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

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Preliminary version, March 2009

Keywords: job loss, mental health, income shock, psychological well-being

JEL Codes: I10, J12

Abstract

The objective of this paper is to examine the impact of job loss on family mental well-being.
Negative income shock due to job loss 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. All these elements are likely to have repercussions on family members' mental health. This analysis is based on the complete sample of married/cohabitating couples from the first 14 waves of the British Household Panel Survey, with males in paid employment at the first wave. Controls are included for mental-health related sample attrition and mental health dynamics. To investigate these issues I use a dynamic panel random effects probit model. 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. Three sensitivity analyses are conducted, including instrumental variable estimation (an interaction between job satisfaction with job security and an indicator of declining industry is used as an instrument for redundancy) .
Results to date show evidence that couples in which the husband experiences a job loss are more likely to experience poor mental health and the negative effect is found from both exogenous redundancy and from dismissals. Hence there is evidence of multiple transmission channels through which displacements affect family well-being.

[1] I am grateful to my supervisors, Denise Doiron and Ian Walker for their helpful support, comments and encouragement. I thank the participants of the 12th Society of Labour Economists meeting (Chicago, May 4th-5th, 2007) and of the 2008 PhD Conference in Economics and Business (ANU, November 20th – 21st, 2008) 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. The BHPS data was provided by the Economic and Social Research Council's Data-Archive at the University of Essex and is used with permission. The usual disclaimer applies.

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1. Introduction

The principal aim of this paper is to investigate whether a relationship exists between job loss and family mental well-being. There is little research evidence on this issue to date. 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.

Mental health is more than an absence of mental illness. It 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. It refers to personal emotions, behaviours and thoughts that enable an individual to perform her/his role as a member of the society[3]. Economists' interest in the relationship between job loss and mental health derives from many different factors. Firstly, the poor mental health which follows job displacement may cause direct costs to individuals. Poor mental health conditions may prevent people from working (or from returning to the labour market after a displacement) and the negative stress caused by job loss may reduce individual productivity within the labour market. A growing body of literature shows that short run economic shocks, such as job loss, can have persistent effects on individual productivity and labour market status (see Clark and Oswald, 1994 and Korpi, 1997). Secondly, the analysis of the impact of job loss on family mental health is helpful as the presence of a partner or children may be crucial in the demand for professional health care services. Informal care is an essential complement (sometimes even a substitute) to professional care and negative effects of a shock, such as a job loss, on the whole family may offset this mechanism. Thirdly, the identification of life events, like job loss, that have a large and significant impact on mental health may be useful in the elaboration of health care policies that focus on the occurrence of such events. Mental health care may be intensified if such events are observed[4]. Lastly, mental illness may generate a negative externality, as the costs of dealing with mental health problems have to be borne by society as a whole.

A public health approach to mental health and mental illness is characterised by concern for the health of a population and by awareness of the linkage between health and the physical and psycho-social environment[5]. Recent American and British government studies indicate that mental disorders impose a large emotional and financial burden[6] 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

[3] See UK Department of Health (2001)
[4] See Lindeboom (2002).
[5] See United States Surgeon General, Mental Health: A Report of the Surgeon General, United States, Department of Health and Human Services (1999).
[6] The indirect cost of all mental illness imposed a loss of approximately $79 billion on the US economy in 1990 and most of this amount (around 80%) reflects morbidity costs. Indirect costs also include mortality costs in productivity losses for incarcerated individuals and for the time spent by individuals in providing family care.

rehabilitation[7]. The *Global Burden of Disease* study conducted by the World Health Organization, the World Bank, and Harvard University, reveals that mental illness, including suicide, accounts for over 15% of the burden of disease in established market economies, such as the United States. This is more than the disease burden caused by all cancers. Unipolar major depression, bipolar disorder, schizophrenia and obsessive-compulsive disorder are identified as among the top 10 leading causes of disability worldwide (see Murray and Lopez, 1996).

The novel contribution of this paper is the analysis of the cross effect of job loss on partners' psychological well-being and the direct effect on individuals' mental health. The analysis is based on the first 14 waves of the British Household Panel Survey. An indicator of psychological distress is derived from the General Health Questionnaire (GHQ) and information on reasons for terminating the employment spell is used to distinguish between different types of job loss.

While dismissals are more likely to be correlated with relevant omitted variables, redundancies are based on the characteristics and the environment of the employer. Papers studying the effects of layoffs on future earnings and probabilities of employment support these statements. Job losses from plant closures (Gibbons and Katz, 1991; Doiron, 1995) or redundancies (Arulampalam, 2001) have a smaller effect on future earnings than other types of displacements. Furthermore, using information on the workforce growth rate by industry, I identify redundancies occurring in declining industries. These are treated as involuntary exogenous job losses. The stability of the results is tested using three sensitivity analyses. Estimation is achieved with a dynamic panel random effects probit model. This raises some methodological issues, including that of dealing with the initial condition problem and attrition bias. Following the approach suggested by Wooldridge (2002a) to deal with the problem of initial condition in non linear models with unobserved effects and lagged dependent variables, modelling includes the distribution of the unobserved effect conditional on the initial value of the dependent variable. The problem arises because the starting point of a survey is not the beginning of the process and individuals have many unobserved time-invariant characteristics which affect observed outcomes in every period, including the initial period. The existence of sample attrition is investigated and the estimates are adjusted using the inverse probability weighting (see Wooldridge, 2002b).

The main results show that the probability of poor mental health increases for both partners following a man's job loss, even controlling for a large set of individual and family characteristics and modelling the dynamics of past and initial mental health. Both types of job losses considered - redundancies and dismissals - have significant and positive effects on the probability of poor mental health, even if the effect from redundancies is smaller. Further analysis of the results (see paragraph 5.1) shows that the

[7] See United States Surgeon General, Mental Health: A Report of the Surgeon General, United States, Department of Health and Human Services, 1999.

income shock associated with job loss is unlikely to represent the major source of the effect on the individual'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. A redundancy experienced by the husband increases the probability of the partner's having poor mental health of about 5.5 p.p and this effect is higher than the impact on the individual's mental well-being. (4.5 p.p). The impact of dismissals on individual probability of poor mental health is higher (around 21 p.p.), as dismissals are more likely to represent both a current income shock and a stronger impact on the individual's self-esteem and perceived role in society. The main results are stable across different specifications of the model, including the joint estimation of both partners' mental health.

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[8] has 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.[9] 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. Korpi (1997) 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 the search for employment or the productivity of unemployed people who find new jobs.

Secondly, indirect effects of unemployment on health pass through the income channel. Unemployment generates a negative income shock and this may have separate negative consequences on individual health. A recent study from Sullivan and von Watcher (2006) investigates the impact of mass

[8] See Darity and Goldsmith (1996) for a review of psychological studies showing that unemployment has a negative impact on self-esteem.
[9] See Winkelmann and Winkelmann (1998) for a test of the importance of non-pecuniary costs of unemployment.

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 on individual well-being. 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. Clark (2003) shows that income is insignificant in explaining psychological wellbeing and this result is not unique to the BHPS data[10]. Recent literature in health economics confirms these findings. 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. A similar approach is taken by Clark and Oswald (1994), who conclude that at most ten percent of the psychological impact of unemployment is financial.

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 (see Strom, 2003 for a review) showing that men's unemployment has a significant 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. Social science literature[11] in the last two decades has focused on the relationship between parental job loss and children's well-being. Job loss negatively affects family's economic security, and an increased reliance on public assistance has been found to have detrimental effects on children's cognitive achievements[12]. A few studies analyse the social cost of unemployment, in terms of collective well-being. Di Tella et al. (2003) show that losses from recessions in terms of general happiness are large and the psychological costs should be computed on top of GDP decreases and unemployment rate increases. Both employed and unemployed people suffer a psychiatric cost as the unemployment rate rises. Employed people suffer a fear of unemployment, while jobless people feel they are less likely to find new work quickly.

This paper attempts to add, in various ways, to the different strands of literature mentioned above. Firstly, I analyse the impact of men's job loss on the probability of partners' poor mental health. This approach is novel and has rarely been investigated in previous literature. Secondly, I use a dynamic random effects probit model, in order to control for past mental health effects, modelling the distribution

[10] From Esterlin (1974) onwards, income has been shown to be a poor predictor of different measures of individual well-being (see Diener et al, 1999; Di Tella et al, 2001).

[11] See Voydanoff (1990) and Kalil and Ziol-Guest (2007).

[12] See Morris, Duncan and Rodriguez (2004).

of the individual unobserved effect. Furthermore, I deal with the possible endogeneity of job loss, focusing on involuntary displacements and showing that my results are stable across different models. Lastly, I analyse the existence of multiple transmission channels 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[13] 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[14]. A sample is constructed of all married or cohabitating couples in the first 14 waves of the BHPS, with male between 16 and 65[15], in paid employment at the first wave. The data is organised into couple-year form. The objective of this paper is to analyse the impact of job loss on individuals who directly experience the displacement and on their partners, focusing on couples who remain together. For this reason, if a union ends, the partners are subsequently dropped from the analysis sample. A separate analysis could be devoted to the consequences of job loss on the risk of family dissolution. It is generally found that married people have higher levels of psychological well-being (see, for example, Clark and Oswald, 1994). Therefore, our results are likely to have conservative lower bounds for the population at large. 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.

I use both 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 1,700 couples and 16,600 observations. The balanced one is composed by 821 households and 11,494 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[16], and whether he/she did any paid work or was away from a job in the week prior to the

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[13] 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.
[14] For further details, see Taylor et al. (2006).
[15] Those couples where the man reaches 65 during the survey period are dropped at the time the man reaches 65.
[16] The proposed alternatives are: self employed, in-paid employment (full time or part time), unemployed, retired from paid work, on maternity leave, looking after family or home, full time student/at school, long-term sick or disabled, on a government training scheme, or other situations.

interview. Retrospective information about labour force behaviour and all employment spells over the previous year is also collected. 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[17]. Information on the reason[18] 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 only dismissals, redundancies and temporary job endings as job losses. Also, only job losses experienced by the male partner are considered.

Mental health is assessed using the General Health Questionnaire Caseness score[19]. 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. Responses are coded on a four point scale of the frequency of a feeling, in relation to the individual's usual state: "not at all", "no more than usual", "rather more than usual", "much more than usual". The twelve answers[20] are combined into a total GHQ score[21], that indicates the level of mental distress, giving a scale running from 0 (the least distressed) to 12 (the most distressed)[22]. In the original manual of the General Health Questionnaire (see Goldberg, 1978), variations in the best threshold to adopt were discussed[23]. In this analysis I have used different cut off points of the GHQ to define poor mental health, in order to show that the results are stable. 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[24]. 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).

Income is measured as lagged yearly labour household income and current yearly non-labour income. The use of yearly income helps to smooth out effects of unusually high income receipt in any one month. Empirically, both yearly and monthly income produce very similar results. Other variables included are:

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[17] See Paull (1997) and Paull (2002).

[18] 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.

[19] Previous literature refers to the GHQ as one of the most reliable indicators of psychological distress or "disutility". See Argyle (1989) and Clark and Oswald (1994).

[20] 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?

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

[22] 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.

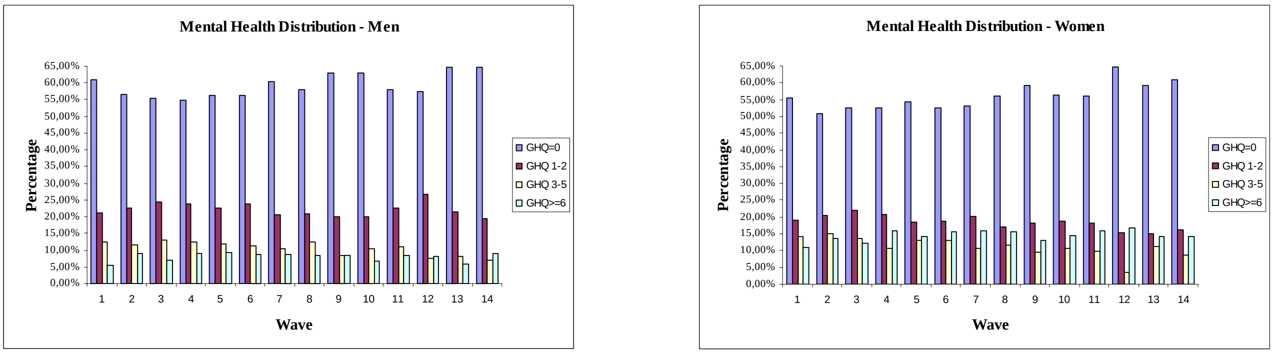
[23] When optimum thresholds were calculated for each diagnosis separately, it was found that the thresholds of 2 or 3 were optimum in all cases, although for depression a threshold of 3 or 4 was equally good.

[24] 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.

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. The complete list of the variables used in my empirical model is reported in Appendix Table 1.

Figure 1 displays the distribution of the GHQ score across the 14 waves, for men and women. The distribution is skewed to the left in all the 14 waves and the percentage of people in poor mental health is higher for women. 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 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.

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 presents the relationships between psychological well-being and a number of economic and demographic variables. With respect to labour force status, 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.

Table 2 presents the number of redundancies by year in unbalanced sample. In total, there are 713 displacements consisting of 475 redundancies, 55 dismissals and 183 temporary job endings. If a husband experiences more than one type of job loss in any year, this information is used in the analysis[25]. 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

[25] There is a limited incidence of repeated job loss of the same type in the same year mostly involving temporary job endings. Sensitivity analysis is conducted with the addition of dummies for the observations with multiple occurrences and results are very similar. Details are available from the author.

displacement for any of these causes is around 4 to 5%. This shows the importance of large samples when studying this topic.

Table 1 – Well-being in the analysis sample

BHPS Waves 1 to 14							
Sex	**Average well-being**	**% Poor mental health**	**N. observations**				
Female	1,88	12,74%	2023				
Male	1,37	7,98%	1092				
Age groups	**Men - Average well-being**	**% Poor Mental Health**	**N. observations**	**Women - Average well-being**	**% Poor Mental Health**	**N. observations**
16-29	1.16	6.62%	951	1.81	11.03%	1605
30-49	1.47	8.66%	8475	1.96	13.74%	9583
50-65	1.22	6.92%	4265	1.75	11.42%	4588
Work status						
Self employment	1.23	7.52%	771	2.18	15.17%	567
In paid employment	1.33	7.54%	12391	1.78	11.86%	10773
Unemployed	3.00	23.24%	185	3.25	24.68%	243
Retired	1.30	5.48%	219	1.31	7.83%	868
Long term sick	6.08	49.33%	75	4.06	33.89%	422
Children						
Age 0-4	1.36	7.39%	2678	1.92	12.65%	2878
Age 5-10	1.49	9.19%	2328	1.83	13.25%	2627
Age 11-15	1.41	8.41%	1712	1.95	13.79%	
No children	1.33	7.69%	6973	1.86	12.37%	8392
Self reported health						
Excellent	0.94	4.95%	4141	1.14	6.45%	3692
Good	1.21	6.47%	6847	1.55	9.67%	8073
Fair	2.01	12.01%	2165	2.67	19.30%	2969
Poor	3.92	31.59%	440	4.27	36.56%	919
Very poor	5.70	45.92%	98	5.32	43.54%	209
Education						
Degree	1.69	10.91%	2053	1.99	13.06%	1684
HND/A level	1.41	8.22%	6080	2.00	13.96%	5452
O/Cse	1.21	6.71%	2846	1.70	11.17%	5307
No qualification	1.23	6.59%	2687	1.90	13.15%	3415
Non labour income						
<=500	1.25	6.69%	2853	1.82	11.96%	3009
500-1000 (incl.)	1.39	7.80%	2615	1.83	11.91%	2779
1000-2000 (incl.)	1.36	7.89%	3841	1.72	11.59%	4176
2000-5000 (incl).	1.50	9.22%	2537	2.05	14.09%	2825
<5000	1.40	8.61%	1835	2.03	14.59%	3078

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

Table 2 – Number of redundancy

Wave	N. redundancy	%
1	57	3.31%
2	70	4.71%
3	70	5.10%
4	62	4.61%
5	35	2.77%
6	31	2.42%
7	36	3.05%
8	14	1.24%
9	28	2.76%
10	17	1.55%
11	37	3.76%
12	14	1.51%
13	3	0.34%
14	1	0.12%
Total	475	

Table 3 presents mental health dynamics 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 experiencing poor mental health after redundancy have similar condition one year later but their mental health status two years after the shock (only 23% still has a GHQ score greater or equal to 6).

Table 3 – 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%

My analysis takes into account the issue of sample attrition[26]. Attrition dynamics have been investigated using probit models for response/non response probabilities at each wave, conditioning on individual observed characteristics at wave 1[27]. The dependent variables equal 1 if the individual responds and 0 otherwise. 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 income pattern is less clear.

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. In this framework, I assume there is an individual, unobserved, time-invariant component of mental health status that is constant across the interview interval (1 year) and that can be accounted for by using panel data estimation. Moreover, panel data allows for the estimation of state dependence effect, i.e. for the causal impact of

[26] The complete list of sample size, dropouts and attrition rates by wave is reported in Appendix Table 2.
[27] Results are available on request.

previous poor mental health status. To model the probability of poor mental health following a job loss, I use dynamic panel probit specification on both balanced and unbalanced samples.

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

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

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

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 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:

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

The modelling of initial conditions is generally a complex problem and I follow Wooldridge (2002a) in estimating parameters including the distribution of unobserved effects conditional on initial conditions. The probability of observing poor mental health for individual i at time t conditional on the regressors and the individual effect is[28]:

$$\Pr(y_{it} = 1 | y_{it-1}, x_{it}, c_i) = \Phi(\beta' x_{it} + \gamma' y_{it-1} + c_i) \qquad (2)$$

Instead of maximizing the log likelihood function $\sum_{i=1}^{N}\sum_{t=1}^{T} \log f_t(y_t | x_t, y_{t-1}, c, \theta)$, 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 conditional maximum likelihood approach results in a likelihood function based on the joint distribution of the observations conditional on their initial

[28] 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[28]. Lastly, $f_t(y_t | x_t, y_{t-1}, c, \theta)$ is a correctly specified density for the conditional distribution on the left hand side of equation (2).

observations. This model can be estimated using standard random effects probit software. The distribution of the individual specific effect can be written as:

$$c_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 x_i + \mu_i \tag{3}$$

where $\mu_i|(y_{i0}, x_i) \sim Normal\ (0, \sigma^2_\mu)$

Therefore, the probability of observing poor mental health for individual i at time t conditional on the regressors and the individual effect is:

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

This model is separately estimated for each partner.

Finally, I estimate the joint probability of partners' poor mental health using a bivariate probit model[29], including two equations relating both partners' mental health to the independent variables[30]. The random error terms in the equations are assumed to be correlated and this implies that the covariance of the error terms equals a constant, rather than zero as is assumed in the case of the individual probit models. In practical terms, this model allows for the direct effect of partners' mental health status. In both equations I control for partners' health conditions, education, age groups, age squared, age of youngest child, income, region and year dummies.

[29] See Greene (1993)
[30] The model has been tested allowing for correlation within the same households. The main results are unchanged

4.1 The attrition correction

To allow for attrition, I use an inverse probability weighted (IPW) estimator and apply this correction in the pooled probit model[31] (see Wooldridge, 2002b and 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 probabilities $1/\hat{p}_{it}$ from models of response for all waves, 2 to 14, are used as weights[32] in the estimation of the pooled probit model following:

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

where s_{it} is a binary variable equal to 1 for response of individual i at wave t and equal to zero otherwise. Wooldridge (2002b) shows that under the ignorability assumption[33] 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, I do not adjust the standard errors.

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 divorce could be correlated due to a common trait of the individual or match not observed in the data. With panel data, time-invariant and match-specific unobserved effects can be modelled and controlled for.

My treatment of redundancies as uninformative about individual traits is based on the legal definition of redundancy. The British legislation is quite explicit and the term redundancy should not refer to a dismissal caused by an individual worker's behaviour. The redundancy law allows three reasons for redundancy: total cessation of the employer's business (whether permanently or temporarily), cessation of

[31] 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.
[32] This estimator is implemented using the pweight option in STATA.
[33] $P(s_{it}=1|y_{it}, y_{it-1}, x_{it}, x_{i0})=P(s_{it}=1|x_{i0}), t=1,\ldots T$

business at the employee's workplace and reduction in the number of workers required to do a particular job. Moreover, 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). The job must disappear before the employer makes an employee redundant and the employee cannot be replaced. Employees qualify for redundancy payments if they have worked for the employer continuously for at least two years up to the date of displacement.

Also, the distinction between types of displacements is supported by recent literature based on the BHPS. Arulampalam (2001) finds that redundancies overall have less of a scarring effect; specifically, she finds that the earnings loss due to redundancies is about one half of that due to other displacements and 81% of men made redundant found jobs without any spell of non-employment. 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 argue that the institutional system often blurs the distinction between the different categories and separate displaced workers from industries with decreasing employment in order to further separate exogenous variations in job losses[34]. I follow this approach and I construct a more stringent definition of redundancy using information on the industry of the job which has been terminated.[35] This data is sourced from the published UK government statistics and used to construct a three-years moving average workforce growth rate for every industry. Then, each employment spell is linked with the relevant growth rate. Redundancies from jobs in industries with declining employment are treated separately and are considered as exogenous job displacements. The model assumes 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[36] and I observe the impact of redundancy on mental health, conditioning on not experiencing other job changes. The decision of whether to include or exclude the other job changes does not affect the sign or significance of my results[37]. As explained above, my sample comprises married or cohabitating couples with male in paid employment at wave 1. As a consequence, males in my sample can change their labour force status in the following waves and I control for these changes in the model, using binary variables for self employment, retirement,

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

[35] Unfortunately, information on plant closures is not available in the BHPS.

[36] I control for: changes for improvement (promotion or better job with different employer), retirement, end of a temporary job and job change with no reason declared.

[37] For reasons of parsimony, I only present the results from models in which job change variables are included. Results from models with excluded variables are available on request.

unemployment, long-term sickness and other reasons for being outside the labour force (i.e. family care, full time study, government training scheme).

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.

4.3 Sensitivity analyses: redundancy payments, instrumental variable estimation and fixed effect

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, I use a smaller sample, based on 7 waves only, to test the stability of my 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.

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, I believe that this model is likely to be very conservative and this analysis alleviates potential concerns regarding the self-reported nature of employment history information.

A second sensitivity analysis is run using instrumental variable estimation and constructing an instrument for involuntary redundancy. The well-known assumptions of instrumental variable estimation are that I am looking for an instrument that is related to redundancy but that is uncorrelated with mental health. Using a two step estimator, the first step is a linear probability model for redundancy and the second step is a random effects probit model for poor mental health, as explained above. Information on job satisfaction with job security in the year prior to job loss is interacted with an indicator for declining industry. The BHPS data contain detailed information about job satisfaction. Individuals in paid employment are asked about:

- overall satisfaction

- satisfaction with pay
- satisfaction with the work itself
- satisfaction with hours worked
- satisfaction with job security

I assume that the overall job satisfaction can be represented as a linear combination of the four components and I assume that the interactions between the single components of job satisfaction and the indicator of declining industry are exogenous with respect to mental health. A natural concern is that job satisfaction can be related with individual's mental health. I assume that the single components of the overall satisfaction are more objective and therefore can be treated as exogenous. The instrument for redundancy is an interaction between job satisfaction with job security (in the previous year) and an indicator of declining industry[38].

I test the validity and the relevance of my instruments using an F test of joint significance in the first stage regression and Sargan's statistic for overidentifying restrictions. The selected instruments are jointly significant (following the rule of thumb of Staiger and Stock, 1997) and the null hypothesis of the validity of our overidentifying restrictions cannot be rejected. Furthermore, I verified the pseudo R squared of the second step equation by including the instruments in it. The instruments are not significant and difference in the pseudo R squared (with and without the inclusion of the instruments) is extremely low[39].

A third 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 μi and the vector xi 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.

5. Results

The results from the estimation of man's and woman's probability of poor mental health (including coefficients and average partial effects[40]) are presented in Tables 4-5[41]. The dependent variable is a binary

[38] Particularly, the satisfaction variable can assume three values (corresponding to three dummy variables): satisfied, not satisfied/dissatisfied (neutral), not satisfied. As explained above, I constructed two binary variables for industries with a growing/declining workforce. Each of the three satisfaction categories is interacted with the two industry categories and these interactions are used as instruments for redundancy. The omitted category is composed of people not satisfied with their job security and working in an industry with increasing workforce
[39] The difference in the pseudo R squared is 0.0008.
[40] APE from the random effects dynamic model are only presented for some significant variables. APE are calculated following Wooldridge (2002a) and are averaged over the population distribution of heterogeneity using the population averaged parameter $\beta c = \beta / (1+\sigma^2{}_{\mu})^{½}$. Standard errors of the APE have been calculated using the delta method.
[41] 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.

indicator of poor mental health which is equal to 1 if GHQ score is greater or equal to 6[42]. Both the pooled and the random effects specification were estimated on the balanced and the unbalanced samples[43]and all the coefficients are stable across the two samples. The coefficients for the random effects model are not directly comparable to those reported for the pooled models, due to a different scaling of the error variance,[44] but it is possible to compare the relative effects of pairs of variables across the two models.

A husband's job loss increases the probability of poor mental health for both partners and this result is stable across all the estimated models and sensitivity analyses. These results confirm my original hypothesis: an exogenous and involuntary job loss experience is associated with a high risk of distress for the two partners, and may lead to a significant negative effect on family well-being. The main element affecting women's probability of poor mental health is expected to be the income shock, as psychological elements are more likely to have a strong impact on individual well-being. The results from the random effects and the pooled model show that a man's redundancy increases the probability of partner's poor mental health by around 5 p.p and the coefficient is significant at 1%. Men's dismissals are not significant determinants of the spousal probability of poor mental health. Nevertheless, the coefficient has the expected sign and the average partial effect is quite high (around 4 p.p). This suggests that such insignificance could also be driven by the small number of dismissals in the analysis sample. Also, partners are dropped from my sample when they separate or divorce and it is possible that the dismissal's effect plays a significant role in this decision.

A redundancy experience has a strong impact on the probability of individuals' poor mental health too. The average partial effect is around 4.6 p.p in the pooled probit model and 5.8 p.p. in the random effects model. The average partial effect of dismissal is the highest (around 21 p.p.). 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 difference in the size of the effect between redundancy and dismissal is consistent with this hypothesis: the redundancy coefficient is likely to capture a negative income shock and only a limited incidence of

[42] The set of covariates includes: redundancy, dismissal, lagged poor mental health status, self-assessed health binary variables and long term health conditions (hearth disease/blood pressure problems and breathing problems) for both partners, poor mental health status at wave 1, age groups, age squared, education, age of the youngest child in the household, lagged household labour income and current household non labour income. I also control for year and region effects, man's other job changes and woman's labour force status.
[43] Results from the balanced sample are not reported here but are available on request.
[44] The pooled probit model assumes that the error term is distributed as a whole as N(0,1). The random effects probit model assumes ε_{it} to be N (0,1), so that the overall variance equals (σ^2_{μ}+ 1).

other psychological factors. The transmission mechanism has been further investigated, interacting redundancy with occupations and income groups and unpacking the 12 GHQ components (see paragraph 5.1).

Table 4 – Woman's probability of poor mental health

	POOLED PROBIT	POOLED PROBIT APE	POOLED PROBIT IPW	POOLED PROBIT IPW APE	PROBIT RE	PROBIT RE APE
Man's redundancy	0.262551	0.055187	0.306454	0.065388	0.273256	0.04924
	(0.084884)**	(0.020359)**	(0.087008)**	(0.021587)**	(0.089751)**	(0.0187797)
Man's dismissal	0.181800	0.036762	0.139940	0.027350	0.233302	
	(0.234007)	(0.052330)	(0.245867)	(0.052070)	(0.271333)	
Observations	13525	13525	12910	12910	13525	
Number of man					1515	
ICC					0.2522593	

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 5 – Man's probability of poor mental health

	POOLED PROBIT	POOLED PROBIT APE	POOLED PROBIT IPW	POOLED PROBIT IPW APE	PROBIT RE	PROBIT RE APE
Redundancy	0.300234	0.046528	0.317819	0.050158	0.413241	0.0587455
	(0.099546)**	(0.018475)	(0.100103)**	(0.019061)	(0.112031)**	(0.0215355)
Dismissal	0.934564	0.214564	0.863193	0.192086	1.095155	0.2106709
	(0.250880)**	(0.083983)	(0.261579)**	(0.084057)	(0.279439)**	(0.0803578)
Observations	10437	10437	10069	10069	10437	
Number of man					1468	
ICC					0.268275	

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))

My results are tested including redundancies from declining industries in the main model[45]. These are treated separately and considered as exogenous. The sign and significance of the redundancy variable is unchanged in both partners' mental health equations: there is a positive effect in increasing the probability of poor mental health and the size of the effect is even higher than the one in the previous model (around 9 p.p in the woman's equation and 8 p.p in the man's equation). The higher impact of redundancy can be

[45] In this model we assume that people whose wives have declining mental health are not more likely to get jobs in depressed industries Results from models including the redundancy in declining industry variable are not presented for parsimony and are available on request. .

partially due to the higher income shock from reduced re-employment possibilities for people working in declining industries.

A similar approach has been taken by constructing a model where redundancies occurring in recession years (2000 and 2001) are treated separately and I test the difference between these and normal redundancies. If redundancies contained a large endogenous mental health effect we would expect significant differences between redundancies in recession years and normal redundancies. Nevertheless, redundancies in recession years have not a significant effect in increasing the risk of poor mental health and the difference with normal redundancies is not significantly different from zero. This confirms my treatment of redundancies as uninformative about individual characteristics.

Further, the impact of job loss on both partners' mental health is jointly estimated in order to allow for the direct effect of partners' mental health status. Results are presented in Table 6 and are similar to the previous models. A man's redundancy significantly increases both partners' probability of poor mental health, while dismissal is significant in man's model only.

Table 6 – Joint estimation of partners' probability of poor mental health

	Man's probability of poor mental health	**Woman's probability of poor mental health**	**Man's probability of poor mental health**	**Woman's probability of poor mental health**
	POOLED BIVARIATE PROBIT	**POOLED BIVARIATE PROBIT**	**POOLED BIVARIATE PROBIT IPW**	**POOLED BIVARIATE PROBIT IPW**
	(0.060638)	(0.045895)**	(0.060832)	(0.046741)**
Man's redundancy	0.268810	0.281366	0.271596	0.286404
	(0.100366)**	(0.092289)**	(0.101587)**	(0.095956)**
Man's dismissal	0.866363	0.089151	0.899533	0.058436
	(0.259617)**	(0.290568)	(0.272178)**	(0.291884)
Observations	9879	9879	9726	9726

Note: Dummy variables for year, lagged man's employment status and region are omitted for parsimony. Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

The main results form the first sensitivity analysis, with the estimation on the redundancy pay sample, confirm my original hypothesis. As already explained, workers are eligible for redundancy payments after two years of tenure. Nevertheless, information on redundancy payments was collected in the BHPS only after 1995. Therefore, this sensitivity analysis is based on a sub-sample, including 9,300 observations and around 1,300 families. This sample contains a lower number of redundancies as the percentage incidence of redundancy is definitively lower after wave 4. On the other hand, this sensitivity analysis yields conservative results, both because of the lower number of redundancies and because people who receive redundancy payments are certainly less affected by the income shock. In this model, I construct a new redundancy variable, equal to 1 if the man reports a job loss for redundancy *and* he received a redundancy payment in the same year. This sample contains 185 redundancies, 79 of which do not correspond to a redundancy payment. Therefore, these are excluded from my analysis. The number of dismissals in this sample is extremely low (23 occurrences).The results of this sensitivity analysis confirm previous findings: a man's redundancy increases the probability of his partner's poor mental health, and the average partial effect is around 5.5 p.p. The size of the effect is similar to that of the original redundancy variable in this sample. All the other results are consistent with the previous analysis and the sign and significance of the main variables are unaffected. The probability of men's poor mental health is separately estimated. The sign and significance of dismissal is unchanged, as are the other main socio-economic variables. The redundancy indicator is positive, but it is not significant, even if the p value is very 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. Moreover, I estimate a simplified model, including individual age, health, education, non labour income, other job changes, region and year dummies. The new redundancy variable is significant at 10% in this model. Lastly, I 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[46].

This result is consistent with my original interpretation: redundancy mostly causes an income shock, while the effect of psychological factors is limited. 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). Partners have previously been found to be more sensitive to the income shock than the actual individual and this last result shows that women's perception of such shock is unchanged, even if the family receives partial compensation.

Results from the two-steps regression are similar to the previous ones. In this model, the redundancy variable has been replaced with the predicted value from the first step equation. As in the previous models, I estimate 3 different specifications: pooled probit, pooled probit with IPW correction and random effects probit. The sign and significance of the job loss variables is unchanged. Men with dismissal or redundancy experience are far more likely to be in poor mental health at the end of the year.

In the third sensitivity analysis, I re-estimated individual and spousal probability of poor mental health using a logit fixed effect model, in order to allow for some correlation between the unobserved effect and the vector of independent variables. As already explained, the number of observations is smaller because only individuals with variation in their poor mental health status can be included. Nevertheless, the results are consistent with the previous findings: redundancy significantly increases the risk o poor mental health for the individual and the spouse while dismissal is relevant only in the individual's equation. All the

[46] Results from both the sensitivity analyses are available on request.

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.

Finally, I further checked the stability of my results, by relaxing the hypothesis of constant variance of the error term in my model. I estimated a heteroskedastic pooled probit model, that allows 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.

I now turn to the discussion of other interesting results, arising from the independent variables included in the main model (see Tables 7-8-9[47]). The results from the separate estimation of husband's and wife's mental health are similar to the ones coming from the joint model.

Past mental health and physical health[48] are important determinants of current mental health status. In all the three specifications of my models (pooled probit, pooled probit IPW and random effects probit) the estimated coefficients of the lagged poor mental health indicator are large (around 18 percentage points in the pooled probit models) and highly significant. The partial effect of lagged mental health 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. The coefficient of the initial period poor mental health status is positive and significantly different from zero in all the specifications (around 8 p.p.). This implies that there exists a positive correlation between the initial period observations and the current probability of poor mental health. People who report excellent physical health are less likely to be in poor mental health, while the probability increases for men and women with poor or very poor reported health status[49]. Partners' health is an important determinant of women's mental health status and having a husband in poor health increases the chances of wife's poor mental health.

My model includes other socio-economic variables, such as age, education, occupation and income. The omitted group is composed by individuals in good health, between 30 and 49, with high degree and no children. Younger women seem less likely to be in poor mental health (the omitted group is composed of women between 30 and 49) and there is an inverse U relationship between mental health and age. The probability of poor mental health is greater with higher levels of education. This result is consistent with

[47] More results are presented in the Appendix
[48] 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.
[49] The omitted category is composed of men or women who report good health.

previous literature based on BHPS data (see Clark, 2003 and 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. The estimation of man's probability of poor mental health also includes controls for occupation dummy variables[50]. Men with low-skilled occupations (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, in order to avoid the effect of the husband's contemporaneous job loss[51]. Higher labour earnings increase the probability of women's poor mental health while non labour income has the opposite effect, even if the coefficient is not significant. This is consistent with previous literature on mental health (see 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. The fact that non-labour income is positively correlated with individual well-being, whereas labour income is not, might support this interpretation. Another possible explanation is that it is relative income, not absolute income that drives mental well-being (see Clark and Oswald, 1994). Employment status is an important determinant of women's mental health and women who are self employed or unemployed seem more likely to be in poor mental health.

Table 7 – Woman's probability of poor mental health

	POOLED PROBIT	**POOLED PROBIT APE**	**POOLED PROBIT IPW**	**POOLED PROBIT IPW APE**	**PROBIT RE**	**PROBIT RE APE**
Self reported health: excellent	-0.172176	-0.029372	-0.169114	-0.028542	-0.176756	-0.022017
	(0.043096)**	(0.006877)**	(0.045071)**	(0.007102)**	(0.050743)**	(0.007219)
Self reported health: poor	0.846204	0.227149	0.841215	0.223625	0.951346	0.2123068
	(0.055773)**	(0.019320)**	(0.057805)**	(0.019871)**	(0.066751)**	(0.0264539)
Self reported health: very poor	0.993725	0.289210	0.975305	0.280398	1.194342	0.2867239
	(0.109581)**	(0.041768)**	(0.113457)**	(0.042897)**	(0.124379)**	(0.0446287)
Self reported health: fair	0.361652	0.075154	0.357115	0.073287	0.388778	0.0699915
	(0.037394)**	(0.008748)**	(0.038723)**	(0.008923)**	(0.043995)**	(0.0118194)
Partner self reported health: excellent	-0.021475	-0.003867	-0.039842	-0.007065	0.006761	
	(0.036308)	(0.006499)	(0.037634)	(0.006594)	(0.044003)	
Partner self reported health: poor	0.154937	0.030604	0.122648	0.023565	0.201078	0.0349124
	(0.068010)*	(0.014566)*	(0.070992)+	(0.014564)	(0.082558)*	(0.0158943)
Partner self reported health: very poor	0.483092	0.114553	0.456645	0.106025	0.633653	0.130192
	(0.116334)**	(0.034112)**	(0.126446)**	(0.036106)**	(0.142004)**	(0.0376187)
Partner self reported	0.022974	0.004202	0.020108	0.003636	0.046263	

[50] I include occupation status prior to job loss for individuals who experience a displacement.
[51] 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.

health： fair						
	(0.041583)	(0.007679)	(0.043113)	(0.007862)	(0.049178)	
Partner long term conditions: chest/breathing	-0.011809	-0.007574	-0.002201	-0.000394	-0.002841	
	(0.053016)	(0.008287)	(0.054195)	(0.008320)	(0.063506)	
Partner long term conditions: heart/blood pressure	0.037662	0.012828	0.003609	0.000648	0.100081	
	(0.050723)	(0.009298)	(0.049977)+	(0.009615)	(0.065879)	
Poor mental health (t-1)	0.760931	0.189248	0.781172	0.194184	0.365811	0.066877
	(0.038002)**	(0.011870)**	(0.039722)**	(0.012507)**	(0.045564)**	(0.0122613)
Poor mental health (wave1)	0.374442	0.081214	0.400489	0.087162	0.612219	0.122682
	(0.044371)**	(0.011239)**	(0.046508)**	(0.011946)**	(0.074735)**	(0.0217004)
Age 16-29	-0.167116	-0.027699	-0.155815	-0.025689	-0.211166	-0.0322886
	(0.066662)*	(0.010052)**	(0.069151)*	(0.010409)*	(0.079475)**	(0.0118882)
Age 50-65	-0.080302	-0.014271	-0.061639	-0.010917	-0.107114	
	(0.063528)	(0.011074)	(0.066088)	(0.011561)	(0.072100)	
Age squared	-0.000105	-0.000019	-0.000123	-0.000022	-0.000141	
	(0.000039)**	(0.000007)**	(0.000042)**	(0.000007)**	(0.000049)**	
Hnd/A level	-0.002787	-0.000505	-0.008607	-0.001541	-0.032620	
	(0.051649)	(0.009347)	(0.054332)	(0.009714)	(0.078861)	
O/Cse	-0.093684	-0.016644	-0.101173	-0.017760	-0.121141	
	(0.053361)+	(0.009295)+	(0.055851)+	(0.009590)+	(0.081772)	
No qualification	-0.120124	-0.020808	-0.108841	-0.018772	-0.184095	
	(0.060245)*	(0.009969)*	(0.062844)+	(0.010405)+	(0.092122)*	
Household lagged labour income	0.013907	0.002520	0.011719	0.002102	0.016619	
	(0.008046)+	(0.001457)+	(0.008511)	(0.001525)	(0.011156)	
Household non labour income	-0.002152	-0.000390	-0.001048	-0.000188	-0.007221	
	(0.022895)	(0.004148)	(0.023791)	(0.004267)	(0.032801)	
Woman – Self employed	0.146469	0.028843	0.145675	0.028414	0.145619	
	(0.075078)+	(0.015985)+	(0.083431)+	(0.017615)	(0.099452)	
Woman - Unemployed	0.394616	0.089367	0.417459	0.094869	0.418404	0.0805662
	(0.107749)**	(0.029350)**	(0.110294)**	(0.030412)**	(0.117147)**	(0.0274728)
Woman – long term sick	0.056830	0.010646	0.069139	0.012915	0.144567	
	(0.081737)	(0.015815)	(0.085224)	(0.016555)	(0.108266)	
Woman- not in the labour force	-0.043349	-0.007745	-0.053140	-0.009378	-0.034818	
	(0.039951)	(0.007041)	(0.041535)	(0.007220)	(0.050021)	
Constant	-1.143664		-1.191444		-1.186057	
	(0.128563)**		(0.140857)**		(0.172906)**	
Observations	13525	13525	12910	12910	13525	
Number of man					1515	
ICC					0.2522593	

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

	Man's probability of poor mental health	Woman's probability of poor mental health	Man's probability of poor mental health	Woman's probability of poor mental health
	POOLED BIVARIATE PROBIT	POOLED BIVARIATE PROBIT	POOLED BIVARIATE PROBIT IPW	POOLED BIVARIATE PROBIT IPW
Man's poor mental health (t-1)	0.891467	0.046661	0.894573	0.031616
	(0.056642)**	(0.064310)	(0.060327)**	(0.066161)
Woman's poor mental health (t-1)	0.029435	0.729009	0.024352	0.738749
	(0.060638)	(0.045895)**	(0.060832)	(0.046741)**
Man's self reported health: excellent	-0.097925	-0.030756	-0.104601	-0.035150
	(0.049341)*	(0.041227)	(0.049004)*	(0.041577)
Man's self reported health: poor	0.957669	0.049217	0.966109	0.019879
	(0.083715)**	(0.096380)	(0.084112)**	(0.098435)
Man's self reported health: very poor	1.386282	0.527913	1.387284	0.595012
	(0.164054)**	(0.171046)**	(0.173248)**	(0.180820)**
Man's self reported health: fair	0.302599	-0.021871	0.305944	-0.018389
	(0.052931)**	(0.050517)	(0.054562)**	(0.051687)
Woman's self reported health: excellent	-0.047103	-0.160031	-0.051243	-0.162606
	(0.050804)	(0.048732)**	(0.050935)	(0.050085)**
Woman's self reported health: poor	0.131432	0.868580	0.132686	0.848644
	(0.088072)	(0.068372)**	(0.087961)	(0.068122)**
Woman's self reported health: very poor	0.011012	0.988472	-0.007286	0.973809
	(0.184756)	(0.130769)**	(0.178420)	(0.136034)**
Woman's self reported health: fair	0.073086	0.341615	0.057664	0.342840
	(0.053619)	(0.044929)**	(0.055167)	(0.044860)**
Man's poor mental health (wave1)	0.393832	0.142269	0.379994	0.129288
	(0.074029)**	(0.079321)+	(0.080193)**	(0.078811)
Woman's poor mental health (wave1)	-0.015880	0.377172	-0.036756	0.387495
	(0.070401)	(0.053817)**	(0.069213)	(0.054600)**
Man's age 30-49	0.127769	-0.074767	0.126731	-0.073095
	(0.112606)	(0.096497)	(0.109507)	(0.099456)
Man's age 50-65	0.211272	-0.070196	0.199896	-0.067374
	(0.151610)	(0.132362)	(0.148236)	(0.134586)
Man's age squared	-0.000126	-0.000025	-0.000129	-0.000007
	(0.000071)+	(0.000062)	(0.000070)+	(0.000065)
Woman's age 30-49	0.012629	0.205388	-0.005143	0.211698
	(0.093948)	(0.083104)*	(0.090594)	(0.086564)*
Woman's age 50-65	-0.174870	0.103470	-0.213848	0.100852
	(0.140169)	(0.125484)	(0.141112)	(0.127972)
Woman's age squared	0.000096	-0.000113	0.000106	-0.000134
	(0.000071)	(0.000065)+	(0.000075)	(0.000065)*
Man - HND/A level	-0.099975	0.045080	-0.101710	0.040206
	(0.059412)+	(0.056750)	(0.061347)+	(0.057737)
Man - O/Cse	-0.254199	-0.047971	-0.248702	-0.043562
	(0.073222)**	(0.067003)	(0.073252)**	(0.067690)
Man - No qualification	-0.314673	0.062545	-0.316889	0.066425
	(0.079264)**	(0.070437)	(0.079428)**	(0.071629)
Woman – No	-0.227338	-0.137624	-0.211557	-0.139116

qualification				
	(0.083242)**	(0.078013)+	(0.086153)*	(0.079669)+
Woman - HND/A level	-0.177769	-0.048160	-0.187176	-0.047373
	(0.066959)**	(0.064531)	(0.070448)**	(0.065531)
Woman – O/Cse	-0.149881	-0.123118	-0.146088	-0.125740
	(0.070698)*	(0.068186)+	(0.073870)*	(0.069843)+
Household lagged labour income	0.012925	0.004428	0.012230	0.002758
	(0.012943)	(0.012198)	(0.011584)	(0.011079)
Household non labour income	-0.013795	-0.006172	0.000124	-0.007252
	(0.037885)	(0.037727)	(0.034204)	(0.033024)
Woman – Self employed	0.089440	0.056222	0.081400	0.066638
	(0.098766)	(0.090603)	(0.098339)	(0.091406)
Woman - Unemployed	-0.063702	0.439195	-0.084956	0.417811
	(0.169602)	(0.121453)**	(0.155855)	(0.126719)**
Woman – long term sick	-0.086128	0.060945	-0.098785	0.071380
	(0.150060)	(0.109349)	(0.137592)	(0.104548)
Constant	-1.520952	-1.338345	-1.504544	-1.111937
	(0.242265)**	(0.225475)**	(0.258617)**	(0.213675)**
Observations	9879	9879	9726	9726

Note: Dummy variables for year, lagged man's employment status and region are omitted for parsimony. Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 9 – Man's probability of poor mental health

	POOLED PROBIT	**POOLED PROBIT APE**	**POOLED PROBIT IPW**	**POOLED PROBIT IPW APE**	**PROBIT RE**	**PROBIT RE APE**
Poor mental health (t-1)	0.874933	0.182796	0.882250	0.185613	0.446173	0.0636781
	(0.057124)**	(0.016865)	(0.058858)**	(0.017471)	(0.066761)**	(0.016259)
Self reported health: excellent	-0.115924	-0.014104	-0.119669	-0.014634	-0.096571	-0.0090385
	(0.047550)*	(0.005571)	(0.048500)*	(0.005702)	(0.058836)	(0.0061582)
Self reported health: poor	0.967156	0.219827	0.961840	0.218802	1.116538	0.2115883
	(0.082011)**	(0.026931)	(0.084287)**	(0.027622)	(0.099294)**	(0.0380492)
Self reported health: very poor	1.386236	0.380322	1.410737	0.391217	1.586549	0.3520617
	(0.160270)**	(0.062852)	(0.169572)**	(0.066734)	(0.184666)**	(0.0682682)
Self reported health: fair	0.330885	0.049436	0.326354	0.048897	0.349085	0.0460827
	(0.051545)**	(0.008969)	(0.053520)**	(0.009306)	(0.060859)**	(0.0122019)
Poor mental health (wave 1)	0.421645	0.070068	0.404781	0.066863	0.699771	0.1131164
	(0.074602)**	(0.015658)	(0.077787)**	(0.016129)	(0.112352)**	(0.0292732)
Age 16-29	-0.129184	-0.014907	-0.129785	-0.015084	-0.161039	
	(0.100199)	(0.010539)	(0.101757)	(0.010771)	(0.118010)	
Age 50-65	-0.035268	-0.004398	-0.036644	-0.004603	-0.072910	
	(0.078551)	(0.009699)	(0.079828)	(0.009933)	(0.094510)	
Age squared	-0.000056	-0.000007	-0.000064	-0.000008	-0.000073	
	(0.000048)	(0.000006)	(0.000050)	(0.000006)	(0.000062)	
Professional occupation	0.052733	0.006849	0.046105	0.006010	0.108259	
	(0.066128)	(0.008853)	(0.067304)	(0.009009)	(0.087645)	
Associate	-0.100853	-0.011943	-0.110527	-0.013107	-0.103711	

professional & technical occupation						
	(0.072094)	(0.008009)	(0.073299)	(0.008106)	(0.092496)	
Clerical & secretarial occupation	0.031079	0.003994	0.009658	0.001233	0.003784	
	(0.081131)	(0.010638)	(0.082745)	(0.010630)	(0.102685)	
Craft & related occupation	-0.231653	-0.026133	-0.251099	-0.028292	-0.276711	-0.0285343
	(0.066119)**	(0.006612)	(0.068466)**	(0.006776)	(0.087116)**	0.0100171
Personal & protective service	-0.073948	-0.008869	-0.083292	-0.010000	-0.073582	
	(0.082168)	(0.009374)	(0.085157)	(0.009662)	(0.115237)	
Sales occupation	-0.168347	-0.018826	-0.095034	-0.011278	-0.114288	
	(0.112127)	(0.011023)	(0.120769)	(0.013348)	(0.135282)	
Plant & machine operatives	-0.104684	-0.012471	-0.103302	-0.012411	-0.104345	
	(0.069487)	(0.007814)	(0.071590)	(0.008132)	(0.093259)	
Other occupations	-0.155284	-0.017571	-0.170504	-0.019255	-0.164274	
	(0.101326)	(0.010222)	(0.102708)+	(0.010236)	(0.136211)	
Hnd/A level	-0.103991	-0.013008	-0.095798	-0.012078	-0.133965	
	(0.056866)+	(0.007071)	(0.057564)+	(0.007213)	(0.085387)	
O/Cse	-0.226369	-0.025796	-0.220323	-0.025363	-0.240671	
	(0.070159)**	(0.007228)	(0.071623)**	(0.007467)	(0.103629)*	
No qualification	-0.274051	-0.030370	-0.273347	-0.030572	-0.338208	
	(0.078389)**	(0.007610)	(0.079861)**	(0.007833)	(0.113946)**	
Household lagged labour income	0.013720	0.001728	0.012121	0.001538	0.023886	
	(0.010701)	(0.001347)	(0.011190)	(0.001417)	(0.014697)	
Household non labour income	-0.004854	-0.000611	0.011188	0.001419	-0.013298	
	(0.029120)	(0.003668)	(0.032932)	(0.004180)	(0.045180)	
Constant	-1.376894		-1.249102		-1.610723	
	(0.233576)**		(0.252060)**		(0.285728)**	
Observations	10437	10437	10069	10069	10437	
Number of man					1468	
ICC					0.268275	

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))

It is interesting to notice that partners' employment status is not significant in the man's mental health equation, but the woman's unemployment dummy has a negative sign. This idea has been explored, constructing a model in which the redundancy variable is interacted with woman's employment status, in the estimation of man's probability of poor mental health[52].If the income shock is really determinant in lowering an individual's well-being, I 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). Nevertheless, none of the interactions is significant and there is no significant difference between redundancy occurring in one or two-income families. This suggests that 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

[52] The complete table of results is not reported for reasons of parsimony, but is available on request. Some relevant results are reported in table 19.

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.

5.1 Interpreting the effect of redundancy

One of the most important points of this paper is the analysis of the transmission channels of the shock on individual's and partner's mental health. More specifically, this paper tries to clarify whether the main impact of job loss on mental well-being comes from the income shock or from psychological factors. To this regard, I estimated some additional models of the individual probability of poor mental health and this paragraph presents some interesting results. All these additional models include new variables (or interactions between variables) in the main equation of man's and woman's probability of poor mental health and this should help to clarify the role of income shock with respect to the psychological components. 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 some relevant socio-economic characteristics (such as income groups, occupation, number of children, long term unemployment). Lastly, the GHQ score is unpacked and I compare the effects of job loss on various psychological components. 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"[53]. The level of income before the shock is likely to influence the perception of the severity of the income shock. I construct five interactions between redundancy and non labour income categories, 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 redundancy experiences in the lowest income group and in the middle income group (omitted) are significantly different[54]. 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, experienced by middle and high income people because this analysis is focused on *non labour* income[55]. One would expect that people in the top if the income distribution have

[53] See Eliason (2004).
[54] Wald test: p=0.02
[55] A similar test has been run by interacting the redundancy variable with labour earnings, but no significant difference between income groups has been found.

higher savings and therefore more resources to cope with the income shock. 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 employment[56].

The analysis has been expanded using a model in which redundancy is interacted with man's occupations. The results are consistent with the previous findings regarding income groups: men with low-skilled occupations are less likely to be seriously distressed after a redundancy and the difference is significant. Craftsmen seem less likely to be in poor mental health than managers and professionals after a job loss[57]. People in high skilled occupations are likely to experience a higher income shock but, on the other hand, previous higher income should mean greater ability to cope with such shock. Again, this confirms previous results on the transmission channels: the prestige effect related to high-skilled occupations is likely to have a strong effect on individuals' self-esteem and other psychological factors.

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, I constructed and interaction between the redundancy variable and an indicator of long term unemployment (equal to 1 when the man experiences a redundancy and he is still unemployed in the following year). 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 also confirms that the impact of job loss on family mental health is mostly found in the short term. and it 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. Secondly, this result is consistent with the findings of Clark and Oswald (1994), who show that the unemployment effect on well-being is higher in the period immediately following the shock.

In the third model, I add 4 interactions between redundancy and the age of the youngest dependent child in the household. The underlying idea is that job loss is worse when one has strongest family obligations and families with young children certainly have higher income shock after a redundancy. The omitted group is composed of people who have been made redundant and do not have children. We compare these people with families with children in three age categories: 0-4, 5-10, 11-15. Firstly, the

[56] See Allegretto (2004).
[57] Wald test: p=0.02 and p=0.04

presence of very young children (age 0-4) significantly reduces the probability of poor mental health[58] of about 2 p.p., while children in other age groups do not have a relevant effect. Secondly, Wald test shows that there is no significant difference between experiencing a redundancy with no children and losing a job with young children in the family (age 0-4 and 5-10). Redundancy's impact is significant both for people with young children and for people with no children (between 4 and 6 p.p). The income shock does not seem to be crucial, as other psychological factors may affect individuals regardless of their family's obligations.

Lastly, the psychological effect of redundancy has been further explored, unpacking the 12 GHQ components. As explained above, the General Health Questionnaire includes 12 different questions regarding different emotional and psychological aspects of individuals' lives. Particularly, individuals are asked about: sleep loss, feeling under strain, ability to overcome difficulties, unhappiness, loosing confidence, feeling worthless, concentration, perceived individual role, decision-making ability, enjoyment of normal activities, ability to face problems and general happiness. I run 12 separate regressions on each of these components on both partners' equations, 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 male 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. These results confirm that the negative impact on individuals' mental well-being come from psychological elements that arise regardless of income shock and because employment is a provider of social relationships, identity in society and individual self-esteem. These elements have a higher impact on the individual who directly experiences the displacement, while the major impact on partner's well-being come from the income shock and the financial stress associated with it.

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

[58] Wald test: p=0.059.

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.

I use a dynamic panel random effects probit model and I deal with the initial condition problem and attrition bias, modelling the distribution of the unobserved effect conditional on the initial value of any exogenous explanatory variables and using an IPW estimator, in order to control for attrition. My main results show that the probability of poor mental health increases following a man's redundancy for both partners, even controlling for past mental health. I check the stability of my results using different models (as well as a balanced and an unbalanced sample), and conducting two 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. 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. These outcomes derive from factors independent on income shock. Both types of job losses considered - redundancies and dismissals - have significant and positive effects on the individual probability of poor mental health even if the effect from redundancies is smaller.

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 change 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

Table 1 – Variable definition

Self Assessed Health (binary variables)[59]	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
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	Omitted educational category
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)[60]: 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

Table 2 – 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%

[59] 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?”
[60] See BHPS User Guide and *Quarterly Labour Force Survey, March-May 1992: User Guide*, September 1992.

Table 3 – Woman's probability of poor mental health

	POOLED PROBIT	POOLED PROBIT APE	POOLED PROBIT IPW	POOLED PROBIT IPW APE	PROBIT RE	PROBIT RE APE
Long term conditions: chest/breathing	-0.042715	-0.002126	-0.072417	-0.012525	0.004843	
	(0.047771)	(0.009486)	(0.049935)	(0.009698)	(0.068573)	
Long term conditions: heart/blood pressure	0.068488	0.006951	0.088283	0.016519	0.039292	
	(0.048055)	(0.009533)	(0.053420)	(0.009741)+	(0.061299)	
Children 0-4	-0.014530	-0.002617	-0.014970	-0.002668	-0.062853	
	(0.051608)	(0.009239)	(0.053370)	(0.009451)	(0.064674)	
Children 5-10	0.005102	0.000926	0.003053	0.000548	-0.016804	
	(0.048071)	(0.008746)	(0.049854)	(0.008965)	(0.060756)	
Children 11-15	0.021495	0.003934	0.039800	0.007275	-0.000432	
	(0.049781)	(0.009202)	(0.051146)	(0.009526)	(0.058945)	
Man's change for improvement	-0.077930	-0.013487	-0.058321	-0.010106	-0.126483	
	(0.079123)	(0.013061)	(0.082042)	(0.013723)	(0.089169)	
Man's retirement	-0.015877	-0.002848	-0.039496	-0.006913	-0.047033	
	(0.150703)	(0.026772)	(0.156972)	(0.026798)	(0.175491)	
Man's dismissal	0.181800	0.036762	0.139940	0.027350	0.233302	
	(0.234007)	(0.052330)	(0.245867)	(0.052070)	(0.271333)	
Man's temporary job ended	0.022162	0.004070	0.044551	0.008214	-0.003466	
	(0.158506)	(0.029507)	(0.167336)	(0.031697)	(0.181159)	
Man job change no reason	-0.013477	-0.002425	-0.011914	-0.002124	-0.031225	
	(0.053776)	(0.009611)	(0.055604)	(0.009853)	(0.060273)	
Constant	-1.143664		-1.191444		-1.186057	
	(0.128563)**		(0.140857)**		(0.172906)**	
Observations	13525	13525	12910	12910	13525	
Number of man					1515	
ICC					0.2522593	

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 5 – Joint estimation of partners' probability of poor mental health

	Man's probability of poor mental health	Woman's probability of poor mental health	Man's probability of poor mental health	Woman's probability of poor mental health
	POOLED BIVARIATE PROBIT	POOLED BIVARIATE PROBIT	POOLED BIVARIATE PROBIT IPW	POOLED BIVARIATE PROBIT IPW
Declining industry	0.004141	-0.030794	0.004662	-0.050578
	(0.044901)	(0.039852)	(0.044943)	(0.040524)
Man's self reported health: excellent	-0.097925	-0.030756	-0.104601	-0.035150
	(0.049341)*	(0.041227)	(0.049004)*	(0.041577)
Man long term health conditions: chest/breathing	0.074040	-0.044026	-0.014352	-0.013313
	(0.066422)	(0.058491)	(0.070834)	(0.058738)
Man long term health conditions: heart/blood	0.062982	0.078327	0.149943	0.068003

pressure				
	(0.072234)	(0.061155)	(0.069691)*	(0.067329)
Woman long term health conditions: chest/breathing	-0.009601	-0.016284	0.068807	-0.070998
	(0.067791)	(0.064041)	(0.068653)	(0.065259)
Woman long term health conditions: heart/blood pressure	0.122082	0.009964	0.057166	0.028589
	(0.069247)+	(0.068622)	(0.070794)	(0.062243)
Man's change for improvement	-0.140061	-0.158515	-0.142186	-0.150738
	(0.103340)	(0.092813)+	(0.105675)	(0.090794)+
Man's retirement	-0.562445	-0.051138	-0.583421	-0.016019
	(0.274178)*	(0.176438)	(0.250691)*	(0.178362)
Man's dismissal	0.866363	0.089151	0.899533	0.058436
	(0.259617)**	(0.290568)	(0.272178)**	(0.291884)
Man's temporary job ended	0.132671	0.067394	0.088991	0.050378
	(0.195145)	(0.186604)	(0.204830)	(0.184707)
Man job change no reason	0.030131	-0.007019	0.042611	-0.007693
	(0.064848)	(0.058286)	(0.065515)	(0.058500)
Constant	-1.520952	-1.338345	-1.504544	-1.111937
	(0.242265)**	(0.225475)**	(0.258617)**	(0.213675)**
Observations	9879	9879	9726	9726

Note: Dummy variables for year, lagged man's employment status and region are omitted for parsimony. Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 6 – Man's probability of poor mental health

	POOLED PROBIT	POOLED PROBIT APE	POOLED PROBIT IPW	POOLED PROBIT IPW APE	PROBIT RE	PROBIT RE APE
Declining industry	0.011886	0.001501	0.014941	0.001902	0.018459	
	(0.043528)	(0.005512)	(0.045102)	(0.005763)	(0.051174)	
Long term conditions: chest/breathing	0.089113	0.011879	0.087572	0.011743	0.166537	
	(0.066723)	(0.009398)	(0.067969)	(0.009618)	(0.085082)+	
Long term conditions: heart/blood pressure	0.034315	0.004418	0.034490	0.004472	0.064316	
	(0.067979)	(0.008941)	(0.069380)	(0.009186)	(0.088644)	
Children 0-4	-0.086933	-0.010522	-0.088422	-0.010767	-0.110309	
	(0.062668)	(0.007277)	(0.063833)	(0.007448)	(0.077645)	
Children 5-10	0.026179	0.003340	0.024101	0.003095	0.021995	
	(0.060265)	(0.007791)	(0.061444)	(0.007985)	(0.074726)	
Children 11-15	-0.003311	-0.000416	0.001213	0.000154	0.017593	
	(0.062577)	(0.007852)	(0.063843)	(0.008111)	(0.076628)	
Job change for improvement	-0.147836	-0.016782	-0.148494	-0.016979	-0.147567	
	(0.102480)	(0.010410)	(0.103651)	(0.010604)	(0.115849)	
Retirement	-0.595184	-0.047816	-0.627365	-0.049653	-0.614718	-0.0509321
	(0.276233)*	(0.012246)	(0.273260)*	(0.011511)	(0.301431)*	(0.0201443)
Dismissal	0.934564	0.214564	0.863193	0.192086	1.095155	0.2106709
	(0.250880)**	(0.083983)	(0.261579)**	(0.084057)	(0.279439)**	(0.0803578)
Temporary job ended	0.134295	0.018674	0.114537	0.015809	0.112381	
	(0.196182)	(0.029938)	(0.197976)	(0.029598)	(0.218613)	
Job change no reason	0.051529	0.006683	0.060624	0.007958	0.062222	
	(0.061751)	(0.008235)	(0.063052)	(0.008549)	(0.071364)	
Constant	-1.376894		-1.249102		-1.610723	
	(0.233576)**		(0.252060)**		(0.285728)**	
Observations	10437	10437	10069	10069	10437	
Number of man					1468	
ICC					0.268275	

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. ($\sigma^2_\mu / (1 + \sigma^2_\mu)$)

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