2 provides an overview of the existing literature and Section 3 briefly presents the General Health Questionnaire and a definition of mental health. Section 4 is focused on data construction and Section 5 includes some descriptive characteristics of the sample. Section 6 discusses the estimation methods and Section 7 presents the main results of this analysis. Finally Section 8 concludes.

2. Overview of existing literature

Job loss has a strong impact on many economic channels that may influence mental health.

Literature to date has focused on both direct and indirect effects of unemployment on health, as well as on the transmission mechanisms.

First of all, job loss has a direct impact on well-being. A large empirical psychological literature[1] investigated the impact of unemployment on the incidence of low-life satisfaction, depression, low self-esteem, unhappiness, and even suicide. Some of these outcomes may be related to lower income, but some of them arise because employment is not only a source of income, but also a provider of social relationships, identity in society and individual self esteem.[2]

A British study by Clark and Oswald (1994) uses cross sectional data from the first wave of the BHPS to test whether unemployed people are relatively happy or unhappy. Their results show that unemployed people have much lower levels of mental well being (measured through the GHQ) than those in work.

Indirect effects of job loss on health have been studied focusing on income effects of unemployment.

A large literature shows that job losers experience significant and long lasting declines in earnings (see Ruhm, 1991, Couch, 2006) and that job loss can lead to increasing earning instability (see Stevens, 1997).

[1] See Darity and Goldsmith (1996) for a review of psychological studies showing that unemployment has a negative impact on self esteem.

[2] See Winkelmann and Winkelmann (1998) for a test of the importance of non-pecuniary costs of unemployment.

A separate strand of literature underlines the relationship between income and health (see Deaton and Paxson, 1999), even if recent research deemphasizes these effects in favour of more lasting characteristics, such as education (see Cutler, Deaton, and Lleras-Muney 2006).

A recent study from Sullivan and von Watcher (2006) investigates the impact of mass layoffs on mortality. Their results show that the relationship between job loss and mortality follows a U shape; mortality rates are particularly high in the years following a job loss and after a prolonged period of time. This is consistent with an initial increase in mortality from acute stress and a long term increase in mortality from chronic stress resulting from permanently lower average earnings.

Nevertheless, there are potentially contrasting effects of declines in earnings and employment caused by job losses. Ruhm (2000) reports that mortality declines in recessions, as workers have more time to invest in their health, face fewer work-related accidents, and experience no pressure at work.

Few studies make substantial efforts to quantify pecuniary and non-pecuniary costs of unemployment, focusing on the two elements at the same time. The big issue is not only to identify income effect, but also to clarify whether this is the major channel through which job loss may affect mental health.

Winkelman and Winkelman (1998) use the first six waves of the GSOEP to test the impact of unemployment on life satisfaction and their main result is that the detrimental effect of unemployment persists after individual specific fixed effects are accounted for. They decompose the cost of unemployment into pecuniary and non pecuniary costs and conclude that pecuniary costs are small compared with the non-pecuniary ones.

Literature to date has not given enough consideration to the causal relationship between job loss and poor health, as well as to the adverse effects on family well being.

In this paper I try to combine causal effects of exogenous job loss on individual mental health and cross effect on partner psychological well being. Even controlling for income, I recognise that there still is a redundancy effect. Looking for the transmission mechanism will be an important extension of this study.

Adequate longitudinal data allow to control for unobserved, time-invariant, individual specific effects and lagged information are used to control for individual mental health prior to the job change.

3. Mental health indicators

"Mental health is more than an absence of mental illness. Mental health affects our capacity to learn, to communicate, and to form and sustain relationships. It also influences our ability to cope with change, transition and life events. Mental health may be central to all health and well-being"[3].

One way to assess people's feelings of subjective well being and mental health is to use their scores from the General Health Questionnaire. Previous literature refers to the GHQ as one of the most reliable indicators of psychological distress or "disutility"[4].

People's answers to 12 questions[5] are coded on a four point scale[6]. These twelve are combined into a total GHQ score[7], that indicates the level of mental distress, giving a scale running from 0 (the least distressed) to 12 (the most distressed).

[3] UK Department of Health (2001)

[4] See Argyle (1989) and Clark and Oswald (1994)

In the original Manual of the GHQ (Goldberg, 1978), variations in the best threshold to adopt are discussed. Goldberg (1998) underlines the main difficulties of the definition of a proper GHQ threshold and deals with variations of this threshold in different settings[8]. Following these motivations, I use GHQ-12 as a dichotomous indicator with a cut-off point at a score of 3.

4. Data construction

This analysis uses data collected in all the 14 waves of the British Household Panel Study (BHPS), which is a nationally representative sample[9] of about 5,500 households, recruited in September 1991. The BHPS is an indefinite life panel survey and the longitudinal sample consists of members of original households and their natural descendants. In order to analyse the possible impact of job loss on partners' mental health, I constructed a sample of all married or cohabitating couples in the BHPS. I organised the data into couple-year form and chose the man as representative of the couple. Then I only kept couples in which the man is aged between 20 and 65 years.

Information on labour market behaviour and periods of unemployment is collected in different sources within the BHPS[10]. At each interview, the individual is asked about her/his current employment situation[11]. Information about labour force behaviour before the interview is also collected in a job history file, that contains information related to all employment spells started after the 1st September of the year prior to the interview. Job history information is collected for individuals who experiment at least one change in the reference period. For each employment spell, the job history file collects the starting date, the end date and the reason for leaving that particular job. Thus, there may be some overlap between subsequent job history files. Individuals are asked about reason for leaving and they can chose among a complete set of alternatives[12].

A complete data set, related to all the individual work histories in the first 11 waves of the BHPS, has been elaborated by G. Paull[13]. The unit of observation of this data set is each interview provided by each individual during the first 11 waves of the BHPS. Each record contains a series of labour forces spells since leaving fulltime education until the time of the interview. The spells are defined in terms of spell state, start date and

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[5] Questions: have you recently: Been able to concentrate on whatever you are doing, Lost much sleep over worry; felt that you are playing a useful part in things; felt capable of making decisions about things; felt constantly under strain; felt you couldn't overcome difficulties; been able to enjoy your normal day to day activities; been able to face up to your problems; been feeling unhappy and depressed; been loosing confidence in yourself; been thinking of yourself as a worthless person; been feeling reasonably happy all things considered.

[6] The possible answers to these questions are: not at all, not more than usual, rather more than usual, much more than usual.

[7] The score is calculated summing the number of times the person places himself or herself in the fairly stressed or highly stressed category.

[8] When best threshold were calculated for each diagnoses separately, it was found that the threshold 2/3 was best for all of them, although for depression a threshold of 3/4 was equally good.

[9] Additional samples of 1,500 households in each of Scotland and Wales were added to the main sample in 1999, and in 2001 a sample of 2,000 households was added in Northern Ireland, making the panel suitable for UK-wide research.

[10] For a complete analysis of work histories in BHPS see Paull (1997) and Paul (2002).

[11] The answers to this question are recorded in the variable 'wjbstat'. 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.

[12] The relevant variable is wjhstpy. The alternatives are: promoted, leave for better job, made redundant, dismissed or sacked, temporary job ended, took retirement, stop for health reasons, left to have a baby, children/home care, care of other person, other reason

[13] See Paull (1997) and Paul (2002).

end date[14]. This data set has been constructed using data related to the main activity and other works[15] and I focused on main activities. This data set is absolutely complete for the first 11 waves of the BHPS and reconcile multiple information about employment spells. Nevertheless, this does not include the information about the reason for leaving the employment spell, that is essential in order to identify exogenous job loss and should be collected from the job history files.

Using individual identifier, spell start and end dates, I matched the employment spells, collected in the G. Paull work history data set, with a valid reason for leaving the relevant employment spell, from the single wave job history file. This led me to construct a single work history file, organised in panel format, where each individual has a number of entries equal to the number of his employment spells. The new work history file collects information about: spell work status, start date, end date and reason for leaving that particular spell.

Reconciling the data from the individual and job-history record files, sourced from different questions, there is a reasonable level of agreement, but there still are some differences which are not generally systematic. The analysis relies on spells end dates, in order to match spells with valid reasons for leaving, so for missing end dates substantial effort was spent in processing the data and to reduce both left and right censoring. Inconsistencies from mis-recording or differences in recorded dates have been solved by reconciling spells with the same end date and linking these with a valid reason. Information about employment spells ended after wave 11 (and thus not included in the Paull data set) have been collected from the single waves job history files.

I focused on men job changes and I constructed a complete data set of job changes, where each entry records the number of job changes within one year and the relevant reasons for leaving. I also collected the information about the industry from the original job history file.

Then, I matched my original sample of all married and cohabitating couples with this new work history data set, containing information about all men’s job changes. The final sample contains about 7,500 couples and 37,000 observations.

The target of my analysis is to link variations in mental health (recorded in each interview) with different job changes, occurred during the whole year prior to the interview date. I want to inspect the impact of these job changes on both individual’s and his partner’s mental health, distinguishing job changes from different reasons.

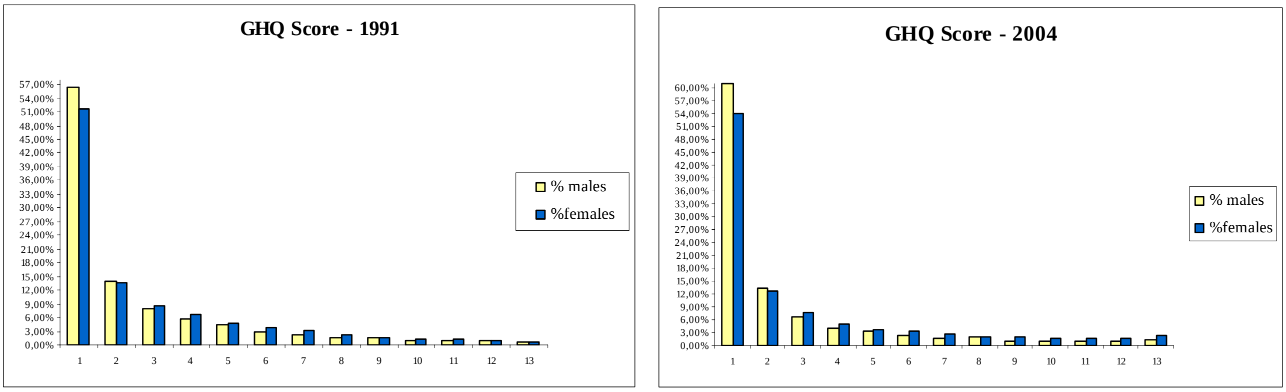
5. Descriptive statistics

This section presents some descriptive statistics, with a focus on the relationship between mental health and job changes. Figure 1 displays the distribution of the GHQ score across the whole sample in 1991 an 2004. The distribution is skewed to the left, with a mean score of 1.49 (1991) and 1.45 (2004) for men and 1.77 (1991) and 1.97 (2004) for women. The percentage of individuals who report no distress at all (GHQ score equal to zero) is greater for men.

[14] Spells are in chronological order and all dates are measured in months.

[15] Work history data reconcile information from current employment status (recorded in individual information file), job history file, wave 2 and wave 3 information about combined employment and family history (blifemst and clifejob file).

Figure 1: GHQ score in UK (1991-2004)



Note: 0= less distressed; 12: most distressed. The data is based all the couples with man aged 20-65.

Table 1 (see Appendix) reports the percentage of people with poor mental health across the 14 waves. Overall, there is a significant higher percentage of distressed women but the trend of the distributions is quite similar. I group the reasons for leaving the current employment spell into 8 categories: redundancy, dismissal, change for improvement (including promotions and changes for better job), retirement, family reasons (including children birth, home care and care of other person), health reasons, start college, temporary job ended, other reasons. Table 2 and 3 present the number of job changes in the analysed sample and the incidence of repeated job changes in the same year.

Lastly, table 4 shows the pattern of people with poor mental health and the mean of GHQ score across all the 14 waves, underlining the differences associated with job changes. On a scale from 0 to 12, the GHQ score of individuals who have a redundancy experience is roughly one unit above that of individuals who change job for improvement. Comparing the percentages of individuals with poor mental health, I find that a randomly selected person with a redundancy experience is much more likely to be distressed than a randomly selected person with at least one job change for improvement. The percentage of people with poor mental health in the improvement sample ranges from 12.09% in 1993 to 21.08% in 1998, while the same percentage is between 20% in 2003 and 40.28% in 1995 in the redundancy sample.

Nevertheless, this evidence is not enough for establishing a causality relationship. It is essential to examine transition in mental health following a particular job change experience, in order to understand the trajectory of mental health before and after the job change.

Table 5 and 6 show further details about the change in mental health associated with different job changes. Table 5 shows the mean of GHQ score in the year prior to the job change experience, and the subsequent transition in mental health. GHQ score is higher after both dismissal and redundancy experience, while there is an improvement in mental health after a change for promotion or better job.

Table 6 focuses on transition between different ranges of GHQ scores. People with a redundancy experience are more likely to have worse mental health after job loss. More than 30% of individuals with very good conditions prior to the redundancy (GHQ equal to 0 or 1) report higher distress in the following observation, and among these, nearly 8% exhibits very high distress (GHQ score between 8 and 12). On the other hand, 47% of people who had high distress before change for improvement (GHQ score between 5 and 7) are in excellent conditions after the change.

Lastly, I present some descriptive characteristics of people with different job changes experiences, especially focusing on age, income and education level.

Table 7 presents differences in age: the percentage of younger workers is higher among individuals with job change experience, and particularly among dismissed workers. Table 8 and 9 present income and education level, by job change experience. Overall, the percentage of people with low monthly pay (less than £1,000) is higher in the redundancy and dismissal samples than among people with no job change. Nevertheless, even people who changed for improvement exhibit a lower level of monthly pay: these individuals are more likely to be at the beginning of their career, looking for better positions. The proportion of individuals with high degree or higher qualification is considerably higher among people with an improvement change (around 52%), while the majority of dismissed workers and people with a redundancy experience have low qualification.

6. Estimation Methods

This paper primarily use panel data methods, in order to address the issue of individual heterogeneity. The dependent variable is mental health, which takes values from 0 to 12. Mental health is measured on an ordinal scale, and hence ordered probit or logit would be the appropriate econometric technique. Nevertheless, no ready formulation of the model is available for taking into consideration the individual time invariant fixed effect[16]. I propose to collapse the mental health variable into a dichotomous indicator of poor mental health, using a cut-off point at a GHQ score of 3, as explained above. The binary variable does not use all the available information, but it enables to use limited dependent variable panel models.

The random effect probit model splits the error term into a time invariant component α_i and an idiosyncratic error term.

In particular, I assume the following underlying latent model:

$$Y^*_{it} = \alpha_i + x_{it}\beta + \varepsilon_{it} \qquad i=1,\ldots..N,\ t=1,\ldots.T$$

where Y^*_{it} is a continuous but unobserved index of mental health of individual i in period t, x_{it} is a vector of explanatory variables and α_i is a fixed effect which takes into account intrinsic differences in mental health and unobservable time invariant individual characteristics.

One important assumption in this framework is that a year (the interview interval in BHPS) is short enough for people unobserved component of mental health to remain constant.

This assumption will be discussed in a future development of this analysis, where a different econometric technique will be used. Particularly, job loss will be included as an independent variable and I will apply the instrumental variable approach. The selected instruments could be interactions between job loss, an involuntary binary variable and a declining industry indicator.

Rather than observing Y^*_{it} , the following is observed:

$$Y_{it} = \begin{cases} 1 \text{ if } Y^*_{it} > 0 \\ 0 \text{ otherwise} \end{cases}$$

[16] See Winkelmann and Winkelmann (1998).

We assume ε_{it} ~I.I.D.N. (0,1), $\alpha_i|xi$~N (0, σ^2_α) and the unobserved individual effect is assumed to be independent of Xi, that is E ($\alpha_i|xi$) = E (α_i) = 0.

The presence of a time invariant component implies a non-diagonal covariance matrix of the composite error term $u_{it}=\alpha_i+\varepsilon_{it}$, with Var ($u_{it}$) = $\sigma^2_\alpha+1$.

The likelihood function of the random effect probit model relies on:

$$\Pr(y_{it}=1|\, x_{it}, \alpha_i) = \Pr(y_{it}=1 \,|\, X_i, \alpha_i) = \Phi(\alpha_i + x_{it}\beta)$$

The random effect model allows to incorporate individual unobserved effect, which may be a substantial component of poor mental health, but relies on two assumptions:

- strict exogeneity of the explanatory variables, i.e. $E(\varepsilon_{it}|xi_1,\dots xi_T, \alpha_i=)0$
- independence between the individual fixed component and the regressors, i.e. E ($\alpha_i|xi$)=E (α_i)=0

Whenever one of these assumptions fails, the estimates for the effect of job change on mental health are not consistent. In many applications, the key point of using panel data is to allow for α_i to be correlated with x_{it}. The fixed effect model achieves this purpose explicitly and E ($\alpha_i|xi$) is allowed to be any function of xi[17]. By relaxing the independence assumption, we can consistently estimate partial effects in the presence of time-constant omitted variables, that can be correlated with $x_{it.}$ This makes the fixed effect estimator more robust than the random effect. Nevertheless, the main shortcoming of the fixed effect model is that we cannot include time constant regressors among x_{it}, without further assumptions. If α_i can be correlated with each element of x_{it}, there is no way to distinguish the effects of time constant observables from time constant unobservables. When empirically estimating the fixed effect model, this usually implies dropping a large number of observations, with time constant covariates.

Another way to cope with the independence assumption is adopting a correlated random effect probit model, which allows for the unobserved time fixed component to be correlated with some elements of x_{it}. Chamberlain (1980) allowed for correlation between α_i and xi by assuming a conditional normal distribution with linear expectation and constant variance. Following Chamberlain suggestion, I model:

$$\alpha_i = \overline{zi}\,'\xi + \eta_i$$

Where $\overline{zi}$ the time average t = 1,….T of the vector zit ($z_{i1t,}\dots\dots z_{iMt}$)' containing the M elements of x_{it} describing observed number of job changes or the observed number of job changes for one particular reason (i.e. the observed number of changes for improvement).

Thus, the number of job changes affects mental health through the usual direct channel, as well as through α_i. The number of job changes reveals something about the individual unobserved fixed component (some person specific characteristics, related to the individual personality) that has an impact on individual's mental health.

In this analysis, I will use the random effect model and then I will propose the logit fixed effect as a sensitivity test of my model, in order to check the robustness of my results. Moreover, I will try to model individual heterogeneous characteristics, considering the possibility that individual specific time invariant component is correlated with the average number of job changes for improvement.

[17] See Wooldridge (2002).

I model the probability of poor mental health, with respect to:

- a set of binary variables, equal to 1 if the individual has a job change experience
- a set of continuous variables, indicating the total number of job changes within a year

This allows to estimate the impact of a job change experience on the probability of poor mental health, as well as the impact of repeated job changes.

Mental health is recorded at each interview and is related to all job changes occurring in the year prior to the interview[18]. I construct two different models, in order to consider the impact of man's job changes on the probability of poor mental health both for the individual and for his partner.

The key point of this analysis is the identification of exogenous job changes variables. I want to be sure that I am focusing on the impact of job change on mental health, ruling out individuals who leave their job because of their poor mental health. I focus on individuals who change job for: improvement (promotion or better job), temporary job ended, retirement, start college/university, redundancy.

This means I do not include job changes for health reasons and dismissals, as I cannot be sure that these job changes are not caused by poor mental health. Retirement is considered as an exogenous job change. Nevertheless, there is a small possibility that high distress leads to early retirement. I inspected the incidence of retirement in early age and I concluded that this is very limited in my sample. Moreover, the consistence of my results is unchanged even omitting retirement binary variable. Job changes for redundancy need special attention. In order to consider exogenous job loss, I should only include plant closure lay-offs. Unfortunately, this information is not available in BHPS. The reason for leaving the employment spell is self reported and this may lead to many potential measurement errors. Plant closure would probably cause people to cite 'made redundant' as their reason for job change, as well as downsizing, mergers and takeovers of firms. Moreover, my major concern is that redundancy is probably less stigmatic than being sacked/dismissed. UK 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). Therefore, the legislation is quite explicit and the term redundancy should not refer to any dismissal caused by individual behaviour. This should rule out the possibility of a dismissal caused by individual poor mental health.

Nevertheless, redundancy is a commonly accepted phrase used to cover any involuntary separation and my concern is that the two terms ('dismissal' and 'redundancy') may be interchangeable for many workers[19].

Therefore, I decided to construct an indicator of exogenous redundancy, using the information about industry workforce growth rate. This data is sourced from the published UK government statistics and I constructed a three years moving average growth rate for each industry. Then, each employment spell is linked with the relevant industry growth rate and this allows to distinguish between redundancies from industries where

[18] Job changes since 1st September of the year prior to the interview.
[19] See Borland et al. (1999).

employment is falling and from industries where employment is rising. I construct two dummy variables for declining and increasing industries and I interact the redundancy binary variable with the declining indicator. Therefore, I obtain a binary variable, equal to one if the worker has been made redundant in an industry where employment is falling and this enforces some exogeneity over the cause of job loss.

In this model, I assume that people in poor mental health are not more likely to get jobs in depressed industries than people in good mental health.

Among the regressors, I also include some individual characteristics (i.e. age, education level, number of children) and two exogenous income variables, net monthly pay in the year prior to the interview and investment income. In one specification of my model, I also include an indicator of previous year poor mental health, in order to control for the effect of individual mental health before job change.

Lastly, I calculate marginal effects[20] of all the independent variables on the probability of poor mental health.

When the covariates are continuous variables, the marginal effect of xi on P(Y=1) is given by $\partial Pi / \partial xi$ and it is based on the average of probabilities. When I include binary variables among the regressors, the marginal effect is given by [P(Y=1 | xi; xi=1) - P(Y=1| xi; xi=0)].

7. Results

The first results from a random effect probit model are presented in Table 10. The dependent variable is a binary indicator of poor mental health and it is equal to 1 if GHQ score is greater or equal to 3. Table 10 presents both the coefficients and the marginal effects from a random effect probit model and then compares these with a logit fixed effect model, in order to check the robustness of the main findings.

The first set of covariates includes job changes binary variables and particularly: redundancy, change for improvement (promotion or better job), retirement, temporary job ended. In the first most parsimonious model, I control for individual’s age and for the number of children within the household and I consider the impact of the total number of job changes. In the second version of this model, I also include education binary variables and income variables. As explained above, the redundancy variable refers to job loss in depressed industries, as an indicator of exogenous job separation.

The first results emerging from model 1 show that the redundancy experience has a positive impact on the probability of poor mental health. Men who have been made redundant are 5% more likely to report poor mental health than those without any redundancy experience. On the other hand, job changes for promotion (with the same employer) or for better job (different employer) reduce the probability of poor mental health, by around 8.5%. Retirement has a positive impact on individual mental health as well, and the marginal effect is even higher (around 9.4%).

Model 1 also shows that the probability of poor mental health declines following the end of a temporary contract or the termination of an employment spell for starting college or university. The impact of temporary job ends may be linked to the specific nature of the contract, that incorporates a pre-definite end date. It is also possible that the end of a temporary contract coincides with the beginning of a permanent or a better job.

[20] Marginal effects and the standard errors are computed at the mean of the data using the delta method.

Job change is perceived as a stressful experience and increasing the total number of job changes also increases the risk of high distress. In this first model, I also control for the number of dependent children in the household, in order to explore potential added stress created by combining job changes and family. The coefficient is positive and significant, but the size is quite small.

The underlying idea is that job loss impact is worse when you have obligations and a further development of my model will include interaction between redundancy and dependent children, as well as between redundancy and financial obligations (mortgages, credit card debts…).

Increasing individual's age decreases the probability of high distress, but the impact size is very small.

As explained above, one issue with random effect estimates is that they do not allow for correlation between time invariant individual characteristics and the independent variables. When such a correlation exists, the estimator are biased. Therefore, in order to check the robustness of my results, I compare these with the logit fixed effect model[21]. The number of observations is much lower, because we loose all the information from individuals with time-constant covariates.

When the time invariant unobserved characteristics are controlled for, the estimation results remain significant and of the same sign: the exogenous redundancy binary variable is positive and significant at 1%, and increases the probability of poor mental health. All the other job change variables decrease the probability of poor mental health, but a higher number of job changes is associated with higher distress.

The last three columns of table 10 show an extended version of the first model, including education binary variables, as well as individual monthly pay (recorded in September of the previous year) and annual investment income.

I include four education binary variables. The base category is the last one, including individual with low or no qualification. Having higher education reduces the probability of poor mental health by around 2% and two of the three included dummy variables are significant. The sign and significance of job changes variables is identical to the previous model: once again, the only negative impact on mental health comes from a redundancy experience. The coefficient of redundancy binary variable is significant at 5% and the marginal effect slightly drops in size (4.7%, from previous 5.2%). Therefore, even when controlling for a larger set of individual characteristics, the impact of different job changes on the probability of high distress is unchanged.

Income variables are significant and have the expected sign: a £ 1,000 per year increase in monthly pay decreases the probability of poor mental health by 0.7%, while a £ 10,000 per year increase in the household investment income decreases the same probability by around 2%.

When checking the robustness of these results by using the logit fixed effect model, the impact of job change and job loss on mental health is the same and this is consistent with the results from the international literature, see Clark et al. (2001). This first set of results leads me to consider the specific channels through which job change affects individual well being. The persistence of results, even when controlling for income variables,

[21] I base my analysis on a random effect probit model. Nevertheless, a random effect logit model has also been constructed, and I compared these estimates with a fixed effect logit model. The Hausman test $(\delta_{FE} - \delta_{RE})'$ $[\text{Avar}(\delta_{FE}) - \text{Avar}(\delta_{RE})]^{-1}$ $(\delta_{FE} - \delta_{RE})$ suggested that a potential correlation between x_{it} and α_i exists and therefore, FE estimates are more reliable. As I will show in the following pages, FE results always confirm sign and significance of RE estimates in my model.

suggests that income shocks are just a partial explanation of the consequences of job change on mental health. Other factors, such as changes in the individual perceived role in the society, self esteem or other psychological elements may deserve further consideration. Some further explanations may be found considering the role of job satisfaction.

The impact of job changes on partner's mental health is separately examined in Table 11. The natural concern about job loss exogeneity is now overcome as we analyse the impact of male's job changes on his partner's mental health. The results from the random effect model show that a man's redundancy increases the probability of poor mental health for his partner. The coefficient is significant at 1% and the marginal effect is even higher than the impact on individual's distress (7.6% vs. 5.2%).

This result confirm my original hypothesis: an exogenous and involuntary job loss experience is associated with a high risk of distress for the whole family, and may lead to significant negative effect on family well being. This analysis will be expanded, by studying the impact of women's job changes on men's mental health and by focusing on children well being.

On the other hand, women whose partner moves to a better job are less likely to be in serious distress by around 5.2% and the end of a temporary job decreases the probability of poor mental health by 5.3%. Man's retirement is associated with a decrease in the probability of partner's high distress and this is consistent with the impact of retirement on individual mental health. Surprisingly, the number of children does not have a significant impact on woman's mental health, as well as education binary variables. Fixed effect logit model confirm all the previous results. The last two columns show estimates from the extended model, including education binary variables and income variables. Job changes binary indicators maintain the same sign and significance, and the impact of man's redundancy is even higher than the effect in the first more parsimonious model. An exogenous redundancy increases the probability of partner's high distress by around 8.6%, while an improvement change decreases it by 5.7%. Women seem to be very sensitive to their partner's job changes and controlling for men's income does not decrease the specific effect of job change. Job change is perceived as a stressful experience for the whole family, and increasing the number of men's job changes in the same year also increases the probability of women's poor mental health.

Man's income is significant and has the expected sign. An increase in man's monthly pay or in the household investment income decreases the probability of woman's poor mental health. Investments marginal effect is quite relevant: an increase in annual household investment income by £ 10,000 decreases the probability of woman high distress by around 5%. It may be worthwhile to expand this analysis, looking for the main channels through which job loss affects family well being, considering the role of social interaction and social support, as well as other psychological effects of job insecurity.

Table 12 and 13 show the results from a random effect probit model, including job changes continuous variables. The analysis is focused on the impact of multiple job changes in the same year on individual and partner's mental well being. The results are consistent with the previous ones and confirm that redundancy increases the probability of high distress. People who experiments repeated redundancies in the same year are more likely to be in poor mental health, and the impact is even stronger on their partner well being (6.6% vs

4.2%). All the included job change variables are significant and have the expected sign and the results are consistent with the previous model.

Even when controlling for education and income effects, the job change variables are significant and have a clear effect on individual distress. It is interesting to note that, as in the previous model, increasing the number of job changes has a negative impact of mental health, even if people who experiment multiple job changes for better job or promotion seem less likely to be highly distressed and the same is true for their partners. Therefore, we cannot claim that the job change experience itself is strictly perceived as a stressful event for the family, but it is essential to deeply analyse the reasons for changing, and especially the voluntary dimension of the change.

Table 12 also presents results from a correlated random effect model, that allows correlation between the individual unobserved time invariant component and some job changes variables. Particularly, following Chamberlain (1984), I introduce the average number across years of individual job changes and the average number of individual job changes for promotion or better job.

As explained above, I model:

$\alpha_i = \overline{zi}\,'\xi + \eta_i$

where α_i is the unobserved fixed effect and $\overline{zi}$ contains the time average of all job changes and the time average of job changes for improvement. In this way I wish to verify if these new variables may be correlated with unobserved individual characteristics, that has an impact on mental health. The estimated coefficient capture the impact of the average number of job changes on the individual unobserved component. One possible interpretation of this model is the following: unobserved individual ambition, or any other unobserved "taste for improvement" or incentive to look for jobs fitting with individual aspiration, that that could be revealed through the average number of improvement changes, has an impact on the probability of individual's poor mental health. Thus, the average number of job changes affects the probability of poor mental health, both directly and through this "personality channel". When we look at the estimation output from the CRE model, we find that both the two coefficients (the elements of the parameter vector ξ) are statistically significant and this evidence supports the existence of correlation between the individual effect and the job changes variables. The main results from the CRE model support the evidence of a negative impact of redundancy experience on individual mental health, as well as the role of other job changes variables. A further development of this model would be the analysis of woman's job changes, and particularly of job changes for family reasons. A CRE model could be applied in this framework, in order to verify if an unobserved "taste for family", that may be revealed through job changes for family reasons, has an impact on individual mental health. In this way, I may be able to verify the direct impact of job changes for family reasons on mental health, as well as the impact through this personality characteristics.

One natural concern in this analysis may be that people with different mental health status may be differently distributed according to job change experiences. In other words, I want to be sure that the impact of job change variables is clear and not affected by the fact that, for example, people in poor mental health are more likely to experience redundancy or that, on the other hand, people with good mental health, are more likely to look for better jobs. I cope with this concern by analysing a random effect model, that controls for individual's poor mental health in the year prior to job change. Table 14 presents the estimates for this model, considering both man and woman poor mental health. I analyse a simple model, including all job changes binary variables, individual's age and the number of dependent children. This new specification confirm the previous results and is consistent with the hypothesis of a significant impact of job changes variables on individual probability of poor mental health. The marginal effect of individual's poor mental health before the change is significant and relevant in size. On the other hand, the significance of the redundancy variable is not reduced: redundancy experience increases the probability of poor mental health for the two partners. The main difference with respect to the previous model is that, when controlling for past mental health, changes for improvement do not have a significant impact on woman's probability of poor mental health any more, even if the sign of the coefficient is consistent with previous results. Nevertheless, the size of the marginal impact of redundancy is still considerable.

All these results confirm the existence of a connection between job loss and job change and family well being. This analysis deserves further development, in order to clarify the impact on children well being and the transmission mechanism of this effect.

8. Conclusion and Discussion

In this study, I analyze the impact of job loss and job change on family mental health, using the sample of all married and cohabitating couples in BHPS. Using GHQ scores data and employment histories information, I distinguish different job changes (dismissal, redundancy, study, temporary job ended, retirement, better job) and I analyze the impact of these episodes on family mental health. My main results show that the probability of poor mental health increases following a man's redundancy for both the two partners, even controlling for past mental health. Increasing the total number of job changes in the same year has a negative impact on mental health and this is supportive of the idea that job change is a stressful event for the whole family. On the other hand, changes for better job or promotion, as well as man's retirement, have a positive impact on both partners' mental health. This leads me to consider the specific channels through which job change affects individual and family distress. The income shock may play a relevant role, but my results are unchanged even when controlling for two different and exogenous income variables. A large literature in economics and sociology has shown that unemployment is strongly correlated with the incidence of depression, low self-esteem, unhappiness, and even suicide. Some of these outcomes may derive from factors independent on the income situation and these dynamics could be similar when considering the impact on partner's mental well being.

It will be worthwhile to explore the transmission mechanism of a job loss shock, trying to isolate the effects of unemployment on income. This analysis could be expanded by considering the role of social support and distinguishing the impact of job loss and job change on family well being in high unemployment areas. A further development of this study will consider the impact of job change on children well being and will focus on the impact of woman's job change on man's mental health.

Moreover, it could be interesting to evaluate the role of job change expectations, as a potential form of "insurance" from mental health adverse consequences of job change. In other words, it may be worthwhile to explore whether individuals who expected to loose their jobs have some wage compensation and whether these expectations protect these individuals and their families from high distress following job loss.

Another crucial element is the role of job satisfaction. Job changes for promotions or better job are associated with a low probability of high distress within the family and it may be worthwhile to explore whether this trend could be exclusively linked to an increase in wages. A more extensive consideration of job satisfaction, including individual aspirations or employment responsibilities may help to understand the trend of mental health following job change. I believe these connections will be even stronger in the analysis of women job changes, when considering the combined role of family and employment responsibilities as determinants of individual mental health.

Taking into account the psychological cost of job loss may provide a starting point when considering long term effects in terms of "tastes for work" or labour supply within the family, and could be important when conducting a cost-benefit analysis of employment generating policies. These factors may be included in the study of social costs of unemployment and may play an important role in the elaboration of family support policies. As a conclusion, I believe this analysis underlines the strict link between employment conditions and individual and family well being. Different job changes have different impact on mental health and earning profiles may just be a partial explanation. I believe further study and research should be devoted to these consequences of job loss, which could be included in the discussion of the cost or consequences of involuntary job displacement.

Appendix

Table 1: Percentage of poor mental health by gender

Poor mental health	% males	% females
1991	21,60%	26,19%
1992	23,16%	29,79%
1993	21,12%	29,04%
1994	22,93%	29,64%
1995	22,22%	29,21%
1996	22,17%	31,11%
1997	21,13%	30,26%
1998	21,65%	29,36%
1999	20,15%	26,06%
2000	20,28%	28,50%
2001	22,84%	29,00%
2002	19,89%	28,03%
2003	19,41%	26,35%
2004	19,04%	26,01%

Note: Poor mental health: GHQ score >=3

Table 2: Job changes in the analysed sample

Number job changes	Reason
1415	Redundancy
221	Dismissal
2675	Improvement
309	Health
334	Retirement
46	Family
48	College
752	Temporary
1448	Other
7248	Total

Note: Data is based on the question: please tell me which alternative best describes why you stopped doing that job. The data is based on the pooled sample, with an unbalanced panel.

Table 3: Repeated job changes (in the same year)

Redundancy	Number of people
2	85
3	12
Dismissal	
2	8
Improvement	
2	241
3	27
4	1
Temporary job ended	
2	91
3	21
4	8

Table 4: Average mental health and proportion of individuals with poor mental health, by job change, 1991-2004

	Total	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
All															
Mean GHQ score	1,54	1,49	1,62	1,55	1,67	1,61	1,62	1,56	1,57	1,48	1,52	1,66	1,43	1,43	1,45
Sd	(2,64)	(2,48)	(2,63)	(2,58)	(2,71)	(2,66)	(2,68)	(2,67)	(2,65)	(2,64)	(2,69)	(2,75)	(2,56)	(2,57)	(2,7)
% Poor mental health	21,12%	21,59%	23,15%	21,11%	22,93%	22,21%	22,16%	21,13%	21,64%	20,14%	20,28%	22,83%	19,89%	19,40%	19,04%
No job change															
Mean GHQ score	1,49	1,37	1,55	1.51	1.59	1.53	1.58	1.52	1.49	1.48	1.48	1.56	1,37	1,42	1,45
Sd	(2,59)	(2,35)	(2,58)	(2,52)	(2,61)	(2,54)	(2,64)	(2,6)	(2,55)	(2,66)	(2,61)	(2,65)	(2,48)	(2,56)	
% Poor mental health	20,67%	20,36%	22,21%	20,82%	22,36%	21,54%	22,01%	21,25%	20,82%	20,09%	20,10%	22,03%	19,48%	19,40%	19,12%
Redundancy															
Mean GHQ score	2,19	2,48	2,26	2,5	2,52	2,83	2,01	2,16	2,07	1,61	1,99	2,12	1,76	1,71	2,37
Sd	(3,12)	(3,24)	(2,76)	(3,41)	(3,35)	(3,48)	(2,68)	(3,13)	(3,12)	(2,65)	(3,25)	(3,24)	(2,75)	(2,8)	(3,16)
% Poor mental health	30,39%	35,29%	37,74%	31,25%	31,68%	40,28%	34,38%	28,24%	28,13%	24,10%	23,76%	30,26%	22,22%	20,00%	34,48%
Improvement															
Mean GHQ score	1,3	1,61	1,21	1,08	1,32	1,29	1,15	1,43	1,44	1,12	1,32	1,52	1,09	0,95	0,94
Sd	(2,45)	(2,69)	(2,04)	(1,95)	(2,33)	(2,63)	(1,98)	(2,83)	(2,5)	(2,17)	(2,66)	(2,60)	(2,25)	(1,96)	(2,20)
% Poor mental health	16,80%	21,28%	16,67%	12,09%	17,16%	17,04%	12,68%	17,92%	21,08%	15,26%	15,75%	19,26%	15,17%	14,13%	9,62%

Note: Poor mental health: GHQ score >3. The data is based on the pooled sample, with an unbalanced panel. Standard deviation in parenthesis

Table 5: Change in mental health by job change experience

Redundancy		**Dismissal**		**Improvement**		**No change**	
	GHQ score (mean)		GHQ score (mean)		GHQ score (mean)		GHQ score (mean)
t	1,86	t	1,61	t	1,62	t	1,49
	(2,83)		(2,31)		(2,54)		(2,5)
t+1	2,12	t+1	2,27	t+1	1,3	t+1	1,5
	(3,1)		(3,82)		(2,45)		(2,62)

Note: Data is based on the pooled sample, with an unbalanced panel. Standard deviation in parenthesis

Table 6: Transition in mental health by job change

Complete sample					
			GHQ score at t+1		
		0-1	2-4	5-7	8-12
GHQ score at t	0-1	81,95%	12,00%	3,80%	2,20%
	2-4	53,64%	28,21%	10,79%	7,34%
	5-7	37,14%	27,65%	18,87%	16,32%
	8-12	32,34%	18,32%	17,97%	31,35%
Redundancy					
			GHQ score at t+1		
		0-1	2-4	5-7	8-12
GHQ score at t	0-1	68,00%	18,89%	5,33%	7,68%
	2-4	35,97%	27,74%	17,37%	18,90%
	5-7	35,17%	27,58%	23,44%	13,79%
	8-12	23,84%	21,53%	14,61%	40,00%
Improvement					
			GHQ score at t+1		
		0-1	2-4	5-7	8-12
GHQ score at t	0-1	78,19%	14,09%	4,10%	3,50%
	2-4	57,53%	23,26%	9,24%	9,58%
	5-7	47,00%	21,87%	6.25%	24,21%
	8-12	25,26%	18,94%	29,47%	26,31%

Note: Data is based on the pooled sample, with an unbalanced panel

Table 7: Age composition by job change

Age	Complete sample	No job change	Redundancy	Dismissal	Improvement	Temporary job ended
20-35	27%	24%	33,00%	59,00%	53,00%	46,00%
35-50	41%	42,00%	40,00%	33,00%	38,00%	33,00%
50-65	32%	34,00%	27,00%	8,00%	9,00%	21,00%

Table 8: Income variables by job change

Income variables	Complete sample	No job change	Redundancy	Dismissal	Improvement	Temporary job ended
Monthly pay						
Less than £500	6,69%	7,10%	7,43%	11,00%	7,00%	11,00%
Between £ 500 and £ 1000	35,33%	37,51%	47,28%	56,54%	48,44%	42,15%
Between £ 1000 and £ 2000	39,36%	45,11%	34,42%	27,23%	36,69%	37,42%
Between £ 2000 and £ 4000	8,24%	9,51%	6,71%	4,71%	7,39%	7,31%
Greater than £ 4000	10,38%	0,77%	4,15%	0,52%	0,48%	2,15%
Mean annual investment income	535	570,19	330,64	161,01	329,85	210,34

Table 9: Education level by job change

	Complete sample	No job change	Redundancy	Dismissal	Improvement	Temporary job ended
High degree	15,43%	15,14%	9,49%	5,16%	20,79%	20,78%
Other higher qualification	27,32%	27,10%	25,35%	30,52%	31,80%	23,00%
Gce	30,32%	30,20%	33,83%	34,74%	31,42%	30,83%
Low/No qualification	26,93%	27,56%	31,84%	29,58%	15,99%	25,38%

Table 10: Men job changes and mental health

	MODEL 1 RE	ME	MODEL 1 FE	MODEL 2 RE	ME	MODEL 2 FE
	Poor mental health		Poor mental health	Poor mental health		Poor mental health
Redundancy	0.216920	0.0518745	0.470057	0.199331	0.047221	0.419861
	(0.080174)**	(0.02121)	(0.152156)**	(0.082005)*	(0.02134)	(0.157748)**
Improvement	-0.518613	-0.084886	-0.805009	-0.561549	-0.089591	-0.876546
	(0.055422)**	(0.00681)	(0.104924)**	(0.057080)**	(0.00665)	(0.108776)**
Retirement	-0.640433	-0.093410	-0.880377	-0.644474	-0.093654	-0.897139

	(0.128265)**	(0.01144)	(0.266523)**	(0.128698)**	(0.01139)	(0.269570)**
Temporary job ended	-0.327996	-0.058217	-0.624221	-0.358476	-0.0623626	-0.707456
	(0.088619)**	(0.01273)	(0.172004)**	(0.092926)**	(0.01276)	(0.182441)**
Total number of job changes	0.260272	0.055661	0.379175	0.288917	0.061726	0.429741
	(0.028823)**	(0.00623)	(0.057185)**	(0.029799)**	(0.00643)	(0.059683)**
Start college	-0.795166	-0.104268	-1.627472	-0.783571	-0.103381	-1.718086
	(0.309194)*	(0.0201)	(0.556802)**	(0.315206)*	(0.0209)	(0.610342)**
Age	-0.002352	-0.000503	-0.018088	-0.001994	-0.000426	-0.018682
	(0.001398)+	(0.000)	(0.005421)**	(0.001441)	(0.00031)	(0.005832)**
Number of children	0.033733	0.007214	0.034017	0.036334	0.007762	0.022167
	(0.013223)*	(0.00283)	(0.033199)	(0.013356)**	(0.00286)	(0.033583)
High degree				0.057504	0.012560	-0.185674
				(0.054285)	(0.01212)	(0.311965)
Other higher qualification				-0.079507	-0.016649	-0.010791
				(0.043397)+	(0.0089)	(0.186714)
Gce				-0.090663	-0.0189867	-0.119963
				(0.043644)*	(0.00895)	(0.206867)
Monthly pay (September last year)				-0.032789	-0.007005	0.008363
				(0.009735)**	0.00209	(0.016654)
Investment income				-0.092905	-0.01984	-0.114055
				(0.045910)*	(0.00981)	(0.091957)
Constant	-1.054244			-0.982782		
	(0.066447)**			(0.077503)**		
Observations	31235		15847	30588		15479
Number of man	6790		2379	6673		2331

Note: ME: marginal effects and the standard errors are computed at the mean of the data using the delta method.
Standard Error in parenthesis
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 11: Men job changes and partner's mental health

	MODEL 1 RE	ME	MODEL 1 FE	MODEL 2 RE	ME	MODEL 2 FE
	Partner's poor mental health		Partner's poor mental health	Partner's poor mental health		Partner's poor mental health
Redundancy	0.232490	0.076178	0.494177	0.263567	0.086671	0.585999
	(0.075838)**	(0.02652)	(0.143358)**	(0.077750)**	(0.02748)	(0.148841)**
Improvement	-0.181943	-0.051953	-0.251822	-0.203726	-0.057321	-0.278518
	(0.048832)**	(0.01304)	(0.089560)**	(0.050448)**	(0.01314)	(0.093598)**
Retirement	-0.335152	-0.088905	-0.393049	-0.331318	-0.087381	-0.429517
	(0.108124)**	(0.02444)	(0.211436)+	(0.108508)**	(0.02441)	(0.212087)*
Temporary job ended	-0.189080	-0.053461	-0.396015	-0.169696	-0.048010	-0.319267
	(0.080903)*	(0.02113)	(0.154608)*	(0.085525)*	(0.02254)	(0.167615)+
Total number of job changes	0.142489	0.043296	0.210005	0.150879	0.04555	0.220760
	(0.026617)**	(0.00809)	(0.050677)**	(0.027725)**	(0.00837)	(0.053457)**
Start college	-0.045045	-0.013458	-0.135937	-0.046849	-0.013897	-0.147631
	(0.258907)	(0.07603)	(0.507822)	(0.258211)	(0.07521)	(0.508906)
Woman's Age	-0.006567	-0.001995	-0.008054	-0.006369	-0.001923	-0.007021
	(0.001198)**	(0.00036)	(0.004679)+	(0.001272)**	(0.00038)	(0.005170)
Number of children	0.002063	0.0006267	-0.042348	-0.001536	-0.000463	-0.059912
	(0.011500)	(0.00349)	(0.028855)	(0.011976)	(0.00362)	(0.030312)*
High degree				-0.051262	-0.01527	0.100206
				(0.045802)	(0.01346)	(0.229209)
Other higher qualification				-0.034802	-0.010418	-0.137671

				(0.039870)	(0.01183)	(0.132195)
Gce				-0.046266	-0.013903	-0.151207
				(0.034992)	(0.01146)	(0.136703)
Man’s monthly pay (September last year)				-0.034095	-0.010294	0.040603
				(0.013229)**	(0.00399)	(0.028220)
Investment income				-0.173367	-0.052345	-0.150406
				(0.052448)**	(0.01583)	(0.102770)
Constant	-0.484768			-0.424351		
	(0.054210)**			(0.065750)**		
Observations	32004		19975	29896		18556
Number of man	7002		3033	6605		2840

Note: ME: marginal effects and the standard errors are computed at the mean of the data using the delta method.
Standard Error in parenthesis
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 12: Men job changes and mental health – Continuous job changes variables

	RE	**ME**	**FE**	**CRE**	**ME**
	Poor mental health		Poor mental health	Poor mental health	
Age	-0.002414	-0.000515	-0.018391	-0.002864	-0.00611
	(0.001431)+	(0.00031)	(0.005824)**	(0.001456)*	(0.00031)
Number of children	0.038593	0.00825	0.023439	0.036335	0.007752
	(0.013347)**	(0.00286)	(0.033565)	(0.013255)**	(0.00283)
N. redundancy	0.198930	0.042524	0.407707	0.205838	0.043918
	(0.074971)**	(0.01604)	(0.148091)**	(0.073283)**	(0.01565)
N. improvement	-0.447654	-0.095694	-0.704952	-0.374566	-0.079918
	(0.049753)**	(0.01074)	(0.095778)**	(0.051262)**	(0.01101)
N. temporary job ended	-0.231335	-0.049452	-0.458026	-0.224246	-0.047846
	(0.068919)**	(0.01475)	(0.138966)**	(0.065259)**	(0.01394)
Total number of job changes	0.263973	0.0564291	0.394518	0.216949	0.0462891
	(0.030779)**	(0.00663)	(0.061503)**	(0.032428)**	(0.00696)
High degree	0.057702	0.012611	-0.164704	0.018313	0.003935
	(0.054261)	(0.01213)	(0.311330)	(0.053019)	(0.01148)
Other higher qualification	-0.079671	-0.016693	0.000043	-0.105498	-0.021917
	(0.043382)+	(0.0089)	(0.186364)	(0.042829)*	(0.00865)
Gce	-0.087384	-0.018324	-0.099473	-0.098957	-0.020657
	(0.043629)*	(0.00897)	(0.206493)	(0.043317)*	(0.00884)
Monthly pay (September last year)	-0.034171	-0.007305	0.005989		
	(0.009751)**	(0.00209)	(0.016740)		
Investment income	-0.093277	-0.0199397	-0.115220		
	(0.046036)*	(0.00984)	(0.092355)		
Average n. job changes				0.153709	0.032796
				(0.065956)*	(0.01406)
Average n. improvement				-0.252579	-0.0538913
				(0.130654)+	(0.02787)
Constant	-0.972295			-0.997655	
	(0.077186)**			(0.079231)**	
Observations	30588		15479	30978	
Number of man	6673		2331	6702	

Note: ME: marginal effects and the standard errors are computed at the mean of the data using the delta method.
Standard Error in parenthesis
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 13: Men job changes and partner's mental health – Continuous job changes variables

	RE	ME	FE
	Partner's poor mental health		Partner's poor mental health
Woman's age	-0.006745	-0002036	-0.007014
	(0.001265)**	(0.00038)	(0.005169)
Number of children	-0.000702	-0.0002119	-0.058413
	(0.011972)	(0.00361)	(0.030299)+
N. redundancy	0.218441	0.065934	0.513455
	(0.071064)**	(0.02146)	(0.140035)**
N. improvement	-0.194939	-0.058840	-0.289033
	(0.044521)**	(0.01344)	(0.083818)**
N. temporary job ended	-0.097743	-0.029503	-0.180958
	(0.062906)	(0.01899)	(0.122171)
Total number of job changes	0.150004	0.045277	0.226134
	(0.028644)**	(0.00865)	(0.055116)**
High degree	-0.050521	-0.015048	0.101338
	(0.045806)	(0.01346)	(0.228958)
Other higher qualification	-0.034005	-0.010178	-0.140225
	(0.039873)	(0.01183)	(0.131934)
Gce	-0.045499	-0.013669	-0.150273
	(0.034996)	(0.01046)	(0.136493)
Man monthly pay	-0.036098	-0.010896	0.035586
	(0.013255)**	(0.004)	(0.028248)
Investment income	-0.173556	-0.052386	-0.149091
	(0.052477)**	(0.01584)	(0.102707)
Constant	-0.410921		
	(0.065489)**		
Observations	29896		18556
Number of man	6605		2840

Note: ME: marginal effects and the standard errors are computed at the mean of the data using the delta method.
Standard Error in parenthesis
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 14: Men job changes and mental health (control for past mental health)

	Man poor mental health (RE)	Man poor mental health (ME)	Man poor mental health (FE)	Woman poor mental health (RE)	Woman poor mental health (ME)
Man poor mental health (t-1)	0.691477	0.198037	-0.246108		
	(0.027063)**	(0.00934)	(0.046555)**		
Woman poor mental health (t-1)				0.595431	0.200712
				(0.024196)**	(0.00881)
Redundancy	0.278821	0.076188	0.564101	0.285382	0.0973658
	(0.089823)**	(0.027388)	(0.188077)**	(0.0853725)**	(0.03122)
Improvement	-0.233450	-0.050480	-0.374968	-0.0189206	-0.005896
	(0.047278)**	(0.0091)	(0.094538)**	(0.414392)	(0.01284)
Retirement	-0.358794	-0.071417	-0.500325	-0.159135	-0.04708
	(0.127934)**	(0.02036)	(0.292001)+	(0.1077693)	(0.02995)
Temporary job ended	0.013433	0.003255	-0.306939	0.0614691	0.0196618
	(0.088658)	(0.02162)	(0.193614)	(0.0799719)	(0.02608)
Start college	-0.973295	-0.133655	-2.160051	-0.289968	-0.081267
	(0.446248)*	(0.02539)	(1.089980)*	(0.323473)	(0.07954)
Man's age	-0.002059	-0.000496	-0.029264		
	(0.001309)	(0.00031)	(0.006477)**		
Number of children	0.014509	0.003493	0.027318	-0.0008484	-0.000265

	(0.012765)	(0.00307)	(0.039267)	(0.011503)	(0.00361)
Woman's age				-0.0039889	-0.001250
				(0.011503)**	(0.00037)
Constant	-1.057994			-0.0694608	
	(0.064034)**			(0.0552816)**	
Observations	24684		12179	25334	
Number of man	5522		1881	5648	

Note: ME: marginal effects and the standard errors are computed at the mean of the data using the delta method.
Standard Error in parenthesis
+ significant at 10%; * significant at 5%; ** significant at 1%

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