The impact of job loss on family mental health[1]

by

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Abstract

The objective of this paper is to examine the impact of job loss on family mental well-being. The negative income shock can affect the mental health status of the individual who directly experiences such displacement, as well as the psychological well-being of her/his partner; also, job loss may have a significantly detrimental effect on life satisfaction, self-esteem and on the individual's perceived role in society. This analysis is based on a sample of married/cohabitating couples from the first 14 waves of the BHPS. Controls are included for mental-health related sample attrition and mental health dynamics. In order to correct for the possible endogeneity of job loss, data from employment histories is utilised and redundancies (different from dismissals) in declining industries are used as an indicator of exogenous job loss. Results show evidence that couples in which the husband experiences a job loss are more likely to experience poor mental health.

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1. Introduction[3]

The principal aim of this paper is to investigate whether a relationship exists between job loss and family mental well-being. Economic literature on this issue is quite limited. Even though many relevant contributions analyze the impact of unemployment on individual health and life satisfaction, few studies directly address the causal effect of job loss on mental health, and particularly the cross effect on the partner's well-being.

Medical and psychological literature presents some evidence of spillover effects of happiness and well-being in social network (see Fowler and Christakis, 2008), and also investigates cross over effects of unemployment in couples (see for example Jones and Fletcher, 1993; Westman et al. 2001; Westman et al., 2004), but most of these studies analyse small and unrepresentative samples, and do not directly address the potential endogeneity of unemployment. A few studies in economics looking at the relationship between unemployment and well-being also marginally address the impact on partner's well-being (see Winkelman and Winkelmann 1995), but they do not distinguish between various types of unemployment and mostly analyse happiness rather than mental health.

The main results of this paper show that the probability of poor mental health increases for both partners following a husband's job loss, even controlling for a large set of individual and family characteristics and modelling the dynamics of past and initial mental health.

[3] I thank the participants of the 12th Society of Labour Economists meeting (Chicago, May, 2007); of the 2008 PhD Conference in Economics and Business (ANU, November, 2008) and of the XXIII Annual Conference of the European Society for Population Economics (Seville, June 2009) for their suggestions. Financial support received by the NHMRC through a Program Grant and by the Fondazione Luigi Einaudi is gratefully acknowledged. Any errors should be attributed to the author.

Economic literature has already showed negative impact of unemployment both on the consumption and production side, as well as negative consequences on returning to the labour market. Various studies have looked at the negative effects of parental unemployment on children, in terms of educational and labour market outcomes, but the impact on partners have received much less attention, especially when considering partners' health. Nevertheless, this issue is important for various reasons:

- Poor mental health causes direct costs on individuals, in terms of labour market status and productivity. If one partner's job loss decreases both partners' mental health, this means that economic consequences for both individuals should be taken into account. The same idea applies to economic consequences of poor mental health on the society as a whole (i.e. treatment, rehabilitation, etc.).
- Worsening in partners' mental health may result in increasing family conflicts and decreasing family stability.
- Negative consequences on both partners' psychological well-being certainly imply negative effects on children.

This paper also casts some light on the role of income and psychological effect, looking at the impact of various types of job losses. Results are consistent with previous literature (see for example Kassenboehmer S., Haisken-DeNew J.P. 2009**,** Carrol, 2007; Clark and Oswald, 1994), Clark, 2003; Clark et al., 2001; Winkelmann and Winkelmann, 1998) and show that the income shock associated with job loss is unlikely to represent the major source of the effect on the individual's and partner's mental health. This has some important policy implications: policies aimed at reducing the earnings shock from job losses may alleviate the financial problem, but they will be less effective if the main impact comes from other factors, such as the incidence of low life satisfaction, depression and low self-esteem.

There are various areas in which this paper gives a novel contribution to the economic literature: first, it directly addresses the analysis of the cross effect of job loss on partners' psychological well-being and the potential job loss endogeneity. Results complement the limited evidence on partners presented by Winklemann and Winkelmann in 1995 (using the GSOEP), by using British (and more recent) data and focusing on mental health, rather than on happiness. Second, this paper focuses on the negative effect of the job loss shock on individual's and partner's mental health, while most of the existing literature looks at the relationship between unemployment (as a *status*, rather than a *shock*) on happiness or life satisfaction. Mental health is a broader concept and includes (but is not limited) the analysis of happiness and life satisfaction.

Lastly, this paper includes some methodological novelties with respect to the existing literature. The distinction between job losses occurring in industries with increasing or declining employment allows addressing the risk of reverse causality and selection into unemployment, and a dynamic model with unobserved heterogeneity is used. This approach has rarely been taken in previous literature, but it allows to take into consideration both state-dependence and individual heterogeneity and therefore makes the analysis more accurate. Also, the introduction of dynamics in the model allows considering the effect of the job loss shock with respect to the previous and initial mental health status.

The rest of this paper is organized as follows. Section 2 provides an overview of the existing literature, Section 3 analyses the data and briefly presents mental health indicators. Section 4 discusses the estimation methods and Section 5 presents the main results. Section 6 concludes.

2. Overview of existing literature

The relationship between unemployment and subjective well-being has received increasing attention from economists in recent years. The literature to date has focused on both direct and indirect effects of unemployment on health, as well as on the transmission mechanism.

Firstly, job loss has a direct impact on well-being. A large empirical psychological literature[4] has investigated the impact of unemployment on the incidence of low life satisfaction, depression, low self-esteem, unhappiness, and even suicide. A British study by Clark and Oswald (1994) uses cross sectional data from the first wave of the BHPS to show that unemployed people have much lower levels of mental well-being (measured through the GHQ) than those in work[5].

Recent literature in health economics has investigated the role of income shocks on mental health. Lindeboom et al. (2002) show that changes in income do not affect the mental health status of the individual, measured through cognitive status (orientation, memory, logical ability) and the incidence of depressive feelings. Few studies make substantial efforts to decompose the shock into multiple components. Winkelman and Winkelman (1998) decompose the cost of unemployment on life satisfaction into pecuniary and non pecuniary costs and conclude that pecuniary costs are small compared with non-pecuniary ones.

The question of whether unemployment hurts people other than the individual concerned has received less attention, especially among economists. There is a small body of psychological literature (Strom, 2003 for a review) showing that men’s unemployment has a significant

[4] See Darity and Goldsmith (1996) for a review of psychological studies showing that unemployment has a negative impact on self-esteem.
[5] See also Flatau et al. (2000) for evidence from Australia.

effect on their partners' mental health, sometimes mediated through the effects on men's health. Nevertheless, this literature has often neglected the causal mechanism and the risk of job loss endogeneity.

This paper adds, in various ways, to the different strands of literature mentioned above. Firstly, the impact of husbands' job loss on the probability of partners' poor mental health is analysed. This approach is novel and has rarely been investigated in previous literature. Secondly, a dynamic model with unobserved heterogeneity is used, in order to control for both state dependence and individual heterogeneity. Furthermore, I deal with the possible endogeneity of job loss, focusing on involuntary displacements occurring in industries with declining employment and results are stable across different models. Lastly, the existence of multiple transmission channels is analysed and I discuss the relevance of the income shock on individual's and partner's mental well-being.

3. Data

This analysis uses data collected in the first 14 waves of the British Household Panel Survey (BHPS), which is a nationally representative sample[6] of about 5,500 households, recruited in September 1991. A sample is constructed of all married or cohabitating couples in the first 14 waves of the BHPS, with male between 16 and 65[7], in paid employment at the first wave. The decision of limiting the sample to people in paid employment at the first wave is driven by the fact that job loss can only occur to these individuals, and not to self employed, unemployed or individuals outside the labour force for other reasons. In this way, attention is focussed on the initial work status and a control for changes in status within the following waves is included.

[6] Additional samples of 1,500 households in Scotland and another 1,500 in 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. The additional samples are included in this analysis.
[7] Those couples where the man reaches 65 during the survey period are dropped at the time the man reaches 65.

Sensitivity analyses has been run in order to include couples with husbands unemployed or out of the labour force at wave one, and the results do not change significantly.

This paper analyses the impact of husband's job loss on both partners' mental health. In many households men are the primary earners and their job loss will cause the largest earnings shock hence we are more likely to find impacts through that channel. Secondly, female labour market mobility is much greater and due to a variety of reasons (e.g. child bearing and rearing). Lastly, women have been found to be more sensitive to husbands' working conditions and working hours (see for example Booth and Van Oeurs, 2008) as well as to partners' unemployment (see Clark, 2003).

If a union ends, the partners are subsequently dropped from the analysis sample. In a separate paper, Doiron and Mendolia (2009) analyse the consequences of job loss on the risk of family dissolution and find that the probability of divorce increases following a husband's job loss and the results are stronger and longer lasting for dismissals compared to redundancies. It is generally found that married people have higher levels of psychological well-being (Clark and Oswald, 1994). Therefore, the results are likely to have conservative lower bounds for the population at large since those with more serious effects are more likely to divorce.

Two different samples have been used: a *balanced sample* of respondents, who stay in the survey for all 14 waves, and an *unbalanced sample*, which does not include new entrants but tracks all those who are observed at wave 1. The issue of sample attrition is covered below. The final unbalanced sample contains about 1,400 couples and 9879 observations.

Information on labour market behaviour and periods of unemployment is collected from different sources within the BHPS. At each interview, the individual is asked about his/her current employment situation[8], and whether he/she did any paid work or was away from a job in the week prior to the interview. Paull (1997) 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[9]. Information on the reason[10] for leaving an employment spell is not included in the Paull's data set and was derived from the job history files. In this paper we focus on involuntary displacements and consider dismissals, redundancies and temporary job endings as job losses.

Mental health is assessed using the General Health Questionnaire Caseness score. Previous literature refers to the GHQ as one of the most reliable indicators of psychological distress or "disutility" (Argyle, 1989; Clark and Oswald, 1994). The GHQ Caseness score is constructed from the responses to 12 questions covering feelings of strain, depression, inability to cope, anxiety-based insomnia and lack of confidence. The twelve answers[11] are combined into a total GHQ score that indicates the level of mental distress, giving a scale running from 0 (the least distressed) to 12 (the most distressed)[12].

[8] 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, or other situations.
[9] See Paull (1997) and Paull (2002).
[10] The alternatives are: 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.
[11] The 12 questions are the following. 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 losing confidence in yourself? Been thinking of yourself as a worthless person? Been feeling reasonably happy all things considered?
[12] An alternative is the GHQ Likert score, that is, a well-being score from 0 to 36. It is the sum of the responses to the twelve questions, coded so that the lowest well-being value scores 36 and the highest well-being value scores 0.

In this analysis different cut off points of the GHQ have been used to define poor mental health (Goldberg, 1972 and 1998). I started using GHQ-12 as a dichotomous indicator with a cut-off point at a score of 3 and then I used a more severe notion of mental illness, corresponding to the GHQ-12 score greater or equal to 6[13]. The cut-off for this more restrictive definition was chosen to yield an incidence similar to the proportion of people declaring that their mental health status limited their work activity in the Labour Force Survey (between 8 and 9 percent).

The model also includes a very rich set of other control variables, consistent to the previous literature on this topic (Clark and Oswald, 1994; Winkelman and Winkelman, 1998), such as: health (individual and partner's), highest educational qualification attained, number of children and age of the youngest child in the household, age, occupation and a vector of time and region binary variables. Income is measured as lagged yearly labour household income and current yearly non-labour income. Labour income is lagged, in order to avoid spurious correlations with job loss. Nevertheless, a sensitivity analysis has been run including contemporaneous labour income and results are unchanged. The use of yearly income helps to smooth out effects of unusually high income receipt in any one month. Empirically, both yearly and monthly incomes produce very similar results. The complete list of independent variables is reported in Table 1.

Table 1 here

Figure 1 displays the distribution of the GHQ score across the 14 waves, for men and women. The distribution of mental health status in each wave is skewed to the left and there is a higher percentage of women in poor mental health. There is an increase in the proportion of observations in the poor mental health category (from 5% to 9% for men and from 11% to

[13] Results are shown only for the second definition of poor mental health. Results from the first definition are very similar and are available on request.

14% for women). Differences between men and women are consistent with previous literature and particularly with Clark (2003) who finds that women generally tend to have lower levels of mental well-being and with Nolen-Hoesksema and Rusting (1999) showing that women often report higher satisfaction scores but are more stressed.

Figure 1 here

Table 2 presents the relationships between psychological well-being and a number of economic and demographic variables. With respect to age, the highest percentage of people in poor mental health is found among individuals between 30 and 49. Men and women with long-term illnesses report the lowest score, followed by the unemployed. The presence of very young children in the household is not a determinant of poor mental health status while there is a clear relationship between self reported health and psychological well-being. The percentage of men and women with poor mental health is higher among people with higher education and middle income.

Table 2 here

Table 3 presents the number of job losses by year in the unbalanced sample. In total, there are 418 displacements consisting of 311 redundancies, 31 dismissals and 76 temporary job endings. There is a limited number of men who experience more than one job loss in the same year (for example 2 redundancies; 1 redundancy and 1 temporary job ending; 2 temporary job endings). This information is included in the analysis and a sensitivity analysis is conducted with the addition of dummies for the observations with multiple occurrences.

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. In any one year, the incidence of job displacement for any of these causes is around 4 to 5%. This shows the importance of large samples when studying this topic.

Table 3 here

Table 4 presents transition frequencies in mental health for the complete sample and for men with a redundancy experience, before and after displacement. Rows indicate the previous mental health state while columns indicate the current state. Individuals are far more likely to remain close to their initial mental health state, especially when this is fairly good (GHQ = 0 or 1), or to improve their GHQ score. Nevertheless, people who experience a redundancy are more likely to have worse mental health after the job loss. More than 12% of individuals with very good conditions prior to the redundancy (GHQ equal to 0 or 1) report high distress (GHQ>= 4) in the following observation and nearly 8% are in poor mental health. The third and fourth panel show transition in mental health one and two years after the redundancy. Mental health conditions last for at least one year after the shock: 40% of people health status improves two years after the shock (only 23% still has a GHQ score greater or equal to 6).

Table 4 here

This analysis takes into account the issue of sample attrition[14]. Attrition dynamics have been investigated using probit models for response/non response probabilities at each wave, conditioning on individual observed characteristics at wave 1[15]. There is a clear pattern of age and mental health-related attrition and people in poor mental health at wave 1 are less likely to stay in the sample in the following waves. At the same time, poor (or very poor) self assessed health of both partners is an important source of attrition. On average, men with higher education are more likely to remain in the sample, while the income pattern is less clear.

Table 5 here

[14] The complete list of sample size, dropouts and attrition rates by wave is reported in Table 5.
[15] Results are available on request.

4. Estimation Methods

In this paper panel data methods are used in order to control for person-specific unobserved heterogeneity as well as for the observed heterogeneity captured by the explanatory factors. A primary motivation for using panel data is to solve the omitted variable problem. The underlying assumption is that there is an individual, unobserved, time-invariant component of mental health status that can be accounted for by using panel data estimation. Further, panel data allows for the estimation of state dependence effect, i.e. for the causal impact of previous poor mental health status.

As explained in section 3, mental health is assessed using a score from 0 to 12, and a poor mental health indicator has been defined, corresponding to a GHQ score greater or equal to 6. The decision of using a probit model with a dichotomous indicator of poor mental health instead than an ordered probit model is driven by the intention of looking at really problematic mental health status, and not only at the gradual worsening of psychological well-being. Further, mental health is very volatile and changes in one unit in the GHQ score do not necessarily imply a noticeable change in mental health conditions. Nevertheless, sensitivity analyses have been run on the pooled sample using both linear and ordered probit models and results are unchanged.

This paper takes into consideration the dynamics of mental health, in order to evaluate the role of state-dependence as well as heterogeneity. Previous literature (see for example Contoyannis et al., 2004) has shown that the observed persistence in health outcomes can be explained both in terms of state dependence and unobserved heterogeneity, and this is the reason why I decided to use a dynamic model in this analysis. As we showed in table 4, there is a clear evidence of persistence in mental health status and individuals are more likely to remain close to their initial status than to move far away from it. Contoyannis et al. (2004) have shown that self assessed health is characterized by substantial positive state dependence and unobserved heterogeneity. Including state dependence dramatically reduces the impact of unobserved heterogeneity and the use of a dynamic model allows evaluating the changes with respect to previous mental health conditions rather than the simple effect on mental health status. Lastly, the presence of state dependence means that short-term policy interventions may have longer term implications and this is another reason why dynamic models can be particularly useful.

The latent variable specification of the model estimated can be written as:

$$Y^*_{it} = \beta' x_{it} + \gamma' y_{it-1} + c_i + \varepsilon_{it} \tag{1}$$

$$(i = 1, \ldots\ldots. N, t = 1, \ldots\ldots T_i)$$

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 observable variables (including husband's job losses), y_{it-1} is a vector of indicators for the latent variable (individual's mental health state) in the previous wave, c_i is a fixed effect which takes into account intrinsic differences in mental health and unobservable time invariant individual characteristics, ε_{it} is a time and individual specific error term. ε_{it} is assumed to be normally distributed, and x_i are assumed to be uncorrelated with ε_i, for all t. The variance of the idiosyncratic error term is normalized to equal one.

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

$$Y_{it} = \begin{cases} 1 \text{ if } Y^*_{it} \geq 6 & \longrightarrow -\varepsilon_{it} \geq -6 + \beta' x_{it} + \gamma' y_{it-1} + c_i \\ 0 \text{ otherwise} & \end{cases}$$

The modeling of initial conditions is generally a complex problem and I follow Wooldridge (2002a) in estimating parameters of the distribution of unobserved effects conditional on initial conditions. The problem arises because the starting point of a survey is not the beginning of the process and unobserved time-invariant characteristics affect observed outcomes in every period, including the initial period (Contoyannis, 2004). The probability of observing poor mental health for individual i at time t conditional on the regressors and the individual effect is[16]:

$$\Pr(y_{it} = 1 \mid y_{i,t-1 \ldots} y_{i0}, x_i, c_i) = \Phi(\beta' x_{it} + \gamma' y_{it-1} + c_i) \qquad (2)$$

Instead of maximizing the log likelihood function $\sum_{i=1}^{N}\sum_{t=1}^{T} \log f_t(y_t \mid x_t, y_{t-1}, c, \theta)$, that often leads to inconsistent estimator of θ_0, the random effects estimator can be implemented by "integrating out" the individual effect, using assumptions on its distribution. Wooldridge's (2002a) suggestion is to find the density of $(y_{i0}, y_{i1}, \ldots, y_{iT})$ conditional on (y_{i0}, x_i). This approach results in a likelihood function conditional on (y_{i0}, x_i) for each observation i. This model can be estimated using standard random effects probit software. The distribution of the individual specific effect can be written as:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 x_i + \mu_i \qquad (3)$$

where $\mu_i|(y_{i0}, x_i) \sim Normal\ (0, \sigma^2_\mu)$ and independent of the x variables, the initial conditions and the idiosicratic error term ε_{it}. Therefore, the probability of observing poor mental health for individual i at time t conditional on the regressors and the individual effect is:

$$\Pr(y_{it} = 1 \mid y_{it-1}, x_i, c_i) = \Phi(\beta' x_{it} + \gamma' y_{it-1} + \alpha_0 + \alpha_1 y_{i0} + \alpha_2 x_i + \mu_i) \qquad (4)$$

[16] This equation contains several assumptions. First, the dynamics are correctly specified, that is, at most one lag of y_{it} appears in the distribution given outcomes back to the initial period. Second, the unobserved effect is additive inside the standard normal cumulative distribution. Third, x_{it} satisfy a strictly exogeneity assumption conditional on c_i. Lastly, $f_t(y_t \mid x_t, y_{t-1}, c, \theta)$ is a correctly specified density for the conditional distribution on the left hand side of equation (2).

Where x_{it} is a vector of conditioning variables at time t and x_i is a vector of all explanatory variables in all time periods. This model is separately estimated for each partner.

Finally, the joint probability of partners' poor mental health has been estimated using a bivariate probit model[17], including two equations relating both partners' mental health to the independent variables. The main assumption in this model is that two partner's mental health statuses vary jointly. Therefore, the coefficients of the main model are estimated to take into account this joint distribution. The random error terms in the equations are allowed to be correlated and this implies that the covariance between the two error terms is equal to a constant ρ rather than zero. In practical terms, this implies that the determinants of the risk of poor mental health for one partner are related to the determinants of the poor mental health status of the other partner.

4.1 The attrition correction

To allow for attrition, an inverse probability weighted (IPW) estimator has been calculated and this correction has been applied to the pooled probit model[18] (Wooldridge, 2002b, 2002c). The underlying idea is to estimate (probit) equations for the probability of responding at each wave, with respect to a set of characteristics x_i measured at the first wave. This relies on "selection on observables" and implies that attrition can be treated as an ignorable non-response, conditional on individual characteristics at time zero. The x_i vector includes all the regressors of the model, including initial mental health. Then, the inverse of fitted

[17] See Greene (1993)

[18] This estimator can only be applied to an objective function that is additive across observations, and therefore, cannot be applied to the random effects specification.

probabilities $1/\ddot{\mathbf{p}}_{it}$ from models of response for all waves, 2 to 14, are used as weights[19] in the estimation of the pooled probit model following:

$$LogL = \sum_{i=1}^{N}\sum_{t=1}^{T}(s_{it} / \ddot{\mathbf{p}}_{it})\log L_{it} \qquad (5)$$

where s_{it} is a binary variable equal to 1 for the response of individual i at wave t and equal to zero otherwise. Wooldridge (2002b) shows that under the ignorability assumption[20] the IPW estimator is $\sqrt{n}$ consistent and asymptotically normal. It is also shown that using the estimated probabilities and ignoring the adjustments to the standard errors leads to "conservative inference" (the standard errors are larger than using the true probabilities). Therefore, the standard errors have not been adjusted for the presence of generated weights.

4.2 Exogenous job loss: the redundancy variable

An important issue is the possibility of endogenous job losses and the resulting difficulty in the identification of causal effects. Reverse causality (the increased likelihood of job loss due to poor mental health conditions) can be reduced by taking into account the relative timing of the events. Specifically, mental health is recorded at each interview and is related to all job losses occurring since the 1st September of the year prior to the interview. A second source of endogeneity is the omission of common important variables; the probability of job loss and poor mental health could be correlated due to a common trait of the individual or match not observed in the data.

The treatment of redundancies as uninformative about individual traits is based on the legal definition of redundancy. The British legislation is explicit and the term redundancy should

[19] This estimator is implemented using the pweight option in STATA.
[20] $P(s_{it}=1|y_{it}, y_{it-1}, x_{it}, x_{i0})=P(s_{it}=1|x_{i0}),\ t=1,\ldots.T$

not refer to a dismissal caused by an individual worker's behaviour. The possible reasons for individual or collective redundancy are: 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. Also, the distinction between types of displacements is supported by recent literature based on the BHPS.

Arulampalam (2001) finds that redundancies have less of a scarring effect than other job losses: 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. Nevertheless, the reason for leaving the employment spell is self-reported and this may lead to potential measurement errors. Respondents may be willing to report redundancies in cases of dismissals as redundancy is probably less stigmatic. In another study of the BHPS, Borland et al. (2000) also compare the earnings loss of workers based on the reasons for the termination of the employment spell. They distinguish displaced workers from industries with decreasing employment in order to separate exogenous variations in job losses[21].

Following the approach proposed by Borland et al. (2000), I constructed a more stringent definition of redundancy, taking into account information on the industry of the job which has been terminated[22]. Each employment spell has been linked with the relevant workforce growth rate[23] and redundancies from jobs in industries with declining employment are treated separately and are considered as exogenous job displacements. The underlying assumption is

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

[22] The BHPS contains the information according to the Standard Industrial Classification, until wave 10 and to the New Standard Industrial Classification 92 after wave 10).

[23] A three-years moving average workforce growth rate for every industry.

that people with worsening mental health are not more likely to have jobs in declining industries than other people.

The model controls for the occurrence of other job changes (voluntary, retirement, etc.) or changes in the labour force status (unemployment, out of the labour force, etc.) and the impact of redundancy on mental health is observed, conditioning on not experiencing other job changes.

The risk of job loss endogeneity is lower in the analysis of the partner's mental health. Nevertheless, there is a smaller chance that the partner's mental health status affects the individual's productivity within the labour market and therefore increases the probability of job loss. Therefore, the industry correction has been applied to the analysis of the partner's probability of poor mental health too and redundancies in industries with declining employment are treated separately.

One final concern is that workers are more likely to anticipate the redundancy when it occurs in an industry with declining employment and they may adjust gradually to the shock if this is expected. Therefore, their mental health status could start worsening even before the actual lay-off. Therefore, the estimated model is likely to be very conservative and to underestimate the effect of redundancy on family mental health, if the actual effect has already started before the job loss. This can also partially explain why people seem to recover pretty quickly from the redundancy shock.

5. Results

The results from the separate estimation of the impact of job loss on husbands' and wives' probability of poor mental health (including coefficients and average partial effects[24]) are presented in Tables 6[25] (results for the balanced sample and for the model without attrition correction are available on request).

The unbalanced sample comprises of 9,879 observations in 1,415 couples. The final sample is the result of excluding couples with: i) missing values in the mental health of one partner; ii) missing values in any of the independent variables for one or both partners. A sensitivity analysis has been conducted using different samples for men and women (i.e. not excluding all the individuals with missing mental health or missing covariates for their partners) and the results are unchanged.

Results show that a husband's redundancy increases the probability of partner's poor mental health by around 7 p.p and the individual's risk of low well-being of around 6 p.p in the models with random effects and both the coefficients are significant at 1%. Interestingly, the effect on partner's well-being is higher than the one on individual mental health. Dismissals increase the risk of individual poor mental health of around 18 p.p but are not significant determinants of the spousal probability of poor mental health but the coefficient has the expected sign and the average partial effect is around 2 p.p. This suggests that such insignificance could also be driven by the small number of dismissals in the analysis sample.

[24] APE from the random effects dynamic model are only presented for significant variables. APE are calculated following Wooldridge (2002a) and are averaged over the population distribution of heterogeneity using the population averaged parameter $\beta c = \beta / (1+\sigma^2_{\mu})^{1/2}$. Standard errors of the APE have been calculated using the delta method.
[25] The estimates of the standard errors in the pooled probit model allow for serial correlation within those errors, by using a robust estimator for the covariance matrix.

Also, partners are dropped from the sample when they separate or divorce and it is possible that the dismissal's effect plays a significant role in this decision.

Temporary job endings do not significantly increase the probability of poor mental health for both partners and the average partial effect is around 2 p.p in both partners' equations. This effect can be due to the fact that the end of the contract was pre-determined. For this reason, temporary job endings are likely to have a much smaller effect on individual self esteem and psychological well-being.

Lastly, the impact of job loss on both partners' mental health is jointly estimated in order to allow for correlation between the error terms in the two equations. The statistical test of $\rho=0$ confirms the interdependence of the two equations. Results are very similar to the previous models, in terms of size and significance. The size of the job loss coefficients is slightly lower than in the single equation estimation and this is consistent with the idea of capturing partners' mental health effect in the joint estimation.

Table 6 here

There are a few considerations that it is worthwhile mentioning when comparing the redundancy's effects on the two partners. These effects have a noticeable size. The increased risk of poor mental health after a redundancy is greater in size than the effect of age and education and in the random effect model, the size of job loss effect is comparable to the lagged poor mental health indicator. (see Tables 6-9).

As we have already noticed, the partner's effect is comparable to the individual's and it is even higher in some specifications. There are various factors that may contribute to decrease the partner's mental well-being following a husband's job loss. First of all, job loss implies a negative income shock for the whole family (the model does not control for contemporaneous labour income, because of the risk of spurious correlation with job loss) and this is expected to have a strong effect on partners, especially if the husband's job was the main source of economic subsistence in the family. This idea has been further explored in various sensitivity checks (like interacting husband's job loss with wife's labour force status, see last paragraph of this section).

Second, partners may be sensitive to the pure psychological effect of job loss, even if we expect these factors to be more relevant for the individual. As previous literature has shown, work is a source of social interaction and self-esteem and women's life satisfaction has been found to be very sensitive to their partners' job characteristics (see Both and Van Oeurs, 2008). Husband's job loss may lead to re-consider his role in the family and this may offset the psychological equilibrium of both partners. Also, family conflicts may increase as a result of increased financial and emotional stress. Lastly, husband's job loss may be correlated with local labour market conditions and therefore reduce wife's well-being via lower wages, greater job insecurity or poorer prospects on the labour market.

Looking at the effect on individual's mental health, the comparison between the dismissal and the redundancy marginal effect suggests that income shocks are only a partial explanation of the consequences of job loss on individual's mental health. Other factors, such as changes in the individual's perceived role in the society, self-esteem or other psychological elements deserve further consideration. Some of these elements arise regardless of the income shock and because employment is a provider of social relationships, identity in society and individual self-esteem. One would expect a lower impact of these factors in the case of exogenous job loss (redundancy). The transmission mechanism has been further investigated, interacting redundancy with occupations and income groups and unpacking the 12 GHQ components (see section 5.2).

My results are tested including redundancies from declining industries in the main model[26]. These are treated separately and considered as exogenous. The sign and significance of the redundancy variable is unchanged in both partners' mental health equations and the size of the effect is even higher than in the previous model. This effect can be partially due to the higher income shock from reduced re-employment possibilities for people working in declining industries.

I now turn to the discussion of the effects of the other independent variables in the main model. All the results are presented in Tables 7-9. Past mental health and physical health[27] are important determinants of current mental health status. The partial effect of lagged mental health is around 18 p.p in the pooled probit model and decreases in the random effects model (around 7 p.p) and this is consistent with the idea that one source of correlation over time is an individual specific unobserved effect, which is eliminated using panel data estimation.

People who report excellent physical health are less likely to be in poor mental health and partners' health also is an important determinant of individual mental health status for both men and women. The current version of the model includes self assessed health as a control variable, but a sensitivity analysis has been run, replacing this variable with long term health conditions and results are unchanged.

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[26]Results from models including the redundancy in declining industry variable are not presented for parsimony and are available on request.

[27] Self-reported health status can be criticised for its possible links with mental health conditions. Nevertheless, the main results are not affected by these variables. If the set of dummies is omitted, long term health conditions are significant and increase the probability of poor mental health.

The main model includes other socio-economic variables, such as age, education, family composition, occupation and family income[28]. The probability of poor mental health is greater with higher levels of education. This result is consistent with previous literature based on BHPS data (Clark, 2003; Clark and Oswald, 2002) and may imply that higher education raises individual expectations and may induce some kind of comparison effect. Therefore, this could increase the probability of high distress. Also, men with low-skilled occupations[29] (i.e. craft sector) seem less likely to be in poor mental health and this is consistent with the findings on the effect of higher education.

Household's labour and non labour earnings are separately analysed and labour income is lagged, because this would confound the effect of job loss and income itself. [30]. All the income variables don't have a significant effect on the risk of poor mental health, but higher labour earnings seem to increase the probability of women's poor mental health while non labour income has the opposite effect. This is consistent with previous literature on mental health (Clark, 2003). One explanation could be that higher labour income is correlated with other variables that reduce mental well-being, such as longer hours of work. An additional sensitivity analysis has been run including contemporaneous labour income for both partners and the results are unchanged. Also, labour income does not increase the risk of poor mental health. This confirms that non financial consequences of unemployment play a major role in determining mental health status.

[28] The omitted group is composed by individuals in good health, between 30 and 49, with higher education and no children.
[29] I include occupation status prior to job loss for individuals who experience a displacement.
[30] A further test has been conducted using labour income in the following year, in order to control for the income effect of job loss. Results are very similar and income variables are not significant.

I also control for wives' labour market status in the wives' poor mental health equation and in the joint estimation. According to previous results in the literature (see for example Winkelman, 1995 and Clark, 2003), I find that employment status is an important determinant of women's mental health and women who are unemployed tend to have lower mental well-being. A further development of this paper will analyse the impact of wives' job loss on wives' and partners' mental health. The wife's unemployment dummy has a negative sign in the husband's equation inside the joint estimation of partners' mental health (but it is not significant). This is different from analysing the effect of wife's job loss, because it refers to a status rather than to a shock.

This idea has been explored, constructing a model in which the redundancy variable is interacted with wife's employment status, in the estimation of husband's probability of poor mental health[31]. If the income shock is a strong determinant in lowering an individual's well-being, one would expect a higher impact of redundancy when an individual's partner is unemployed or outside the labour force (the income shock is greater and the family has fewer resources to cope with the shock) but none of the interactions is significant and there is no significant difference between redundancy occurring in one or two-income families. This suggests that the income shock is not the main source of negative effects on psychological well-being. Moreover, men whose partners are unemployed seem less likely to be in poor mental health after a redundancy (even if the coefficient is not significantly different from zero). This is consistent with Clark (2003), who shows that the psychological experience of unemployment is tempered by the labour market status of those with whom the individual is in close contact. The psychological impact of individual unemployment is lower when shared with others in the same household.

[31]Results are available on request.

Tables 7-9 here

5.1 Sensitivity analyses

The first sensitivity analysis is based on a sub-sample where the information about redundancy payments is available. Workers are eligible for redundancy payments after two years of tenure with the same employer. Unfortunately, the information about redundancy payments has been collected in the BHPS after 1995 (but not in 1996) only. Therefore, a smaller sample, based on 9 waves only (1995 and from 1997 to 2004), can be used to test the stability of the results using a different definition of redundancy. In this analysis, the redundancy variable is equal to 1 when the individual reports a job loss caused by a redundancy and he also declares that he received a redundancy payment in the same year. This sample contains 185 redundancies, 79 of which do not correspond to a redundancy payment (and are excluded from this analysis). The number of dismissals in this sample is extremely low (23 occurrences).

A natural concern is that this rules out workers who have been made redundant after a short tenure and who may be more sensitive to the effects of job loss. Furthermore, the redundancy payment certainly eases the transition to unemployment status and limits the income shock, and there is the possibility that some workers choose redundancy voluntarily because of the possibility of getting redundancy payments. Lastly, the sample is smaller and the first 4 waves are excluded (the number of redundancies was higher between 1991 and 1994). For all these reasons, this model is likely to be conservative in alleviating potential concerns regarding the self-reported nature of employment history information.

The main results from this sensitivity analysis confirm the original hypothesis. Husband's redundancy increases the probability of his partner's poor mental health of around 6 p.p. In the individual's equation, the redundancy indicator is positive, but it is not significant, even if the p value (0.191) is close to the 10% significance level. This shows that the result may also be driven by the lower number of redundancies in this analysis sample. I also estimate the individual's probability of poor mental well-being using the less severe definition of poor mental health (GHQ score >=3) and a new definition (GHQ score >=4). The new redundancy variable is significant in both models.

Men's probability of poor mental health is less affected when the income shock is partially overcome, but there is still increased stress, even if the effect is lower (the significance of the result using a less severe definition of poor mental health might confirm this hypothesis). On the other hand, women's perception of the shock is very strong, even if the family receives partial compensation.

A second sensitivity analysis is run relaxing the hypothesis of no correlation between the unobserved individual effect and the vector of covariates and allowing for dependence between μ_i and the vector x_i by using a fixed effect logit model. This method comes at a large cost, since only those individual moving across the poor mental health cut off point can be used in the estimation. Results are consistent with previous findings: redundancy significantly increases the risk of poor mental health for the individual and the spouse while dismissal is relevant only in the individual's equation. All the other results are stable and consistent with previous findings. The logit fixed effect model has also been estimated separating redundancies in declining industries and the results are unchanged.

One additional check of the stability of the results has been conducted, by relaxing the hypothesis of constant variance of the error term in my model. An heteroskedastic pooled probit model has been estimated, in order to allow the variance of the error term to depend on household's income and individual education. The underlying assumption is that the way of defining mental health status varies across individuals with similar characteristics (income and education). For example, highly educated people are more used to answer to questions about their mental health status and are more likely to use different definitions of mental distress with respect to people with lower education.

Table 10 here

5.2 Interpreting the effect of redundancy

One of the most important points of this paper is the analysis of the transmission channels of the unemployment shock on individual's and partner's mental health. More specifically, this paper aims at clarifying whether the main impact of job loss on mental well-being comes from the income shock or from psychological factors.

To this regard, some additional models of the individual's and partner's probability of poor mental health have been estimated and this paragraph presents some interesting results. All these additional models include new variables (or interactions between variables) in the main equation of husband's and wife's probability of poor mental health. Particularly, I try to understand which kind of individuals are more exposed to the risk of poor mental well-being after a job loss, interacting the redundancy variable with relevant socio-economic characteristics (such as income groups, occupation, number of children, long term unemployment). Lastly, the GHQ score is unpacked and the effects of job loss on various psychological components are compared. Complete results from these specifications are not presented for reasons of parsimony, but are available on request.

How a job loss is perceived by the family, and how they will adapt to this shock depends on their “coping resources”[32]. The level of income before the shock is likely to influence the perception of the severity of the income shock. Five interactions between redundancy and non labour income categories are included in the main model, in order to understand which families are exposed to the highest risk of poor mental health. A higher income could indicate more savings and a greater ability to deal with income loss, even if it could also represent greater expectations of future income and stronger perception of the shock. The interactions between redundancy and non-labour income are significant and show that men with lower income are subject to a lower risk of poor mental health after a job loss. Wald test on the estimation results reveals that redundancies in the lowest and middle income group (omitted) are significantly different[33]. Moreover, redundancy has a significant effect on individuals' mental health for people in middle (6.2 p.p) and high income (5.2 p.p) groups only (top 3 categories). This result can't be due to the higher income shock, because this analysis is focused on *non labour* income. This result confirms that income shock is not the crucial element affecting individuals' mental health. Other psychological elements, such as individuals' self-esteem and perceived role in society may affect middle and high income families more strongly (mostly because of the prestige attached to the husband's occupation). These results are consistent with recent research on the consequences of unemployment, showing that job loss is an increasing middle class phenomenon and that job seekers with college degrees have had an especially difficult time finding a new comparable employment[34].

The income shock from job loss is likely to be stronger if the individual is still unemployed one year after the displacement. In order to investigate this issue, an interaction between the redundancy variable and an indicator of long term unemployment (equal to 1 when the man

[32] See Eliason (2004).
[33] Wald test: p=0.02
[34] See Allegretto (2004).

experiences a redundancy and he is still unemployed in the following year) has been included in the main model. The interaction is not significant in the main model and similar results are found using an interaction between dismissal and long term unemployment. This shows that the duration of a dismissal or redundancy does not add anything to the incidence effect. This result is consistent with previous literature on the effect of unemployment duration on other variables, such as earning losses upon re-employment. Arulampalam (2001) has shown that no significant effect of the actual spell duration was found in addition to the incidence effect.

Lastly, the psychological effect of redundancy has been further explored, unpacking the 12 GHQ components. Twelve separate regressions on each of these components on both partners' equations have been run, in order to compare the effects on different psychological elements. As expected, the highest impacts on individual well-being are found to be on: individual perceived role (13 p.p), loss of confidence (9 p.p) and feeling worthless (5 p.p). Other elements, such as general happiness or decision making ability are significantly less affected by a redundancy experience. On the other hand, a husband's redundancy significantly increases the partner's probability of feeling under strain (14 p.p) and decreases partner's general happiness (10 p.p) while there is no impact on individual perceived role, lack of confidence or feeling worthless.

6. Conclusion and Discussion

In this study, I analyse the impact of job loss on family mental health, using the sample of all married and cohabitating couples in BHPS, where the male is in paid employment at wave 1.

Economists' interest in mental health promotion has recently increased, especially considering that mental disorders impose a large emotional and financial burden on ill individuals and their families, including indirect costs for the nation (lost productivity) and direct costs for medical resources used for care, treatment and rehabilitation. Previous literature has not directly addressed the causal effect of exogenous job loss on individual and family mental well-being and when panel data have been used, data sets were small or based on a sub-population. Furthermore, research to date has not addressed the issue of mental health dynamics and health related attrition.

My results show that the probability of poor mental health increases following a husband's redundancy for both partners, even controlling for past mental health and using different models (as well as a balanced and an unbalanced sample), and conducting various sensitivity analyses. The results are stable across all the various specifications of the models, including the joint estimation of partner's probability of poor mental health.

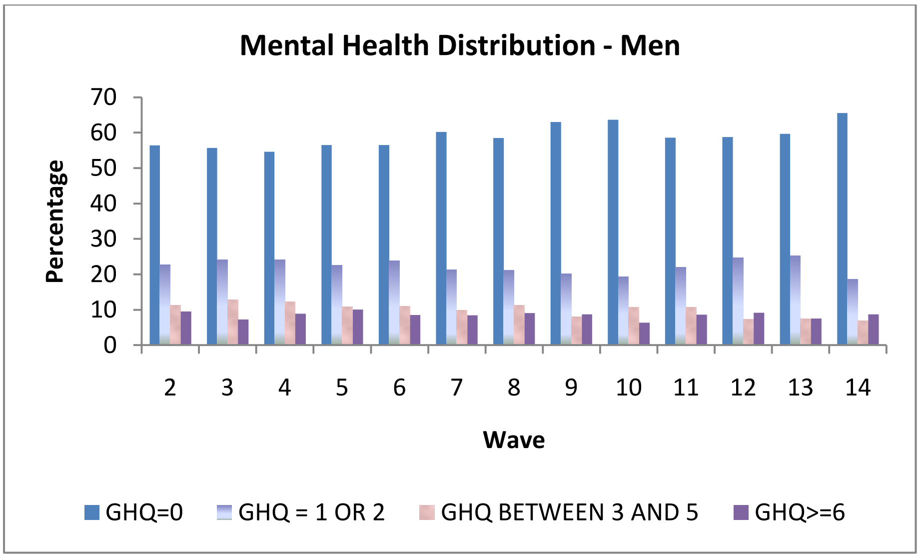
Further analyses have been conducted in order to consider the specific channels through which job loss affects individual and family distress. The income shock plays a relevant role, especially on partner's mental health, but it is unlikely to be the major source of the shock. Other psychological elements, such as low self esteem and individual perceived role deserve further consideration.

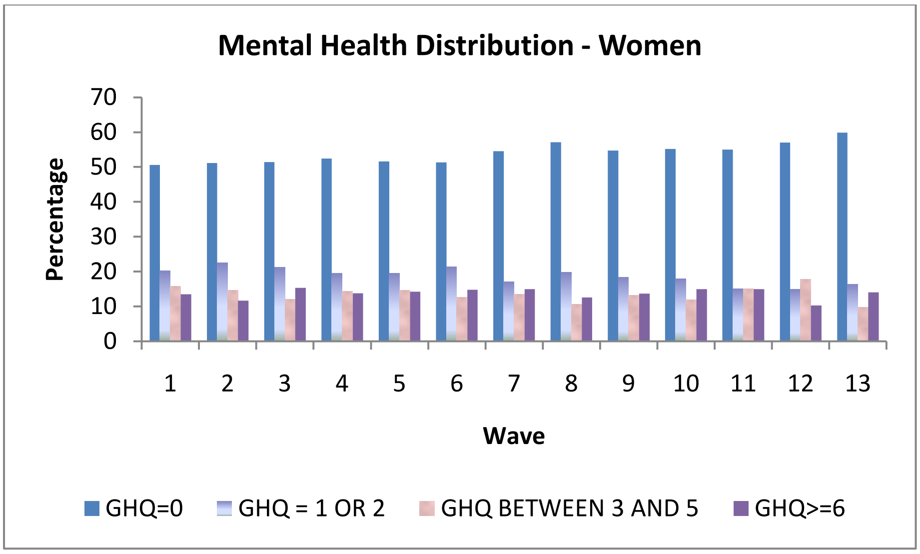
This analysis could be expanded by considering the role of social support and distinguishing the impact of job loss on family well-being in high unemployment areas. A further development of this study will consider the impact of job loss on children's well-being and will focus on the impact of women's job loss on men's mental health.

In conclusion, I believe this analysis underlines the strict link between employment conditions and individual and family psychological well-being. Further study and research should be devoted to these consequences of job loss, which could be included in a discussion of the cost or consequences of involuntary job displacement.

Appendix

Figure 1 – Mental Health Distribution





Note: 0= less distressed; 12: most distressed. The data is based on the unbalanced sample, of all couples with man aged 16-65 in paid employment at wave 1.

GHQ>=6 is the adopted definition of poor mental health.

Table 1 – Variable definition

Self Assessed Health (binary variables)[35]	Excellent, good, fair, poor, very poor (the omitted category is good)
Breathing Disease	1 if yes
Heart Disease	1 if yes
Degree	1 if highest academic qualification is a degree or a higher degree (omitted group)
HND/A	1 if 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 highest academic qualification is GCE O level or CSE (lower high school graduate)
No qualification	1 if no academic qualification
Age	Age in years at 1st December of current wave 3 age groups: 16-29; 30-49; 50-65 (the omitted group is 30-49)
Household labour income	Lagged household labour income (divided by 10,000)
Household non labour income	Current household non labour income (divided by 10,000)
Occupations	Binary variables based on the major groups of the Standard Occupation Classification (SOC)[36]: manager & administrators, professional occupations, associate professional & technical occupations, clerical & secretarial occupations, craft & related occupations, personal & protective service occupations, sales occupations, plant & machine operatives, other occupations (not included in the estimation of spouse's probability of poor mental health)

[35] Self-reported health is defined by a response to "Please think back over the last 12 months about how your heath has been. Compared to people of your own age, would you say that your health has on the whole been excellent/good/fair/poor/very poor?"

[36] See BHPS User Guide and *Quarterly Labour Force Survey, March-May 1992: User Guide*, September 1992.

Table 2 – Mental health status by socio-economic characteristics

Age groups	Men - GHQ score (average)	% Poor Mental Health	Women - GHQ score (average)	% Poor Mental Health
16-29	1.22	7.38%	1.8	11.50%
30-49	1.5	9.21%	1.95	13.75%
50-65	1.28	7.62%	1.67	10.25%
Work status				
Self employment	1.23	7.52%	2.18	15.17%
In paid employment	1.33	7.54%	1.78	11.86%
Unemployed	3	23.24%	3.25	24.68%
Retired	1.3	5.48%	1.31	7.83%
Long term sick	6.08	49.33%	4.06	33.89%
Number of children				
Age 0-4	1.36	7.39%	1.92	12.65%
Age 5-10	1.49	9.19%	1.83	13.25%
Age 11-15	1.41	8.41%	1.95	13.79%
No children	1.33	7.69%	1.86	12.37%
Self reported health				
Excellent	0.94	4.95%	1.14	6.45%
Good	1.21	6.47%	1.55	9.67%
Fair	2.01	12.01%	2.67	19.30%
Poor	3.92	31.59%	4.27	36.56%
Very poor	5.7	45.92%	5.32	43.54%
Education				
Degree	1.69	10.91%	1.99	13.06%
HND/A level	1.41	8.22%	2	13.96%
O/Cse	1.21	6.71%	1.7	11.17%
No qualification	1.23	6.59%	1.9	13.15%
Non labour income (£ per year)				
<=500	1.25	6.69%	1.82	11.96%
500-1000 (incl.)	1.39	7.80%	1.83	11.91%
1000-2000 (incl.)	1.36	7.89%	1.72	11.59%
2000-5000 (incl).	1.5	9.22%	2.05	14.09%
>5000	1.4	8.61%	2.03	14.59%

Note: Poor mental health: GHQ score >= 6. Data based on the unbalanced sample.

Table 3 – Number of job losses in the estimation sample

Wave	**N. redundancy**	**N. dismissals**	**N. temporary job endings**
2	60	1	10
3	61	6	12
4	47	3	9
5	28	3	12
6	28	5	8
7	20	1	2
8	13	3	7
9	17	1	7
10	8	0	4
11	22	6	4
12	7	1	1
13	0	0	0
14	0	1	0
Total	311	31	76

Table 4 – Transition in mental health

Complete sample					
			GHQ score at t		
		0-1	2-3	4-5	>=6
GHQ score at t-1	0-1	81.94%	9.55%	4.09%	4.41%
	2-3	55.58%	22.64%	9.80%	11.88%
	4-5	40.80%	19.06%	17.06%	23.08%
	>=6	37.33%	15.95%	13.97%	32.76%
Redundancy in t					
			GHQ score at t		
		0-1	2-3	4-5	>=6
GHQ score at t-1	0-1	73.37%	14.07%	5.03%	7.54%
	2-3	38.30%	19.15%	17.02%	25.53%
	4-5	31.25%	25.00%	31.25%	12.50%
	>=6	40.00%	11.11%	13.33%	35.56%
Redundancy in t			GHQ score at t+1		
		0-1	2-3	4-5	>=6
GHQ score at t	0-1	83.54%	9.15%	2.44%	4.88%
	2-3	53.85%	23.08%	10.26%	12.82%
	4-5	44.44%	25.93%	11.11%	18.52%
	>=6	34.38%	9.38%	15.63%	40.63%
Redundancy in t			GHQ score at t+2		
		0-1	2-3	4-5	>=6
GHQ score at t	0-1	84.75%	9.6%	2.82%	2.82%
	2-3	63.04%	10.87%	17.39%	8.70%
	4-5	64.29%	21.43%	10.71%	3.57%
	>=6	54.29%	11.43%	11.43%	22.86%

Table 5 – Sample size, drop-outs and attrition by wave

Wave	N.individuals	Survival rate	Drop outs	Attrition rate
1	1723			
2	1488	86.36%	235	13.64%
3	1373	79.69%	115	7.73%
4	1350	78.35%	23	1.68%
5	1268	73.59%	82	6.07%
6	1284	74.52%	-16	-1.26%
7	1183	68.66%	101	7.87%
8	1133	65.76%	50	4.23%
9	1016	58.97%	117	10.33%
10	1097	63.67%	-81	-7.97%
11	995	57.75%	102	9.30%
12	928	53.86%	67	6.73%
13	897	52.06%	31	3.34%
14	864	50.15%	33	3.68%

Table 6 – Probability of poor mental health – Effect of Job loss

Wife's mental health					**Husband's mental health**			
	POOLED PROBIT IPW		**PROBIT RE**		**POOLED PROBIT IPW**		**PROBIT RE**	
Husband's job loss	**COEFF.**	**APE**	**COEFF.**	**APE**	**COEFF.**	**APE**	**COEFF.**	**APE**
Redundancy	**0.309**	**0.065**	**0.379**	**0.069**	**0.288**	**0.044**	**0.434**	**0.059**
	(0.093)**	(0.023)**	(0.100)**	(0.023)**	(0.100)**	(0.018)*	(0.071)**	(0.022)**
Dismissal	**0.063**	**0.012**	**0.191**	**0.027**	**0.920**	**0.208**	**0.979**	**0.177**
	(0.293)	(0.056)	(0.324)	(0.058)	(0.269)**	(0.089)*	(0.295)**	(0.079)**
Temporary job ending	**0.110**	**0.021**	**0.050**	**0.008**	**0.124**	**0.017**	**0.162**	**0.0198**
	(0.186)	(0.038)	(0.212)	(0.034)	(0.204)	(0.03)	(0.226)	(0.030)
Observations	9879	9879	9879	9879	9879	9879	9879	9879
Number of individuals/ couples			1415				1487	
ICC			0.245				0.291	

Joint estimation of partners' probability of poor mental health – Effect of job loss

	Man	**Woman**	**Man**	**Woman**
	POOLED BIVARIATE PROBIT COEFF.		**POOLED BIVARIATE PROBIT IPW COEFF.**	
Husband's redundancy	**0.266**	**0.294**	**0.263**	**0.29**
	(0.099)**	(0.091)**	(0.1)**	(0.094)**
Husband's dismissal	**0.867**	**0.090**	**0.926**	**0.054**
	(0.259)**	(0.290)	(0.275)**	(0.290)
Observations	9879	9879	9879	9879
Test of Rho = o Rho = 0.3. Chi square = 1048. p-value = 0.0000.				

Note: All models control for year and region binary variables and for all variables listed in Appendix table 1. Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. ICC is the intra class correlation coefficient. (σ^2_μ / (1 + σ^2_μ))

Table 7 –Probability of poor mental health – Woman – Other variables

	POOLED PROBIT		POOLED PROBIT IPW		PROBIT RE
	COEFF.	**APE**	**COEFF.**	**APE**	**COEFF.**
Sah excellent	**-0.164**	**-0.028**	**-0.153**	**-0.026**	**-0.165**
	(0.049)**	(0.007)**	(0.049)**	(0.007)**	(0.05)**
Sah poor	**0.858**	**0.229**	**0.853**	**0.227**	**0.986**
	(0.067)**	(0.023)**	(0.067)**	(0.023)**	(0.08)**
Sah very poor	**0.987**	**0.285**	**0.972**	**0.278**	**1.247**
	(0.135)**	(0.051)**	(0.136)**	(0.051)**	(0.155)**
Sah fair	**0.334**	**0.068**	**0.338**	**0.068**	0.378
	(0.044)**	(0.010)**	(0.044)**	(0.010)**	(0.05)**
Partner sah very poor	**0.539**	**0.130**	**0.587**	**0.145**	**0.699**
	(0.172)**	(0.052)*	(0.178)**	(0.056)**	(0.19)**
Partner sah excellent	-0.030	-0.005	-0.027	-0.004	-0.016
	(0.041)	(0.007)	(0.041)	(0.007)	(0.051)
Partner sah poor	0.063	0.011	0.062	0.011	0.0719
	(0.096)	(0.018)	(0.098)	(0.018)	(0.113)
Partner sah fair	-0.009	-0.001	-0.010	-0.001	0.0128
	(0.051)	(0.008)	(0.051)	(0.009)	(0.059)
Poor mental health (t-1)	**0.740**	**0.181**	**0.749**	**0.184**	**0.351**
	(0.045)**	(0.014)**	(0.046)**	(0.014)**	(0.05)**
Poor mental health (wave1)	**0.380**	**0.081**	**0.393**	**0.085**	**0.646**
	(0.053)**	(0.013)**	(0.053)**	(0.0136)**	(0.08)**
Age 16-29	**-0.177**	**-0.029**	**-0.182**	**-0.029**	**-0.237**
	(0.074)*	(0.011)**	(0.074)*	(0.011)**	(0.08)**
Age 50-65	-0.088	-0.015	-0.085	-0.0148	-0.121
	(0.076)	(0.013)	(0.076)	(0.012)	(0.087)
Age squared	-0.0001	-0.00002	-0.0001	-0.00002	-0.0002
	(0.00005)**	(0.000)**	(0.00005)**	(0.000)**	(0.00)**
Hnd/A level	-0.051	-0.009	-0.048	-0.008	-0.074
	(0.060)	(0.011)	(0.061)	(0.011)	(0.091)
O level /Cse (Lower high school)	**-0.127**	**-0.022**	**-0.127**	**-0.022**	**-0.164**
	(0.062)*	(0.010)*	(0.062)*	(0.010)*	(0.094)+
No qualification	-0.133	-0.022	-0.136	-0.023	-0.207
	(0.071)+	(0.011)*	(0.071)+	(0.011)*	(0.107)+
Household lagged labour income	0.004	0.0008	0.004	0.0007	0.0064
	(0.011)	(0.001)	(0.011)	(0.002)	(0.015)
Household non labour income	-0.012	-0.002	-0.016	-0.0028	-0.0041
	(0.031)	(0.005)	(0.032)	(0.005)	(0.0449)
Woman - Unemployed	**0.427**	**0.097**	**0.424**	**0.096**	**0.455**
	(0.124)**	(0.034)**	(0.125)**	(0.034)**	(0.13)**
Woman – Self employed	0.052	0.009	0.048	0.008	0.028
	(0.090599)	(0.017191)	(0.091029)	(0.017126)	(0.120)
Woman – long term sick	0.058263	0.010773	0.063593	0.011752	0.056
	(0.104163)	(0.019925)	(0.105233)	(0.020178)	(0.138)
Woman- not in the labour force	-0.011	-0.002	-0.016	-0.002	-0.001
Long term conditions: chest/breathing	-0.041	0.0002	0.0006	0.0001	0.005

	(0.057)	(0.009)	(0.064)	(0.009)	(0.077)
Long term conditions: heart/blood pressure	0.0188	0.0146	0.0682	0.004	0.0359
	(0.061)	(0.011)	(0.0616)	(0.012)	(0.077)
Partner long term conditions: chest/breathing	0.0016	-0.0072	-0.046	-0.008	0.0155
	(0.063)	(0.0114)	(0.058)	(0.011)	(0.083)
Partner long term conditions: heart/blood pressure	0.078	0.003	0.025	0.012	0.1077
	(0.065)	(0.012)	(0.066)	(0.011)	(0.086)
Children 0-4	-0.029	-0.005	-0.033	-0.006	-0.102
	(0.058)	(0.010)	(0.058)	(0.010)	(0.073)
Children 5-10	-0.049	-0.008	-0.052	-0.009	-0.0913
	(0.055)	(0.009)	(0.056)	(0.009)	(0.070)
Children 11-15	0.033	0.006	0.043	0.0078	0.0214
	(0.057)	(0.010)	(0.058)	(0.0107)	(0.0687)
Husband's retirement	-0.041	-0.007	0.008	0.0015	-0.089
	(0.170)	(0.028)	(0.173)	(0.0312)	(0.201)
Husband's job change no reason	-0.002	-0.0003	-0.004	-0.0007	-0.0081
	(0.058)	(0.010)	(0.058)	(0.010)	(0.0662)
Husband's job change for improvement	-0.149	-0.024	-0.146	-0.024	-0.191
	(0.091)+	(0.013)+	(0.090)	(0.013)+	(0.105)+
Observations	9879	9879	9879	9879	9879
Number of couples					1487

Note: Dummy variables for year and region are omitted for parsimony. Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%
ICC is the intra class correlation coefficient. (σ^2_μ / (1 + σ^2_μ))

Table 8 – Joint estimation of partners' probability of poor mental health – Other variables

	Man	Woman	Man	Woman
	POOLED BIVARIATE PROBIT COEFF.		POOLED BIVARIATE PROBIT IPW COEFF.	
Husband's poor mental health (t-1)	**0.891**	0.046	**0.895**	0.043
	(0.056)**	(0.064)	(0.059)**	(0.066)
Wife's poor mental health (t-1)	0.030	**0.729**	0.033	**0.740**
	(0.060)	(0.046)**	(0.060)	(0.046)**
Husband's sah excellent	**-0.098**	-0.031	**-0.101**	-0.027
	(0.049)*	(0.041)	**(0.048)***	(0.041)
Husband's sah poor	**0.956**	0.047	**0.958**	0.048
	(0.084)**	(0.096)	(0.083)**	(0.098)
Husband's sah very poor	**1.382**	0.522	**1.352**	0.574
	(0.164)**	(0.171)**	(0.171)**	(0.182)**
Husband's sah fair	**0.302**	-0.0218	**0.307**	-0.022
	(0.052)**	(0.050)	(0.053)**	(0.051)
Wife's sah excellent	-0.047	**-0.159**	-0.050	**-0.150**
	(0.051)	(0.048)**	(0.050)	(0.049)**
Wife's sah poor	0.131	**0.867**	0.142	**0.863**
	(0.088)	(0.068)**	(0.086)	(0.067)**
Wife's sah verypoor	0.011	**0.988**	0.001368	**0.974**
	(0.184)	(0.131)**	(0.177)	(0.136)**
Wife's sah fair	0.073	**0.341**	0.074	**0.344**
	(0.053)	(0.045)**	(0.054)	(0.044)**
Husband long term health conditions: chest/breathing	0.074	-0.016	0.074	-0.050
	(0.066)	(0.064)	(0.068)	(0.065)
Husband long term health conditions: heart/blood pressure	0.063	0.009	0.051	0.017
	(0.072)	(0.068)	(0.068)+	(0.067)
Wife long term health conditions: chest/breathing	-0.009	-0.044	-0.022	-0.015
	(0.067)	(0.058)	(0.068)	(0.058)
Wife long term health conditions: heart/blood pressure	0.122	0.079	0.132	0.066
	(0.069)+	(0.061)	(0.070)	(0.062)
Husband's poor mental health (wave1)	**0.394**	0.143	**0.389**	0.142
	(0.074)**	(0.079)+	(0.078)**	(0.078)+
Wife's poor mental health (wave1)	-0.016	**0.377**	-0.034	**0.388**
	(0.070)	(0.054)**	(0.068)	(0.054)**
Husband's age 30-49	0.127	-0.075	0.140	-0.079
	(0.112)	(0.096)	(0.109)	(0.098)
Husband's age 50-65	0.210	-0.072	0.218	-0.070
	(0.151)	(0.132)	(0.147)	(0.133)
Husband's age squared	-0.00013	-0.00002	-0.0001	-0.000000
	(0.00007)+	(0.00006)	(0.00007)+	**(0.00006)**
Wife's age 30-49	0.013	**0.206**	0.007	**0.212**
	(0.093)	**(0.083)***	(0.089)	**(0.086)***
Wife's age 50-65	-0.173	0.106	-0.168	0.112
	(0.140)	(0.125)	(0.137)	(0.126)
Wife's age squared	0.00009	-0.0001	0.000090	-0.0001
	(0.00007)	(0.00006)+	(0.00007)	(0.00006)*
Husband - HND/A level	-0.099	0.044	-0.097	0.039
	(0.059)+	(0.056)	(0.061)	(0.057)
Husband - O/Cse – Low high school	**-0.254**	-0.047	**-0.248**	-0.049
	(0.073)**	(0.067)	(0.073)**	(0.067)

Husband - No qualification	**-0.314**	0.062	**-0.310**	0.064
	(0.079)**	(0.070)	(0.079)**	(0.071)
Wife – No qualification	**-0.228**	-0.138	**-0.225**	-0.141
	(0.083)**	(0.078)+	(0.085)**	(0.078)+
Wife - HND/A level	**-0.177**	-0.048	**-0.183**	-0.044
	(0.066)**	(0.064)	(0.069)**	(0.064)
Wife – O/Cse	**-0.149**	-0.123	**-0.149**	-0.123
	(0.070)*	(0.068)+	(0.073)*	(0.068)+
Household lagged labour income	0.0129	0.004	0.013	0.004
	(0.013)	(0.012)	(0.011)	(0.010)
Household non labour income	-0.0137	-0.006	-0.006	-0.011
	(0.038)	(0.037)	(0.032)	(0.033)
Husband's change for improvement	-0.140	-0.158	-0.148	-0.155
	(0.103)	(0.092)+	(0.105)	(0.090)+
Husband's retirement	**-0.562**	-0.049	**-0.584**	-0.005
	(0.274)*	(0.176)	(0.249)*	(0.176)
Wife – Self employed	0.089	0.056	0.071	0.050
	(0.098)	(0.090)	(0.097)	(0.090)
Wife - Unemployed	-0.065	**0.438**	-0.092	**0.435**
	(0.169)	(0.121)**	(0.154)	(0.125)**
Wife – long term sick	-0.085	0.062	-0.097	0.069
	(0.150)	(0.109)	(0.137)	(0.104)
Declining industry	0.0038	-0.031	0.002	-0.041
	(0.044)	(0.039)	(0.044)	(0.040)
Husband's temporary job ended	0.132	0.067	0.088	0.050
	(0.195)	(0.186)	(0.204)	(0.184)
Man job change no reason	0.030	-0.007	0.042	-0.007
	(0.064)	(0.058)	(0.0655)	(0.058)
Constant	-1.521	-1.338	-1.504	-1.111
	(0.242)**	(0.225)**	(0.258)**	(0.213)**
Observations	9879	9879	9879	9879

Note: Dummy variables for year, lagged husband's employment status and region are omitted for parsimony. Robust standard errors in parentheses. Results for other non significant variables are reported in Appendix table 3.+ significant at 10%; * significant at 5%; ** significant at 1%

Table 9 – Probability of poor mental health – Man - Other variables

	POOLED PROBIT	POOLED PROBIT APE	POOLED PROBIT IPW	POOLED PROBIT IPW APE	PROBIT RE
Poor mental health (t-1)	**0.887**	**0.187**	**0.895**	**0.187**	**0.434**
	(0.058)**	(0.017)**	(0.059)**	(0.017)**	(0.071)**
Sah excellent	**-0.105**	**-0.013**	**-0.107**	**-0.013**	**-0.088**
	(0.048)*	(0.006)*	(0.048)*	(0.005)*	(0.061)
Sah poor	**0.955**	**0.216**	**0.958**	**0.215**	**1.145**
	(0.083)**	(0.027)**	(0.084)**	(0.027)**	(0.103)**
Sah very poor	**1.362**	**0.371**	**1.331**	**0.357**	**1.584**
	(0.166)**	(0.065)**	(0.170)**	(0.066)**	(0.194)**
Sah fair	**0.312**	**0.046**	**0.317**	**0.046**	**0.107**
	(0.053)**	(0.009)**	(0.054)**	(0.009)**	(0.063)**
Partner sah poor	**0.136**	**0.018**	**0.144**	**0.019**	**0.173**
	(0.082)+	(0.012)	(0.083)+	(0.012)	(0.101)+
Poor mental health (wave 1)	**0.385**	**0.062**	**0.381**	**0.061**	**0.673**
	(0.077)**	(0.015)**	(0.078)**	(0.015)**	(0.118)**
Age 16-29	**-0.178**	**-0.019**	**-0.186**	**-0.020**	**-0.219**
	(0.101)+	(0.009)+	(0.102)+	(0.009)*	(0.121)+
Age 50-65	0.013	0.001	0.012	0.001	-0.023
	(0.081)	(0.010)	(0.081)	(0.010)	(0.099)
Age squared	-0.00009	-0.00001	-0.0001	-0.00001	-0.00012
	(0.00004)+	(0.000006)+	(0.00005)*	(0.000006)*	(0.00006)+
Craft & related occupation	**-0.254**	**-0.028**	**-0.269**	**-0.029**	**-0.316**
	(0.067)**	(0.006)**	(0.068)**	(0.006)**	(0.091)**
Hnd/A level	-0.099	-0.012	-0.092	-0.011	-0.132
	(0.058)+	(0.007)+	(0.058)	(0.007)	(0.089)
O/Cse – Low high school	**-0.235**	**-0.027**	**-0.228**	**-0.025**	**-0.253**
	(0.072)**	(0.007)**	(0.072)**	(0.007)**	(0.108)*
No qualification	**-0.289**	**-0.0319**	**-0.283**	**-0.031**	**-0.365**
	(0.081)**	(0.0007)**	(0.081)**	(0.008)**	(0.120)**
Household lagged labour income	0.014	0.002	0.015	0.002	0.024
	(0.011)	(0.001)	(0.011)	(0.001)	(0.015)
Household non labour income	-0.019	-0.002	-0.012	-0.001	-0.023
	(0.030)	(0.003)	(0.031)	(0.004)	(0.053)
Retirement	**-0.569**	**-0.046**	**-0.596**	**-0.047**	**-0.589**
	(0.266)*	(0.012)	(0.261)*	(0.011**	(0.314)+
Declining industry	0.024	0.0031	0.024	0.003	0.037
	(0.044)	(0.005)	(0.045)	(0.005)	(0.053)
Long term conditions: chest/breathing	0.081	0.0108	-0.036	0.010	-0.0619
	(0.067)	(0.009)	(0.067)	(0.008)	(0.093)
Long term conditions: heart/blood pressure	0.046	0.005	0.035	0.018	0.165
	(0.069)	(0.009)	(0.069)	(0.009)	(0.089)+
Children 0-4	-0.069	-0.008	-0.073	-0.008	-0.086
	(0.064)	(0.007)	(0.064)	(0.007)	(0.081)

Children 5-10	0.043	0.005	0.046	0.005	0.051
	(0.061)	(0.008)	(0.061)	(0.008)	(0.078)
Children 11-15	0.027	0.003	0.032	0.004	0.056
	(0.063)	(0.008)	(0.064)	(0.008)	(0.079)
Job change for improvement	-0.127	-0.014	-0.136	-0.015	-0.127
	(0.104)	(0.0109)	(0.104)	(0.010)	(0.117)
Job change no reason	0.043	0.005	0.049	0.006	0.043
	(0.064)	(0.008)	(0.064)	(0.008)	(0.075)
Partner sah excellent	-0.048	-0.006	-0.053	-0.006	-0.030
	(0.050)	(0.006)	(0.050)	(0.006)	(0.061)
Partner sah very poor	0.004	0.0005	-0.013	-0.001	0.174
	(0.178)	(0.022)	(0.178)	(0.021)	(0.204)
Partner sah fair	0.074	0.009	0.074	0.009	0.107
	(0.053)	(0.007)	(0.053)	(0.007)	(0.063)+
Partner Long term conditions: chest/breathing	-0.025	-0.003	0.079	-0.004	-0.066
	(0.066)+	(0.009)+	(0.068)+	(0.009)+	(0.087)+
Partner Long term conditions: heart/blood pressure	0.124	0.0169	0.135	0.004	0.080
	(0.068)+	(0.0100)	(0.068)*	(0.010)+	(0.090)
Professional occupation	0.043	0.005	0.042	0.005	0.095
	(0.067)	(0.0090)	(0.068)	(0.008)	(0.089)
Associate professional & technical occupation	-0.124	-0.001	-0.129	-0.014	-0.133
	(0.074)+	(0.008)+	(0.0745)+	(0.007)+	(0.095)
Clerical & secretarial occupation	0.023	0.003	0.01004	0.001	0.004
	(0.082)	(0.011)	(0.082)	(0.0103)	(0.104)
Personal & protective service	-0.073	-0.008	-0.0860	-0.010	-0.062
	(0.084)	(0.009)	(0.085)	(0.009)	(0.117)
Sales occupation	-0.184	-0.02	-0.159	-0.017	-0.129
	(0.116)	(0.011)+	(0.117)	(0.011)	(0.141)
Plant & machine operatives	-0.132	-0.015	-0.119	-0.014	-0.138
	(0.072)+	(0.007)+	(0.073)	(0.007)+	(0.095)
Other occupations	-0.165	-0.0186	-0.181	-0.019	-0.172
	(0.103)	(0.0103)+	(0.103)+	(0.009)*	(0.139)
Constant	-1.354		-1.339		-1.564
	(0.239)**		(0.241)**		(0.293)**
Observations	9879	9879	9879	9879	9879
Number of man					1487

Note: Dummy variables for year, region and change of employment status are omitted for parsimony. Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%
ICC is the intra class correlation coefficient. (σ^2_μ / (1 + σ^2_μ))

Table 10 – Results from sensitivity analyses

	Wife's mental health			Husband's mental health		
Husband's job loss	**FIXED EFFECT LOGIT**	**REDUND. PAYMENT POOLED PROBIT**	**HETEROSK PROBIT**	**FIXED EFFECT LOGIT**	**REDUND. PAYMENTP OOLED PROBIT**	**HETEROSK. PROBIT**
Redund.	0.671	0.3144	.2304	0.979	0.2601	0.248
	(0.203)**	(.164)+	(.0720)**	(0.255)**	(0.199)	(0.085)**
Dismissal	0.239	-.0416	.0670	1.832	0.9247	0.748
	(0.706)	(.3653)	(0.233)	(0.631)**	(0.358)**	(0.222)**
Temp. job ending	0.046	.0911	.1288	0.329	-0.317	0.137
	(0.406)	(0.188)	(.1424)	(0.460)	(0.317)	(0.165)
Observ.	4605	8475	9879	3391	5892	9879

Note: All models control for year and region binary variables and for all variables listed in Appendix table 1. Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. Samples of women's and men's mental health are different because STATA automatically drops all observations of individuals without variation in poor mental health (this is different between men and women)

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