Investigating the Relationship between Labour Market Status and Minor Psychiatric Morbidity

Longitudinal and Spatial Analysis of the British Household Panel Survey, 1992-2008

Ellen Flint

Thesis submitted for the degree of Doctor of Philosophy

University College London

Declaration

I, Ellen Flint, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

The data used in this thesis were made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-social Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

EFlint

Abstract

Background: Previous research has demonstrated a strong association between labour market status and minor psychiatric morbidity (MPM). This PhD thesis aims to uncover the role of mediating factors, and the extent to which the relationship varies over space and time. In addition, this research seeks to establish the direction of causality and to differentiate between secure and insecure employment, and between various forms of joblessness.

Methods: MPM was measured using the General Health Questionnaire (GHQ-12). Analyses were undertaken using British Household Panel Survey (BHPS) data from 1992-2008. Firstly, unstratified and gender-stratified series of nested linear and logit autoregressive random effects models were run to assess the role of confounding and mediating factors in the relationship between labour market status and MPM. Secondly, three complementary multilevel modelling approaches were used to assess the extent to which independent variation in GHQ-12 scores existed at the Local Authority District (LAD) level, and whether area-level unemployment rate was independently predictive of MPM. Thirdly, unstratified and age-group stratified fixed effects models were run in order to assess the effects of labour market transitions on MPM and therefore to investigate causality and age effects.

Results: Across both genders it was shown that after adjustment for a range of confounding factors: insecure employment, unemployment, permanent sickness and other inactivity were significantly predictive of MPM compared to secure employment. Transition analyses suggest that this relationship is causal. Virtually no independent variation in GHQ-12 scores was found at the LAD level, but unemployment was comparatively less distressing for those living in high unemployment areas. Age was found to moderate the relationship between labour market status and MPM to some degree.

Conclusions: This research deepens our understanding of the causal processes underlying the relationship between labour market status and psychological wellbeing, whilst considering the roles of spatial, temporal and macroeconomic context.

Acknowledgements

Thank you to my primary supervisor, Amanda Sacker, who has given her valuable time, expertise and advice so generously over the course of my studentship. Thank you also to Mel Bartley for sharing her wisdom and insight, and to Nicola Shelton for her stimulating ideas and her counsel. I feel privileged to have had such a dedicated and expert supervisory panel.

In addition, I have been fortunate to benefit from support and guidance from International Centre for Lifecourse Studies (ICLS) members, especially David Blane, whose constructive criticism and positive encouragement throughout the course of my PhD research has been most gratefully received. Thanks also to Gopal Netuveli and Elizabeth Webb for their methodological insights. Being a member of the Centre as a PhD student has provided me with countless valuable experiences and I would like to thank all its members for their interest and input. Many thanks to the Economic and Social Research Council for funding my PhD studentship and the excellent work the International Centre for Lifecourse Studies does.

My MPhil to PhD transfer was examined by Professor Richard Mitchell, who generously gave his time and is thanked for helping me to shape and focus my research. I have also been fortunate to benefit from the expertise of Maria Iacovou at the Institute for Social and Economic Research. Thanks to Maria for her advice on methodological matters.

The British Household Panel Survey is managed by the UK Data Archive at the University of Essex. Many thanks to the study's participants and to the staff at UKDA for making it possible for researchers to access this valuable resource. Thanks in particular to Birgitta Rabe for her help with geographical identifiers. Thank you also to Oliver Duke-Williams for his advice on this subject.

I have been privileged to share the PhD experience with fellow students who have given me support, encouragement and a lot of tea. Special thanks go to Rebecca Landy, Rebecca Lacey, Steven Bell, Robert de Vries and Jessica Abell.

Finally, a million thanks to my husband, Sam; to my parents, Jane and Stephen; and to my sister, Alice.

Contents

Figures

Tables

Appendices

Glossary of Abbreviations

BHPS	British Household Panel Survey
CCR	Claimant Count Rate
GDP	Gross Domestic Product
GHQ	General Health Questionnaire
GHQ-12	Twelve-item General Health Questionnaire
GOR	Government Office Region
ICC	Intraclass Correlation Coefficient
IGLS	Iterative Generalised Least Squares estimation
ILO	International Labour Organisation
LAD	Local Authority District
LFS	Labour Force Survey
LSOA	Lower Super Output Area
MCMC	Monte Carlo Markov Chain estimation
MPM	Minor Psychiatric Morbidity
ONS	Office for National Statistics
OR	Odds Ratio
OSM	Original Sample Members (British Household Panel Survey)
TSM	Temporary Sample Members (British Household Panel Survey)
TTWA	Travel-to-Work Area
UKDA	United Kingdom Data Archive

Chapter 1

Introduction

1 Introduction

During the summer of 2011 the number of unemployed people in the UK hit the 17-year high of 2.5 million, accounting for 8.4 percent of the working-age population. In addition 8.1 million working-age men and women were economically inactive, making up a further 21.2 percent of the workforce (Labour Market Statistics, Office for National Statistics (ONS), 16.11.11). The burden of worklessness has fallen disproportionately on the young, with 19.1 percent of 18-24 year olds unemployed during the summer of 2011, compared to 5.9 percent of 35-49 year olds. Such statistics do not adequately capture the full impact of the economic downturn on the labour market. Among the 1.5 million people working in temporary employment, 38 percent stated that they could not find a permanent job, indicating high levels of job insecurity (Labour Market Statistics, ONS, 16.11.11). There is a wealth of qualitative and quantitative evidence which suggests that joblessness and insecure employment have a negative effect on health and wellbeing, but important questions remain unanswered. In the aftermath of recession and a climate of sustained economic uncertainty it is of vital importance that we gain an understanding of precisely how joblessness and insecure employment affect the health and wellbeing of the population. It is also important for us to establish who is most at risk of the negative mental health effects of joblessness or job insecurity. The young? Women? Residents of high-unemployment regions? Answering these questions will provide an evidence base for targeted policy responses.

This PhD project aims to assess the effects of labour market status on psychological distress, whilst situating the individual their socioeconomic, spatial and temporal context. Furthermore, this thesis will provide an interdisciplinary perspective, using theoretical and methodological approaches from the fields of lifecourse and social epidemiology, health geography and economics.

More specifically, this PhD project aims to uncover:

(a) The specific mechanisms by which labour market status affects psychological wellbeing

(b) How contextual influences operating at the area level affect individual psychological wellbeing

(c) The temporal dimension to the relationship: causal processes and how exposure to joblessness or insecure employment differentially affects psychological wellbeing by age group.

In order to answer these questions, it is necessary to use longitudinal panel data, and to employ appropriate hierarchical modelling methods. The British Household Panel Survey (BHPS) allows researchers to follow a large sample over a period of more than 18 years, using repeated measures on the same individuals over time to explore the chronological sequencing of events and to model change within the lives of individuals, in order to establish causality. The annual data collection provides a greater level of protection against recall bias than alternative longitudinal data sources such as the British Birth Cohort Studies for which the duration of time between data collections is far greater. Using the BHPS also allows the investigator to access a wealth of contextual information. The household structure of the survey allows investigators to take account of the natural ways in which those who share a home influence one another. The BHPS also provides information on where participants lived at each wave of the study. This allows researchers to investigate ways in which area-level conditions might have affected the respondent during their period of residence, and to track the movements of participants over time. The BHPS provides an invaluable insight into the lives of its respondents and allows researchers to take a holistic view. In order to fully exploit this potential, appropriate statistical methods must be employed. Repeated observations on the same person over time are likely to be highly correlated and cannot be considered independent of one another. This clustering must be accounted for using multilevel modelling. Similarly, the clustering of observations on individuals residing in the same area must be accounted for, as described by Duncan, Jones and Moon (1996, 1998). Simple nested hierarchies presumed by multilevel models must be tailored to reflect the 'realistically complex' nature of the world (Best *et al*., 1996).

The timespan of the BHPS, from 1991 up until the latest wave for which data was available at the time of analysis (2008) encompasses an economic recession (1991) and several years of slow recovery and lingering high unemployment rates, followed by a lengthy period of economic boom and low unemployment rates. The final wave (2008) provides data from the very beginning of the current financial crisis. This timespan therefore covers an entire business cycle and allows suggestions to be made as to the effects of recession on psychological wellbeing.

In summary, this PhD thesis sets out to build on our understanding of the mechanisms and causal processes underlying the relationship between labour market status and psychological wellbeing, whilst considering the roles of spatial, temporal and macroeconomic context.

Chapter 2

Background and Literature Review

2 Background and Literature Review

2.1 Introduction

The economic recession and high unemployment rates of the 1980s gave rise to a debate within economics and social science about the extent to which the observed individual-level association between unemployment and poor health could be causal. The present day, with its macroeconomic backdrop of recession and high unemployment rates, is providing a context for a renewed interest in this relationship, involving the application of more advanced quantitative methods. This PhD thesis will not only attempt to uncover the causal mechanisms at work in the relationship between labour market status and unemployment, but also broaden the scope of the investigation to situate the individual in their spatial, temporal, lifecourse and macroeconomic context. First though, a critical engagement with the existing literature is required. This chapter will provide an overview of the work which has previously been done on the relationship between labour market status and psychological wellbeing, encompassing not only unemployment, but also insecure employment, economic inactivity through permanent sickness, and other economic inactivity. It is also necessary to review the research which has been undertaken on the relationship between macroeconomic conditions and the mental wellbeing of populations and individuals, in order to assess the extent to which economic recession may affect psychological health both directly and indirectly through its effects on the labour market. Additionally, this chapter will attempt to summarise the literature on the spatial patterning of mental wellbeing, and the extent to which area-level characteristics are thought to influence individual health outcomes.

2.2 Labour market status

An individual's labour market status describes the extent and nature of their engagement with the formal labour market and can be divided broadly into activity or inactivity. Activity encompasses the employed and self-employed as well as the registered unemployed. Inactivity describes those who do not work in the formal labour market and are not searching for a job. This includes those who do not claim benefits, such as home-makers, and those who claim incapacity benefits for long-term sickness. It also encompasses the retired and those in full time education or on government training schemes. The labour market statistics which are most commonly used to assess the state of the labour market and the national economy are the unemployment rate, the employment rate and the inactivity rate. Unemployed individuals are defined by the International Labour Organisation (ILO) as *'those who are currently not* *working but are willing and able to work for pay, currently available to work, and have actively searched for work'* (ILO, 1982) and their numbers are estimated using the Labour Force Sample surveys (LFS). The unemployment rate is calculated as the number of unemployed individuals divided by the total number of economically active men and women in the population of interest. An alternative approach to assessing the burden of unemployment is to use employment office statistics. In the UK, this is known as the claimant count rate, and is calculated by expressing the number of Jobseeker's Allowance claimants as a percentage of the working age population. Claimant count rate is generally thought to underestimate the true extent of unemployment, as many may consider themselves in need of employment without claiming unemployment benefits. This is particularly true for women. The inactivity rate is calculated as the proportion of the total population who are not economically active, and sums up to 100 percent with the activity rate (OECD, 1998). The employment rate is defined as persons in employment as a proportion of the working age population (OECD, 1998).

Over the past few decades, a number of national labour market trends have become apparent. Firstly, that female employment has increased substantially and that female economic inactivity has declined (Figure 2.1). Secondly, that male employment has decreased over the same period, and that this has been accompanied by increasing rates of male inactivity (Figure 2.2). Thirdly, an increase in the proportion of employed people working in insecure jobs has been observed, as a result of the flexible labour markets which have emerged in the post-Fordist era (Figure 2.3) (Burchell *et al.* 2002). Overall, unemployment rate tracks the performance of the economy, and often lags slightly behind Gross Domestic Product (GDP) growth rate. There is clearly a greater burden of joblessness and insecure employment during times of economic downturn. Any elevated risk of minor psychiatric morbidity (MPM) associated with joblessness and insecure employment will present a greater public health burden during and after economic recession.

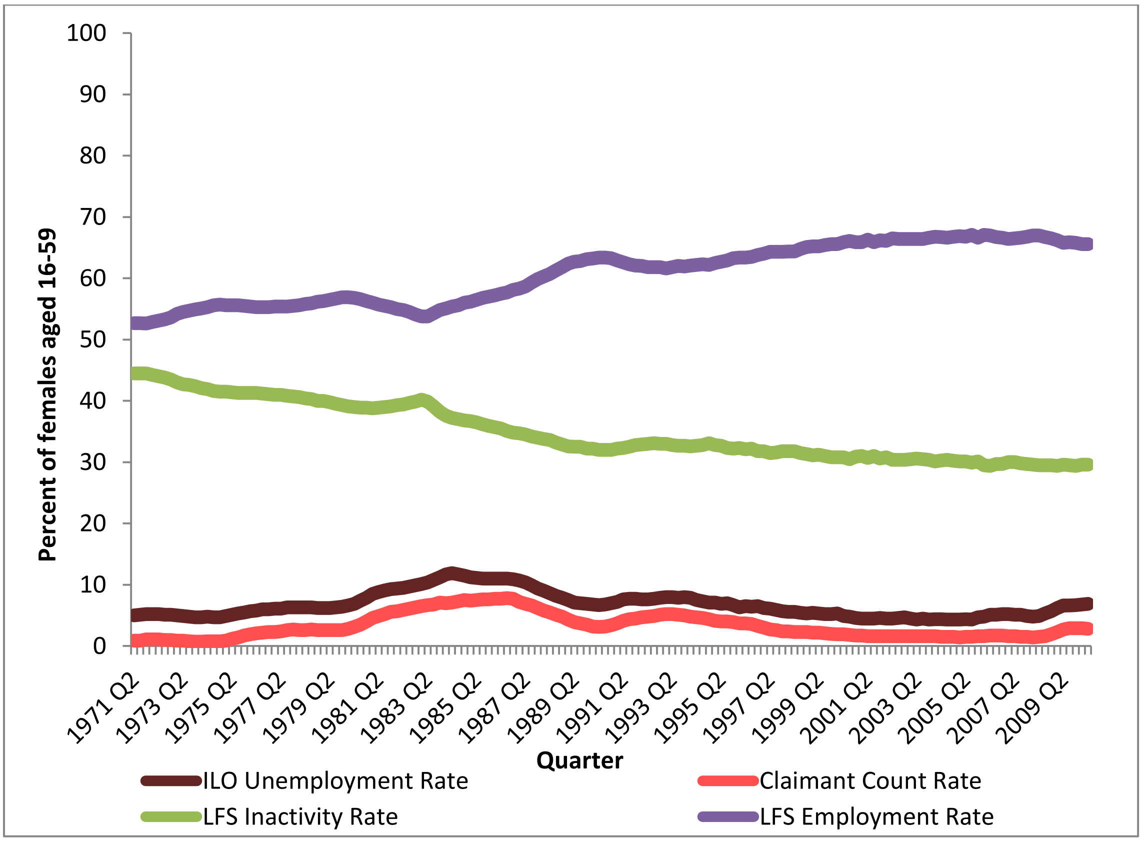

Figure 2.1 Labour Market Status Trends, 1971-2010: Females only. Office for National Statistics

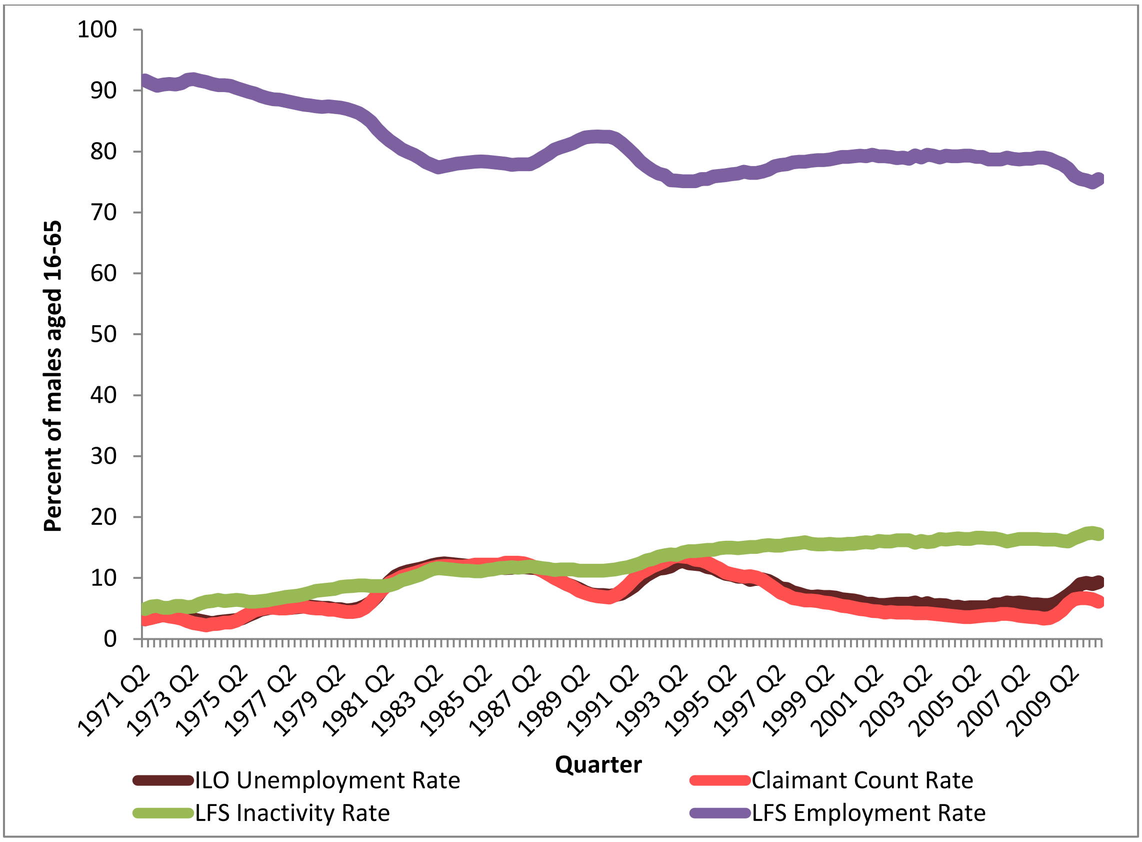

Figure 2.2 Labour Market Status Trends, 1971-2010: Males only. Office for National Statistics

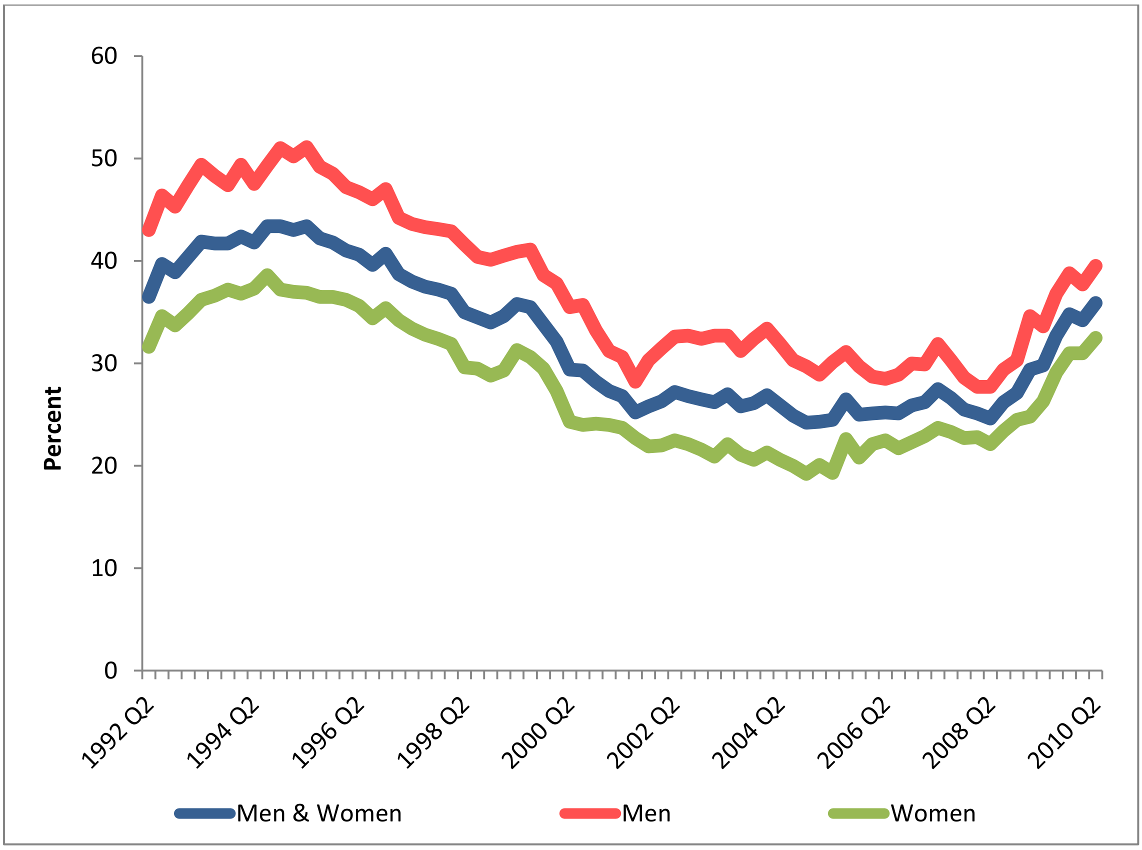

Figure 2.3 LFS Insecure Employment: Proportion of temporary employees who could not find a permanent job (seasonally adjusted)

2.3 Labour market status and psychological wellbeing

Labour market status, in its role as a central organising force in the lives of individuals is thought to have a significant effect on psychological wellbeing. This effect has generally been considered causal, although questions still remain about the nature of this causality and the mechanisms which underlie it. Missing in many studies to date is the situation of the individual within their spatial and temporal context. Another common limitation of work in this field is its failure to consider the differences between the genders with regards to both labour market engagement and psychological wellbeing. Owing to the traditional difficulties inherent in classifying the labour market status of women many studies use only men in their samples. Additionally, only a relatively small number of studies have considered the differing role of labour market status on psychological wellbeing by age and lifecourse stage. There is also an overemphasis on unemployment as the labour market status of interest. As shown in Figure 2.2, the extent to which the unemployment rate encapsulates the level of worklessness in the UK has diminished since the early 1990s and it is now more important than ever to consider the effects of economic inactivity and insecure employment alongside unemployment. Much of the research on unemployment and health was undertaken in the 1980s. Since then, great methodological advances have been made in longitudinal and multilevel modelling, allowing much clearer conclusions about causality to be made. Over the past two decades, the links between labour market status and health have been under-researched, and therefore an opportunity exists for the application of up-to-date methods to investigation of the relationship between labour market and psychological wellbeing, the underlying mechanisms, the direction of causality and how the relationship might vary by age, gender, place of residence and prevailing national macroeconomic conditions. This PhD project aims to make such a contribution.

2.3.1 Unemployment and Minor Psychiatric Morbidity

A large amount of research has been undertaken on the effects of being unemployed on mental health. Brenner's ecological research showed that admissions to mental hospitals peak as unemployment peaks (Brenner, 1973). However, not only does this provide no evidence of causality between unemployment and mental health decline, it does not show that the individuals who are being admitted to mental hospitals are the ones who have lost their jobs or the ones who have managed to retain employment. Jackson and Warr (1984) found a strong association between unemployment and poor mental health among working class men in the UK, and that longer durations of unemployment were associated with worse mental health, especially among middle-aged men. Novo *et al.* (2000) reported a strong association between individual unemployment and poor psychological health in both economic recession and expansion, in a sample of young men and women in Sweden. Theodossiou found that the unemployed suffer significantly higher odds of anxiety, depression and general wellbeing, even when compared with individuals in low-paid employment (Theodossiou, 1998). Bartley *et al.* (2005) commented that the association between unemployment and ill health has become received wisdom, and that the notion is accepted and rarely challenged.

The repeated findings of an association between joblessness and poorer mental health in cross-sectional and ecological studies do not prove that joblessness causes a decline in psychological wellbeing. The results could be due to 'direct selection', in which the association is explained by the idea that individuals with pre-existing mental health problems may find it more difficult to gain and retain employment (Bartley, 1988; Valkonen and Martikainen, 1995; Breslin, 2003). Of course, poor health does increase the risk of unemployment and joblessness (Claussen *et al.* 1999), but it does not appear to be the case that this direction of causation can explain the association between poor mental health and joblessness entirely. Studies of workplace closures, which remove the effects of pre-existing health problems still show that mental health declines following redundancy (Ferrie *et al,* 2001, 2002; Bartley and Fagin, 1990;

Iversen, 1989; Martikainen, 2007; Kivimaki *et al.* 2000; Beale, 1985, 1992; Hamilton, 1990, 1993; Keefe *et al.* 2002). An alternative explanation for the findings is that people who are jobless and people with poor mental health may share certain traits or characteristics, which in turn may make it difficult for them to become employed and remain in their job. This explanation is referred to as 'indirect selection', in which a third variable, such as a character trait, confounds the association between poor mental health and joblessness.

Data from longitudinal studies have been used to address both the possibilities of direct and indirect selection. Evidence from cohort studies repeatedly suggests a causal association between joblessness and poor mental health, ruling out both direct and indirect selection (Montgomery *et al. 1999;* Dooley *et al.* 1994; Fox and Shrewry, 1988; Joelson, 1987; Wadsworth *et al.*, 1999; Weich, 1998; Winefield, 1991; Winkelmann, 1998; Banks, 1992). Notably, Montgomery and colleagues (1999) analysed the 1958 British birth cohort study, which contains individual histories of employment and psychological development. These data allowed investigation of the possibility that the association between poor mental health and joblessness was due to pre-existing presence of psychological traits which predisposed individuals to unemployment and to poor mental health (indirect selection). When pre-existing mental health was taken into account, the study showed that recent unemployment was linked to the onset of declining mental health, and that long-term unemployment led to a decline in the psychological wellbeing of previously healthy individuals. However, some studies have disputed the notion that the association between unemployment and ill health is causal, instead arguing that selection may be just as important (Martikainen *et al.*, 1996). Moser *et al.* (1990) argued that during economic expansion, a greater association is seen between unemployment and ill health because those who cannot find work during buoyant labour market conditions are likely to have chronic illness or disability. In contrast, during a recession, there is a reduced demand for labour and the unemployed have not been 'health selected' to the same degree. Under these conditions, the workforce has been positively health selected, with only the fittest able to find or retain employment (Bartley and Owen, 1996). Novo *et al.* (2000) investigate this in Sweden, looking at somatic and psychological symptoms as outcome variables. They set out to test the suggested relationship between health selection and business cycles with the expectation that unemployment would have lower effects on health during the early 1990s recession than during the mid-1980s expansion. It was found that the both somatic and psychological health complaints increased during the recession in the 'non long-term unemployed' group, and that the gulf between this group and the long-term unemployed group contracted during the recession and expanded during the boom. The long-term unemployed had the same level of symptoms during the boom and the recession. This work therefore found no evidence for the hypothesis that unemployment is less predictive of psychological distress during recession.

Brenner and Mooney (1983) hypothesised that economic recession can affect physical or mental health in three ways. Firstly, that poverty and relative deprivation reduces the extent to which individuals can afford to meet their material needs. This means that individuals will experience stress if they cannot afford to buy the things they need. Jahoda (1933) found that financial stress was the most important predictor of poor mental health following unemployment. However, this observation was made in the Great Depression of the interwar period, when poverty was often absolute. Smith (1985) argued that the material effects of poverty associated with joblessness are no longer as important as they once were before the advent of the welfare state in the UK. Secondly, loss of work and a decline in relative income can result in psychosocial stress, even when this income is sufficient for basic material needs. A seminal insight into the non-material ways in which unemployment affects mental health was provided by Jahoda's 1933 study of the sociological effects of mass unemployment in the town of Marienthal, Austria. Jahoda suggested that the importance of employment is that it imposes a time structure on the day, provides social contact outside the emotionally charged family sphere, assigns social status, clarifies personal identity and promotes organisation and regularity (Jahoda, 1982). Following Jahoda's ideas, Warr (1985) outlined eight pathways through which joblessness can lead to declining psychological wellbeing (Figure 2.4).

Fagin and Little (1984) carried out a descriptive study of 22 families in which the male breadwinner became unemployed, in an attempt to identify the phases in related psychological changes. The initial reaction was found to be one of shock, followed by a period of denial, described as a 'holiday period'. This was swiftly seen to turn into anxiety and distress as job searches repeatedly failed. The final stage was one of resignation and eventual adjustment to the unemployed role (Fagin and Little, 1984). Sinfield, however, is wary of categorising the reaction to unemployment in terms of discreet 'stages', and stresses that adjustment to unemployment varies widely with individual circumstances and a range of other factors (Sinfield, 1981). Warr examined the way in which protracted unemployment affects mental health, stating that affective wellbeing tends to decline rapidly immediately following job loss, but stabilises six months later at a significantly lower level than found in employed samples (Warr and Jackson, 1985). He suggests three ways in which individuals can adapt to the unemployed role (Warr, 1987). Firstly, *constructive adaptation* occurs when unemployed people proactively pursue interests and hobbies outside formal labour markets. In such cases, individuals are able to recreate the psychologically health elements of employment, such as daily time structure, access to social networks and traction.

1. Restricted behaviours and environments: due to lack of money and no ‘reason’ to leave home.

2. Loss of traction: when having nothing to do means that small tasks fill an entire day, and an individual has no super-imposed way of structuring time.

3. Loss of scope for decision-making

4. Reduced opportunities for acquiring new skills, due to lack of money and a lack of motivation associated with being jobless.

5. Increased exposure to humiliating experiences, such as job rejections and generally feeling as though one is regarded as a ‘failure’ or a ‘scrounger’.

6. Anxiety about the future

7. Reduced quality of interpersonal contacts: officials with whom a jobseeker has to interact in his/her job search come to replace the relationships he/she had with colleagues at work, which were more likely to have a more equal power balance.

8. Decline in social position and status.

Figure 2.4 Eight pathways through which joblessness can lead to declining psychological wellbeing (Warr, 1985)

This form of adaptation to the unemployed role results in moderate to high levels of psychological wellbeing, but often requires the individual to be free from the financial constraints normally associated with joblessness. Fryer and Payne (1984) conducted qualitative research to explore how some individuals cope well with unemployment. Eleven such individuals were interviewed, all of whom are described as ‘active’ and ‘goal oriented’. The majority were from middle class backgrounds and had previously been employed in professional or managerial occupations (class I or II of the Registrar General’s classification). All 11 individuals had pursued activities which gave their days an internal time structure and provided social interactions outside the home. Smith (1985) also identified young parents, especially mothers as a group who are resilient to the declines in psychological health usually associated with joblessness. Smith suggests that this is because caring for a young child provides a focus and a time structure to the day. The second form of adaptation outlined by Warr is *resignation.* In such cases, psychological wellbeing may increase slightly from the lowest point immediately following job loss, but this is due to processes akin to institutionalisation (Warr, 1987). An individual’s aspirations, autonomy and competence are reduced such that their expectations are lowered in line with their experiences. Thirdly, Warr contends that a third section of those experiencing unemployment may react with *despair.* In such cases aspiration, autonomy and competence decline, but expectations may decline at a slower rate, leaving an unsatisfactory gulf.

In addition to material factors and the psychosocial effects described above, it is suggested that joblessness may affect mental health by precipitating changes to health behaviours. Bartley and colleagues (2005) suggest that more people may attempt to alleviate stress by self-medication, using illegal drugs and alcohol, by developing unhealthy eating patterns or by smoking. Luoto *et al.* (1998) examined the relationship between unemployment and alcohol consumption in Finland during a period of economic recession and during a preceding period of expansion. It was found that during the boom (1982–1990), being unemployed was not associated with high alcohol consumption for men and women, nor was it during the recession (1991–1995), except among single people. In this study, increased alcohol consumption was only associated with unemployment during a recession and this was the case for single people only. During the period of overall low unemployment, there was no indication that those who were unemployed drank more alcohol. It is worth questioning whether these results are generalisable outside Finland and the Scandinavian countries however, as norms and practices surrounding alcohol consumption are culturally specific. There is a paucity of studies which address the links between health behaviours and employment status in a UK setting, especially within the context of business cycles. Novo *et al.* (2000) undertook a similar study in Sweden, to analyse the association between smoking and employment status amongst young men and women in times of expansion and recession. Daily cigarette smoking had declined during the recession, compared to the boom. Unemployed people, especially women were more likely to smoke. This was especially true during the economic boom.

2.3.2 Economic inactivity and Minor Psychiatric Morbidity

Beatty *et al.* (2000) proposed a 'theory of unemployment, employment and sickness' which aims to explain the rapid increase in incapacity benefit claims in the 1980s and 1990s. Beatty and colleagues start from the reasonable assumption that long-term limiting illness is fairly widespread among the workforce, and always has been. This group are divided into: those who work despite their illness, perhaps in occupations which do not require a high degree of physical activity or positions which allow part time and flexitime arrangements; those who are recorded as sick, by claiming incapacity benefit; those who are sick, but who are registered as unemployed and are actively seeking work; and finally, those who are economically inactive and are not claiming incapacity benefits either. Beatty *et al.* argue that the effects of job loss are to force some people to register as unemployed, but others, who were working whilst enduring an illness, may sign on to incapacity benefit instead. In times of economic recession, when demand for labour contracts, employers are likely to preferentially dismiss workers who are less productive than other workers, perhaps owing to an illness which causes them to take frequent sick days or longer breaks. Beatty and colleagues argue that many of these individuals will initially sign on to jobseekers allowance and become registered unemployed, but in a climate of low labour demand, employers will preferentially hire those who appear to be in good health. Beatty *et al.* provide the metaphor of the 'job queue', in which healthier unemployed individuals 'push in front' of those with longstanding illnesses. It is argued that eventually, the latter will commonly decide to move onto incapacity benefit. This theory therefore suggests that in times of economic recession, more people with longstanding physical disabilities or illnesses will move onto incapacity benefit, as they are selected out of the workforce and out of the 'jobs queue' as well. Beatty and colleagues argue that because of this process, those on long term disability benefits constitute a large amount of 'hidden unemployment', involving people who are capable of work but who do not have the chance. The 'hidden unemployed' are at equal risk of the negative mental health effects of joblessness as the registered unemployed. This is a major omission in the literature, as none of the major studies which investigate the relationship between unemployment and associated mental health declines consider the hidden unemployment which accounts for the massive rise in incapacity benefit claims during times of economic recession (Beatty *et al,* 2000). The loss of traction, time structure, social interaction and status which goes hand-in-hand with many experiences of unemployment (Warr, 1987) also accompanies the experience of claiming incapacity benefit on a long-term basis. It is possible that an extended period of time claiming incapacity benefit could turn an individual who is capable of engaging in a non-manual job from somebody with, for example, back pain, to an individual with back pain and depression. Of course, it is important to be clear about causality when making such statements. Pre-existing physical illness is an important predictor of depression and mental health decline. This is why longitudinal research is much needed in this area.

Not only are there 'hidden unemployed' amongst those claiming incapacity benefits, but also amongst other economically inactive people who cannot easily be classified. People who are economically inactive but are not officially registered as sick can fall into various categories such as students, aristocracy and many women who self-define as home makers or 'housewives'. Bartley *et al.* (2005) point out that for women, there is a higher prevalence of ill health among those keeping house than among the employed or those registered as unemployed. It seems that the mental health risks of joblessness outlined by Warr (1987) apply to such women as well as to those who are officially unemployed, and the hidden unemployed claiming incapacity benefit. Because home making is a socially acceptable and entirely normal gender role for women, this seems to create a 'fourth option' that men don't commonly have access to. To make a generalisation, men are usually employed, unemployed or inactive and claiming incapacity benefit. For women, the home maker role within a household which includes a male breadwinner, can describe women who are home makers and carers of children, women who have been made redundant but who may be seeking work whilst not officially registered as unemployed, and women who are sick but do not claim incapacity benefit. It is possible then, that for women, the 'other inactive' or 'home maker' category is masking a range of different levels of labour market engagement, and potentially some long-term sickness (Dew, 1991). It is important to engage with this difficulty in classifying women. A great many studies look at unemployed men and women, thus excluding many job seeking women who may not be officially registered, and many women who are experiencing joblessness due to unregistered incapacity. As described above, long-term incapacity exposes individuals to the same mental health risks associated with joblessness as unemployment does, owing to psychosocial effects. If women who are classified as 'other inactive' do not have a specific role in the home, such as childcare, which recreates the mentally healthy aspects of employment, then it is likely that they are at higher risk of mental health decline.

2.3.3 Insecure employment, underemployment and Minor Psychiatric Morbidity

It appears that work keeps the mind healthy, but one should not assume that all work is equally beneficial. Warr (1983) set out criteria which describe how a specific job-type can potentially affect a worker's mental health. These criteria also describe 'good' experiences of unemployment, in which individuals attempt to recreate the healthy elements of having a job.

	Good jobs have	Bad jobs have	Good unemployment has	Bad unemployment has
Money	more	less	more	less
Variety	more	less	more	less
Goals, traction	more	less	more	less
Decision latitude	more	less	more	less
Skill use/development	more	less	more	less
Psychological threat	less	more	less	more
Security	more	less	more	less
Interpersonal contact	more	less	more	less
Valued social position	more	less	more	less

Figure 2.5 Criteria for how job properties affect mental health. Source: Smith (1995, pg. 1411) after Warr (1983)

In a recession, not only does unemployment rise, but so too do underemployment and insecure employment. Dooley *et al.* (2003) argue that a paradigm shift away from a dichotomous perspective involving just employment and unemployment is required. This continuum should include those who are underemployed, insecurely employed as well as many of those on incapacity benefit. Burchell (1994) contends that research on the negative health effects of unemployment on mental and physical health should be overtaken by research into the effects of insecure employment, as this is a growing issue in the modern labour market. Job insecurity is defined differently by different authors. Some use the term to describe the subjective experience of being concerned about redundancy, especially when this is a fundamental feature of the casual, low-level service sector in which an increasing proportion of economically active people are engaged. Hartley *et al.* (1991) define insecurity in general terms as the discrepancy between the levels of security a person experiences and the level s/he might prefer. Ferrie (1999) situates 'insecurity' within the backdrop of deindustrialisation, tertiarisation and the trend towards labour market flexibility which has characterised western economies since the late 1970s. Ferrie argues that increasing numbers of people are now being employed in a casual 'secondary' labour market which is characterised by weak contractual arrangements and a lack of labour organisation or unionisation. Insecurity is integral to the experience of working in this section of the labour market (Ferrie, 2001). As demand for labour contracts in a recession, it is possible that those with less legal protection and less labour organisation will be at greater risk of unemployment. The experience of being employed in a casual, short-term fashion is often measured more empirically using the type of contract an individual is employed under. Artazcoz *et al.* (2005) conducted a cross-sectional study of salaried men and women in Catalonia to analyse the association between poor mental health and four types of employment contract: permanent, fixed term temporary contract, non-fixed term temporary contract, and no contract. They found that employment under a non-fixed term temporary contract is associated with poor psychological wellbeing among non-manual female workers and among male manual workers. In addition, it was found that among both male and female manual workers, having no contract is related to poor psychological wellbeing and to job dissatisfaction. This study is limited by its cross-sectional nature, which means that causality cannot be inferred. However, the authors sought to minimise the effects of health selection by excluding participants who had reported a longstanding limiting illness in the past 12 months.

Despite an increasing proportion of economically active people being employed in the low-end service sector, relatively little research has been undertaken to investigate the relationship between endemic job insecurity and mental health. Many of the studies which have been done are cross-sectional. It is therefore difficult to distinguish whether people with certain characteristics, for example poor mental health, are selected into the casual labour market. A greater number of studies have been undertaken to investigate the effects of fear of redundancy for those employed on permanent contracts who are accustomed to the idea that their job is for life (Ferrie, 2001). In times of recession, when company bankruptcies and branch closures or downsizing are more common, it seems likely that many employees may fear job loss. It is likely that this may never materialise, but that prolonged worry could have a negative effect on mental health (Hartley, 1991; Dooley *et al.* 1987; Catalano *et al.* 1986; Lee *et al.* 2004; Joelson, 1987).

2.3.4 Summary

A review of relevant literature points clearly to the conclusion that joblessness affects mental health. This is not just related to unemployment, in which the individual actively searches for work, but also to many of those claiming incapacity benefits in the UK, and to other economically inactive individuals. Longitudinal evidence suggests that the link between joblessness and poor psychological wellbeing is likely to be causal, but that many complex processes are at play. Research by Jahoda, Warr and many others has given us an understanding of the material, psychosocial and health behaviour causal pathways through which joblessness can affect mental health. This research is focussed too heavily on the experience of the economically active unemployed jobseekers, the majority of whom appear to be males, suffering the consequences of unemployment through the cultural lens of their patriarchal breadwinner role. Research by Burchell; Catalano; Ferrie; Hartley and others has shed light on the ways in which the post-Fordist flexible labour markets can expose temporary and casually employed low-end service sector workers to extreme levels of job insecurity, suggesting that this puts them at risk of poorer psychological wellbeing. In addition, too little research has been done on the links between joblessness and poor mental health to include the UK's 'hidden unemployed' or permanently sick. Perhaps the largest gap in the literature on employment status and mental health is the failure of the majority of studies to situate their research against the economic, social and spatial backdrops within which labour markets exist, especially in the context of the UK. We are still left with questions such as: is unemployment in a temporal/spatial context of high national unemployment levels more harmful to mental health than a spell of unemployment during an economic boom? Novo and colleagues have addressed a similar question in the context of Sweden (2000).They conclude that there were no differences in mental health symptoms in the unemployed between the mid-1980s boom and the early-1990s recession, and that business cycles do not affect the relationship between unemployment and mental health outcomes. But overall, men had worse mental health in the recession. This research was cross-sectional, and measured mental health in a sample taken under boom conditions and then in a different sample a few years later under recession conditions. All participants were aged 21 and from the same industrial town in Sweden. These results therefore may be of limited generalisability.

2.4 Conceptualising the relationship between economic recession and population health

In the UK and elsewhere in the developed world an economic recession is commonly defined as a fall in the level of real gross domestic product (GDP) for at least two successive quarters of the year (Delong and Olney, 2006). In the United States the National Bureau of Economic Research's business cycle-dating committee define recession as: "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production and wholesale-retail sales" (NBER, 2003). Since the turn of the twentieth century there has been a long-term, secular trend of GDP growth in Britain and other developed countries (Gartner, 2003). However this has not been a smooth and stable upward trend but is distorted by fluctuations above and below the 'steady state' rate of GDP growth. Levels of both employment and production commonly rise above the long-term trend, and fall below it. Such high-resolution fluctuations in GDP are commonly referred to as 'business cycles' which are made up of two stages. Periods in which production is rising, unemployment is falling and inflation is accelerating are considered to be expansions or 'booms', in which GDP grows faster than the long-term trend. Periods in which production falls, unemployment rises and disinflation or deflation occurs are known as recessions. Interest rates, the level of the stock market and other economic variables also fluctuate along with the business cycle. When set against the long-term upward trend in GDP growth, these short-term fluctuations may appear insignificant, but this literature review will illustrate how they can have a major impact on the health and psychological wellbeing of the population.

How do these national macroeconomic conditions affect the physical and mental health of the population? Studies which have sought to address this question have largely been ecological in design, using national or community-level economic indicators as exposure variables and the prevalence or incidence of morbidity or mortality in the same population as the outcome variable. Perhaps the liveliest debate has been surrounding the effect of business cycles on the most fundamental measure of human health and wellbeing: age-standardised mortality. In the inter-war period, Thomas (1925) suggested that economic expansion was associated with increasing mortality rates in Britain and the US, but these findings did not generate much interest (Tapia Granados, 2005), perhaps owing to their counterintuitive nature. Whilst Thomas' work was corroborated in the 1970s by Eyer (1977) and others, it was challenged by Brenner's influential work (1971; 1979) which suggested a countercyclical relationship between the economy and mortality; i.e. that expansions correlate with a greater rate of mortality decline and recessions correlate with a lower rate, or even rising mortality. However, Brenner's use of aggregate time-series data has since been roundly criticised on statistical and methodological grounds (Wagstaff, 1985; Laporte, 2004; Gravelle *et al.,* 1981). In contradiction to Brenner's work, a procyclical relationship between business cycles and the majority of causes of mortality has been found in a number of studies (Ruhm, 2000; Tapia Granados, 2005; Gerdtham and Ruhm, 2006; Neumayer, 2003).

The long-term mortality decline which began at the turn of the twentieth century in the developed world has not been a smooth and steady decline. Like the concurrent long-term rise in GDP, it has been characterised by fluctuations above and below the secular trend. These fluctuations, it is argued, are related to the similar short-term fluctuations in real GDP growth. As the economy expands, the rate of mortality decline decelerates and mortality rates stagnate or increase. Similarly, as the economy falls into recession, mortality rates decline more rapidly (Tapia Granados, 2005). However, it is important to note that whilst the majority of causes of death conform to these findings, suicide rates appear to be an exception to the procyclical relationship between mortality and the economy. The majority of studies have found that suicide rates increase during recessions and decline during expansions (Brenner, 1987; Khang, 2005; Tapia Granados, 2005; Ruhm, 2000), although this is challenged by Ostamo and Lönnqvist (2001) and Hintikka (1999) who found no change in suicide rates during Finland's deep 1990s recession. Whilst all-cause mortality is an important (although flawed) indicator for physical wellbeing, it may be less indicative of psychological wellbeing and mental health, especially as suicide mortality is not generally considered to follow the same patterns as mortality from other causes.

Ecological studies which have attempted to determine the effects of recession on population-level mental health and psychological wellbeing are uncommon, perhaps owing to the difficulty of collecting national data on these outcomes. In an attempt to determine the effects of economic change on a range of physical, mental and social wellbeing outcomes in Sweden between 1950 and 1980, Brenner (1987) used the following indicators for mental health: rate of utilisation of psychiatric hospitals by age; suicide mortality rate by age, and; cirrhosis mortality rate by age. These population-level indicators may not have included the prevalence of common mental disorders such as anxiety and depression, unless all cases received psychiatric care, resulted in suicide or resulted in deaths from cirrhosis due to substance abuse. It is likely that these data do not provide a complete picture of the level of mental health morbidity in the population at the time. Ruhm (2003) suggests that whilst temporary economic improvements are associated with increases in both acute and chronic physical conditions, there is some evidence that non-psychotic mental disorders decrease as the economy improves. Ruhm emphasises the need for a distinction between mental and physical health when analysing the effects of economic change (2003).

The alternative to these ecological approaches, in which both economic exposures and health outcomes are measured at the community level, are studies in which economic indicators of recession and health outcomes are measured at the individual level. An individual being made redundant, experiencing concern about their employment stability, feeling anxious about the general consequences of economic downturn, falling into debt: these are all examples of individual experiences which are assumed to be more likely to occur to individuals during an economic recession, and to act as risk factors for negative physical and mental health outcomes. As will be shown below, studies which use individual-level data almost universally show an association between indicators of economic downturn (job loss, insecure employment, unemployment, etc.) and poor health outcomes (Catalano, 1991; Ben-Schlomo, 2005). Whilst this may superficially appear to contradict the procyclical relationship between business cycles and physical health conditions which has been observed at the community level, this is not the case, as one cannot confidently draw conclusions about individuals based on community-level data. The individuals exposed to the phenomenon of interest may be different individuals to those suffering the outcome of interest – an issue known as the 'ecological fallacy' (Robinson, 1950).

There is a relative lack of research which uses individual-level data to assess the relationship between recession and mental health. However, there is a wealth of literature on the effects of individual economic experiences on mental health, which does not necessarily set these experiences against a wider economic backdrop of recession or expansion. For example, there has been a high volume of research on the relationships between joblessness and mental health (Dooley, 1994; Hamilton, 1993; Jahoda, 1933; Warr, 1987; Weich and Lewis, 1998, etc.); indebtedness and mental health (Balmer, 2006; Brown, 2005; Drentea, 2000; Jenkins, 2008; etc); home repossession and mental health (Nettleton and Burrows, 1998; Taylor, 2007); but few of these studies have attempted to situate their research in terms of the wider macroeconomic conditions.

Viinamäki *et al.* (2000) did make such an attempt in their study of mental health during economic recession in Finland using random population samples from three consecutive years, 1993-1995. Prevalence of mental health disorders was determined from GHQ-12 scores and information about economic experiences was also collected from these individuals. Present financial status, current employment status, attitude towards the future, levels of social support, and receipt of housing or living allowance in the past year were included as potential independent variables. Data on alcohol consumption, smoking status, use of psychoactive drugs and suicidal ideation were also collected, alongside standard sociodemographic information. It was found that low income and unemployment were associated with poor mental health in each of the study years. Subjective poor health and perception of poor economic situation were also associated with poor mental health consistently. However, overall there was no major change in the mental health profile of the Finns in the study during the economic recession. Viinamäki and colleagues considered the strengths of their study to lie in the fact that they analysed representative samples in consecutive years, thereby allowing detection of changes in mental health over very short timescales. They also commented that in setting their study against the backdrop of severe economic recession (in 1993) followed by some recovery (by 1995), they could relate these population level results to the national economic context. This Finnish study succeeded in combining the study of individual-level exposures and outcomes with a wider perspective on national economic conditions. However, the study design would have been stronger if it had used longitudinal data rather than repeated cross sections.

Novo and colleagues (2000; 2001) have also undertaken research into the effects of business cycles on the individual-level psychological health of young Swedish men and women. Two study groups were recruited from an industrial town in northern Sweden. The first group was surveyed in 1986, during economic expansion and the second group was surveyed in the recession of 1994. It was found that the level of psychological symptoms among the long-term unemployed section of the sample was the same in both the boom and the recession, and that business cycles have more of an effect on those who were not long-term unemployed during the 12 months preceding the survey. For women, psychological symptoms were found to be more prevalent in the 1994 sample, but there was no difference between the 1986 and 1994 samples for the prevalence of psychological symptoms in men. In later analysis of the same data, Novo *et al.* (2001) confirmed that the effects of the business cycles were stronger for women's health than for men. Financial problems and pessimism about the future were found to be strong explanatory factors for somatic and psychological health among both sexes, but the effect was greater for women. A drawback to Novo's approach is that the use of two cross-sectional studies taken eight years apart means that the two groups have experienced different social and economic circumstances, due to having been born at different times. These cohort effects are difficult to control for, and Novo *et al.* recognise that this could be an explanation for their findings. A cohort study would have been an alternative approach, which would naturally have controlled for 'cohort effects', but instead may have introduced other sources of bias, including age bias and the influence of greater education. The authors consider the cohort effect to be smaller than an age effect introduced by following one cohort through the business cycle.

Panel studies follow individuals as they live through business cycles, and allow measurement of their health outcomes along the way. In addition, individual-level economic exposures can be measured, to assess how macroeconomic conditions are affecting each person. This allows more sophisticated analysis of the ways in which recessions can affect different individuals to different extents, and in different ways. Only a small minority of people lose their jobs in the high-unemployment climate of a recession. Longitudinal data allows comparison of someone who remained employed with someone who was perhaps more directly affected by the recession and was made redundant. Equally, we can examine the difference in mental health outcomes between people who have been economically affected by a recession which occurred in their twenties, and someone for whom the recession occurred in their sixties. We can also investigate whether someone living in an economically depressed ex-mining town, where unemployment is endemic even in times of expansion, suffers greater mental health decline in a recession, than a person who lives in a formerly booming service-oriented labour market, with very low pre-recession levels of unemployment. Longitudinal data also allows an examination of the temporal relationship between economic shocks and the potential onset of mental health decline. In addition, it could allow investigation of how long mental health takes to recover, following a recession or associated economic hardship. To the author's knowledge, no research has previously been undertaken on the effects of business cycles on self-rated mental health, in the UK, using longitudinal data set against a backdrop of national economic downturn to reconstruct the temporal and spatial relationships between recession and psychological wellbeing.

It is important not to dismiss the usefulness of ecological study designs, because they can provide near-experimental conditions, in which individual confounding factors remain constant over time (Ben-Shlomo, 2005). It should be recognised that the ecological studies of Brenner, Ruhm, Tapia Granados, and others have challenged preconceptions by showing the countercyclical nature of mortality rates.

A review of relevant literature shows, therefore, that on the national level, economic recession is measured and identified by governments and economists based on a formal definition of two successive quarters of negative real GDP growth, and that other important indicators are unemployment rates, interest rates, inflation rates, and the level of the stock market. Studies which measure the effects of recession at the individual level commonly emphasise employment status and income, as well as perceptions of financial future and subjective assessments of the individual's own wealth.

Studies which measure the effects of recession at the individual level typically use employment status and variables related to labour market participation as the most important measurement of how individuals are directly affected by economic downturn. The literature consistently shows that employment status is related to mental health. As described above, an economy in recession has a lower demand for labour. Therefore a large proportion of the effects of recession on mental health are likely to act through employment status. The business cycles described above have existed against a backdrop of dramatic shifts in the labour markets of developed countries, and in the international division of labour, in the late twentieth century. The post-Fordist shift of the late 1970s changed expectations and experiences of employment. The 'job for life' ideal which characterised the 'golden age' of the mid twentieth century disappeared along with the manufacturing and primary industry dominance on which it had been built (Harvey, 1989). Labour market flexibility is now the goal of policy makers, with a view to increasing competitiveness and adaptability in increasingly globalised markets (Bartley e*t al.* 2005). Deindustrialisation has been accompanied by tertiarisation of the UK economy, in which the service sector expanded and knowledge/information became the most important good. With the loss of primary and secondary sector jobs and the expansion of the service sector, the labour market became increasingly polarised (Harvey, 1989). Whilst high-level service jobs in law, media, software design, advertising, etc bring high salaries and status, they are dependent on low-level service workers such as office cleaners, fast-food waiters and call-centre operators. These so-called 'McJobs' (Ritzer, 1993) are characterised by low pay, low status, insecurity, little potential for advancement and no unionisation or labour organisation. Flexibility is key in the 'new economy' (Ferrie, 2001), and this has led to a widespread erosion in the expectation of job security, especially for low-level service workers. In the context of a flexible, post-Fordist labour market, the effects of recession on unemployment among low-level service workers could have high social and health costs. Equally, the susceptibility of high-level service jobs to redundancies and general instability requires consideration. Relatively little research has been undertaken on how flexible employment affects population health.

2.5 Spatial variations in and contextual influences on Minor Psychiatric Morbidity

Research outlined above has shown that the relationship between the economy and mental health in the UK is dependent largely on the employment status of individuals. The effects of the macroeconomic conditions which affect the mental health of individuals also vary over space. It is overly simplistic to assume that a recession will have the same effects on the regional economy and local labour markets of, say Newcastle, as for example, Oxfordshire's 'M4 corridor'. Equally, one cannot assume that a recession which causes catastrophic job losses in the manufacturing regions will have similarly disastrous effects on the rural economies of East Anglia or North Wales. Economic geographers devote much research to classifying the regional economies of the UK and charting how their individual economic and industrial histories shape their current socioeconomic conditions (Martin and Morrison, 2003; Martin and Townroe, 1992). If the economy has an important and significant effect on psychological wellbeing, one would expect greater levels of mental health decline in regions which experience the highest levels of job losses, shown in Figure 2.6. Former industrial regions such as the west midlands, the north west, and the north east have arguably been worst hit by every economic recession since deindustrialisation began in the 1970s, as foreign companies rationalise, outsource production overseas and cut working hours in the UK's dwindling manufacturing sector. These shifting geographies of regional economic fortunes may be related to regional variations in the incidence of common mental disorders. It seems likely that areas with the greatest proportions of inhabitants experiencing unemployment and financial problems are likely to be areas in which prevalence of common mental disorders are higher.

The work which has been undertaken has generally concluded that there is little or no variation in the prevalence of common mental disorders across small and mid-sized areas, particularly after adjusting for the aggregate characteristics of individual residents (McCulloch, 2001; Weich *et al.*, 2003; Wainwright, 2003; Reijneveld and Schene, 1998; Wainwright, 2004; Pickett and Pearl, 2001; Ross, 2000). A study by Henderson (2005) suggests that this also applies to the United States. Lewis and Booth (1992) found a greater concentration of psychiatric morbidity in the north of England than the south, but suggested that this was due to compositional factors rather than contextual. They also noted that this divide did not hold true for those in social classes I and II, and all but disappeared when rural areas were excluded. Duncan *et al.* (1995) criticised Lewis and Booth's work for being methodologically limited, as the authors used only a single level aggregate modelling approach, rather than the multilevel modelling technique which has since become standard.

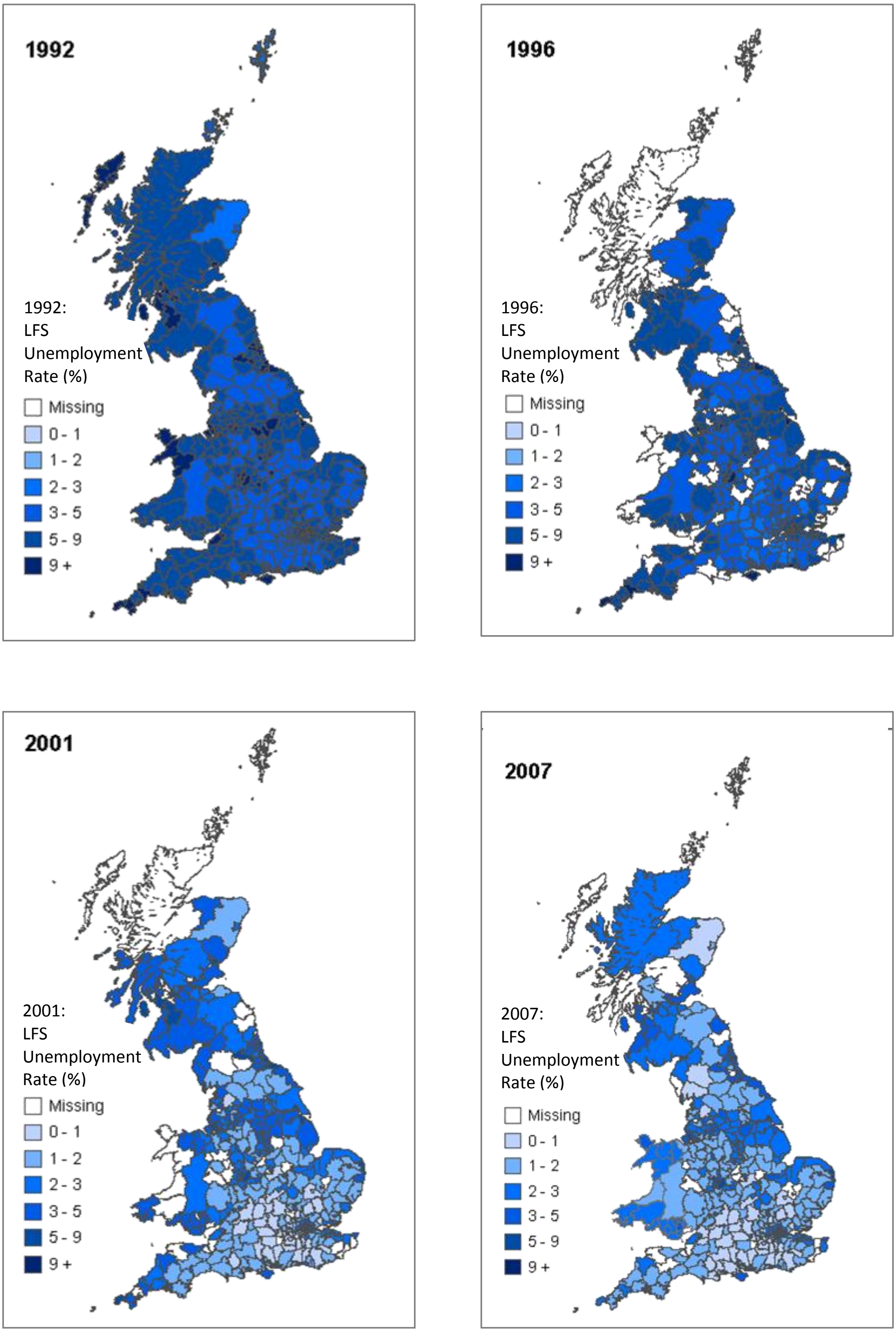

Figure 2.6 LFS Unemployment Rate by pre-2009 Local Authority District for four selected years

Blaxter (1990) also found regional variation in common mental disorders, and suggested that conditions at smaller scales (the so-called ‘neighbourhood’ level) have a greater influence than regional conditions, corroborating earlier work by Birtchnell (1988). This is again criticised heavily by Duncan *et al.* (1995) on methodological and conceptual grounds.

In an editorial piece, Weich (2005) bemoaned the failure of geographers and epidemiologists to adequately establish whether or not contextual factors influence mental health outcomes. He questioned whether previous studies have used the correct spatial scales, commenting on the difficulty of defining ‘neighbourhood’ and the limitations of defining culturally and economically meaningful ‘areas’ using arbitrary administrative boundaries. Weich (2005) also highlighted the difficulty of defining true contextual factors, in opposition to ‘area-level’ measures which are aggregated individual responses. This is particularly difficult to do with regards to economic variables. It is important to use individual economic measures, so that it is clear how local economic conditions are actually affecting individuals’ lives. It is difficult to conceptualise truly contextual economic variables, although these might include factors which indicate the effects of high levels of joblessness or poverty in the area, such as levels of local government public expenditure on jobcentres and employment initiatives, and perhaps most importantly, context-specific local norms regarding attitudes towards joblessness and debt. Perhaps the biggest criticism Weich (2005) levelled at existing attempts to uncover the spatial variations in mental health outcomes is the over-reliance on cross-sectional studies. It seems unlikely that any effects of place on mental health are instantaneous. The most potent factors may be those operating during childhood. We don’t just need to know where people live now, but where they have lived in the past. This combination of spatial and lifecourse approaches may be necessary to finally understand whether place independently effects mental health outcomes.

2.6 Conceptualising and measuring Minor Psychiatric Morbidity

‘Minor Psychiatric Morbidity’ (MPM) is one of many labels used in academic literature to describe the constellation of psychological and emotional symptoms related to depression, anxiety, unhappiness and a lack of wellbeing or positive affect. Usually MPM and its related labels are not used to refer to any specific clinically classified psychiatric disorder such as clinical depression or anxiety, but are considered to be predictive of these conditions. Terms such as ‘psychological distress’, ‘psychological wellbeing’, ‘common mental disorder’ and others are used interchangeably, although disciplinary norms frequently appear to determine which are chosen. While terms such as ‘MPM’ and ‘psychological distress’ prevail in the epidemiological and social science literature, economists often use the same measurement instruments but define the outcome of interest as ‘happiness’ or ‘wellbeing’ (Layard, 2005). These related terms are used interchangeably throughout this PhD thesis. While the diagnostic criteria for related psychiatric conditions such as depression are relatively precise, the measurement of psychological distress in social surveys is less so. The most obvious way to ensure clarity is to focus on the instrument used to measure the phenomenon, and to reach a consensus on what exactly is being measured. Some commonly used instruments include the General Health Questionnaire (Goldberg, 1978), the Malaise Inventory (Rutter *et al.* 1970), the Beck Depression Inventory (Beck *et al.*, 1961), the Kessler Psychological Distress Scale (Kessler *et al.* 2002) and the Warwick-Edinburgh Mental Wellbeing Scale (Tennant *et al.* 2006). Each of these scales have slightly different foci, and purport to measure subtly different elements of psychological wellbeing, distress and minor psychiatric morbidity. The instrument used to measure MPM for the purposes of this PhD project was the 12 item General Health Questionnaire (GHQ-12), as this questionnaire was included in every wave of the British Household Panel Survey and is therefore the measure which was available for use.

2.7 Minor Psychiatric Morbidity and gender

How is minor psychiatric morbidity patterned across the UK population? The general consensus across the literature is that minor psychiatric morbidity levels are higher amongst women than men. In their comprehensive review, Dohrenwend and Dohrenwend found that women had higher overall rates of MPM in 18 out of 19 studies from the post-WWII era (1976). Briscoe (1982) quotes UK general practice MPM prevalence figures, stating that there are between two and three women suffering MPM for every man, but recognises that social selection effects are inherent in the use of treatment statistics. Women are more likely to consult clinicians (Kohn and White, 1976) and are more likely to be diagnosed with affective disorders when they do so (Shepherd *et al.,* 1966; Cooperstock, 1971, 1978). Furthermore, Gove *et al.* (1976) state that findings which purport to show higher rates of diagnosed mental illness amongst women only do so when the outcomes of interest are limited to functional disorders involving personal distress. The gender balance becomes more equal when personality disorders, substance abuse and antisocial conduct are included as outcomes of interest (Dohrenwend and Dohrenwend, 1976). Research using social survey data has produced similarly mixed conclusions on the gender balance of MPM. Using a representative national survey, Gurin *et al.* (1960) found significant gender differences in feelings of social adjustment and emotional problems. The authors suggested that women have a greater tendency to report distress than men, and perhaps also have a greater sensitivity to socioemotional experiences (Gurin *et al.,* 1960). Bradburn (1969) conceptualised psychological wellbeing as having two constituent dimensions, which whilst related, are somewhat independent of one another: positive affect or 'happiness', and negative affect. It was found that women had a greater tendency to report negative affect than men, but only a slightly increased tendency to report positive affect. The author suggested that this may be a result of the socialisation process, in which boys are traditionally expected to exercise more 'control' over strong emotions than girls (Bradburn, 1969). In a review covering studies undertaken in the 1980s, Kohn *et al.* (1998) found no evidence for an overall gender difference in rates of overall psychiatric disorder between men and women. Sacker and Wiggins (2002) noted that men and women are not equally distributed among social classes and that therefore a proportion of the excess MPM seen in women may be a reflection of the social gradient in MPM. Indeed, socioeconomic pattering of MPM has been widely reported, and appears robust to variations in how socioeconomic position or the outcome are conceptualised or measured (Kohn *et* al., 1998). Kessler (1982) reported significant negative relationships between socioeconomic position and psychological distress in eight USA-based studies undertaken during the 1960s and 1970s. Inverse gradients were also found in later UK-based studies (e.g. Weich and Lewis, 1998; Bartley *et al.,* 2000; Kuh *et al.,* 2002).

2.8 Minor Psychiatric Morbidity and age

Research on psychological wellbeing and age has generally found evidence for a U-shaped relationship through the lifecourse. This work, typically based on cross-sectional data using methods which control for confounding factors such as marital status and physical health problems, tends to show that wellbeing decreases towards mid-life and then rebounds in later life (Clark and Oswald, 1994; Winkelmann and Winkelmann, 1998; Blanchflower and Oswald, 2004; Shields and Wheatley Price, 2005; Uppal, 2006), although two meta-analyses have failed to endorse this (McKee-Ryan *et al.,* 2005; Paul and Moser, 2009). Research using cross-sectional data cannot take account of cohort effects related to varying socioeconomic and cultural conditions faced by those experiencing key stages of the lifecourse during different eras. Sacker and Wiggins (2002) found that the 1970 British birth cohort had greater psychological distress than the 1958 cohort and that whilst women's psychological distress has declined over time, the same cannot be said for men. Lewis and Wilkinson (1993) and Oswald and Powdthaveee (2007) suggest that GHQ-12 scores have been worsening over time in the UK, indicating that the U-shape apparent in cross-sectional research could be artifactual. However, a curvilinear relationship was found by Blanchflower and Oswald (2008) after controlling for different birth cohorts and confounding factors such as marital status and income, using data on more than 500,000 Americans and Europeans from the US General Social Surveys and the Eurobarometer surveys. This study found that the U-shape applied to men and women, and that the age at which wellbeing reaches its minimum is generally quite consistent across the data sets, falling within a person's 40s.

2.9 Conclusions

This review of the literature has outlined a wealth of interesting research on the broad subject of labour market status and minor psychiatric morbidity. Studies have predominantly found a strong association between joblessness and psychological distress, which analysis of workplace closure studies and longitudinal data have largely suggested to be causal, although debate remains on this issue. Too few of the studies using longitudinal data have properly interrogated the issue of causality, exploiting the power of hierarchical modelling and chronological sequencing to unpack cause and effect. In addition, little attempt has been made to situate the relationship between labour market status and MPM in the context of the lifecourse, and assess the differential effects of joblessness or insecurity on MPM at different ages. A further fundamental limitation of much of the research in this field has been the overemphasis on male registered unemployment. Whilst this was appropriate under the macroeconomic conditions of the post-war era in which successive governments pursued the goal of full employment, shifts in the nature of the regime of accumulation from the 1980s onwards saw fundamental changes in labour market trends. A growing gulf between declining unemployment rates and rising male inactivity rates characterised the 1990s and 2000s, along with the increasing feminisation of the formal labour market. These changes mean that it is no longer appropriate to consider only unemployment when assessing the relationship between joblessness and psychological distress. Relatedly, the 1990s and 2000s also saw an increase in casual and fixed term contractual working arrangements, building higher levels of job insecurity into the labour market (Burchell *et al*., 2002). Whilst there is a developed literature on the effects of job insecurity on health, there has generally been a failure to integrate this concept into wider studies on the links between labour market status and health, and to consider the individual in their wider spatial, temporal and macroeconomic context. As described above, increasing female participation in the formal labour market has been one of the defining socioeconomic trends of the past few decades and women have not contributed to the overall trend of rising economic inactivity. It is clear that very different socioeconomic processes have been at play between the genders. In addition, research on the gender distribution of common mental disorders tends to show that women are at higher risk of MPM than men, with various sociocultural explanations suggested. Considering this combination of both divergent labour market participation trends and differing risk profiles for MPM, it seems clear that any investigation of the relationship between labour market status and MPM should consider the two genders separately.

A clear limitation of much of the literature is the failure to conceptualise the concentric rings of contextual exposures which affect an individual's mental health and influence their decisions and chances. A disciplinary divide exists between health geographers on the one hand, who have taken on the challenge of assessing the independent contributions of area-level exposures on individual-level outcomes; and epidemiologists on the other, who have increasingly focused on examining the temporality of exposures across the lifecourse. Both of these approaches require the analysis of inherently hierarchical data: the former recognising individuals as nested within geographical areas; and the latter conceptualising repeated observations on the same individuals over time as nested within those individuals. The combination of these hierarchical temporal and spatial dimensions is too seldom attempted. This PhD thesis will integrate these approaches in an attempt to characterise the nature of the relationship between labour market status and psychological wellbeing, through time and across space. To this end, the following research questions will be asked:

2.9.1 Research Questions

i. To what extent does being insecurely employed, unemployed, permanently sick or economically inactive predict MPM (compared to being securely employed), controlling for the effects of potential confounding factors, and exploring the factors which might mediate the relationship? (Chapter 4).

ii. To what extent does area level unemployment affect minor psychiatric morbidity, independently of individual-level exposure to joblessness and insecure employment? (Chapter 5.)

iii. What is the nature of the temporal dimension of the relationship between labour market status and GHQ-12? Causation, process and lifecourse. (Chapter 6).

Before addressing these research questions however, it is necessary to describe the data and methods used in this PhD thesis.

Chapter 3

Data and Methods

3 Data

This chapter provides an overview of the design and scope of the British Household Panel Survey and describes how the three study samples used in this PhD project were defined. In addition the derivation and distribution of the outcome, minor psychiatric morbidity (MPM), the key exposure, labour market status, and hypothesised confounding and mediating variables are presented.

3.1 The British Household Panel Survey

The British Household Panel Survey (BHPS) is run by the ESRC UK Longitudinal Studies Centre and the Institute for Social and Economic Research, based at the University of Essex. The survey is a valuable resource for a wide range of disciplines and its broad subject matter make it invaluable for interdisciplinary research. The primary objective of the BHPS is to allow greater understanding of social and economic change among individuals and households in Britain, and to allow the identification and prediction of the causes, consequences and patterns of these changes (Taylor *et al.,* 2010).

The BHPS has a stratified, clustered design and is based on a nationally representative sample of more than 5,000 households comprising approximately 10,000 individuals. The initial sample for wave one consisted of 8167 addresses which were obtained from the Postcode Address File. All private households at these addresses were then approached for interview. All individuals enumerated at the respondent households were inducted into the longitudinal sample, and are known as Original Sample Members (OSMs). Children within surveyed households enter the BHPS when they turn 16, but prior to this, are interviewed as part of an 11-15 year old youth panel (from wave 4 onwards). Eligibility for the study depended on domestic residence in England, Wales or Scotland (south of the Caledonian Canal). These OSMs were then followed and re-interviewed at successive waves, no matter whether they remained in their original households, moved into other households, entered institutions (excluding prisons) or moved into Northern Scotland. In addition to the OSMs, the sample at all waves beyond wave 1 also included some new entrants. A baby born to an OSM is included in the sample as an OSM (in the anticipation that s/he will be inducted into the youth panel at 11 and the BHPS at 16). If an OSM moves into a new household containing non BHPS sample members, these individuals become temporary sample members (TSMs) and are part of the survey only whilst they continue to live with the OSM. Similarly, if new individuals move in with an OSM, these are considered TSMs whilst they continue to reside with the OSM. The only exception in which a TSM is interviewed whilst no longer residing with an OSM is if the

TSM and OSM are parents of a new OSM birth. This panel design therefore means that the BHPS sample remained broadly representative of the UK population throughout the 1990s. In addition, further sub-samples were added to the BHPS in 1997 and 1999. With the exception of these additional subsamples, sample for each wave therefore consists of all OSMs, their natural descendants, plus all other adult members of their households (TSMs). Household membership is defined on this basis, and then interviews are attempted with all resident household members who are aged 16+ (on December 1st of the wave year). For eligible individuals who cannot respond due to ill health or prior engagements, proxy or telephone interviewing is offered. The survey comprises seven instruments. From wave nine onwards, computer assisted personal interviewing was used, but the structure of the instruments remained consistent.

Firstly, a household coversheet is completed by the interviewer. This contains information on how many times the interviewer has called at the household, observations on the type of accommodation and the outcomes in terms of survey completion. Secondly, a household composition form is completed at first contact with the household. This contains a listing of all household members with basic information such as sex, date of birth, marital status, employment status and relationship to a household reference person. The household reference person is defined as the person legally or financially responsible for the place of residence, and as the elder person if more than one individual is responsible for the accommodation. Thirdly, a 10-minute household questionnaire is administered with the household reference person, containing questions on household-level subjects such as housing tenure and condition. Fourthly, the individual schedule is undertaken with every adult member of the household. This interview takes around forty minutes and covers the following broad range of topics: neighbourhood, demographics, residential mobility, health and caring, current employment and earnings, employment changes over the past year, lifetime childbirth and relationship history (wave 2 only), employment status history (wave 2 only), values and opinions, household finances and organisation. Fifthly, a self-completion questionnaire is undertaken by sample members. This takes only around five minutes to complete and contains subjective or attitudinal questions which are thought to be sensitive and vulnerable to the influence of other household members. It is this part of the survey which includes the GHQ-12 questionnaire, as well as questions on social support. Finally, a proxy schedule and/or telephone questionnaire is offered. The former is used to collect information from household members who are too elderly or infirm to complete the interview in person. A proxy household member, usually the spouse or adult offspring, answers a shortened version of the questionnaire on their behalf. The telephone questionnaire is administered by an experienced interviewer when all other attempts to complete a face-to-face interview have failed. This is based on the proxy schedule.

A number of 'core' questions are included in the interviews every year, allowing analysis of annual change. Other sets of variables are covered periodically and are known as rotating core components. These are not hypothesised to change dramatically over time and their periodical inclusion allows for a broader range of topics to be covered overall, within the constraints of a 40 minute interview. The BHPS also includes time-invariant non-core components which are asked only once during the life of the panel survey. These include variables such as place of birth or school leaving age. This PhD project used only core and time invariant variables, since it was considered necessary to have complete data at all waves.

The advantages of using a survey with a panel design are many. Fundamentally, longitudinal data allow analysis of how individuals experience change over time, in their socioeconomic exposures and environment; and how these changes affect their lives. The panel nature of the BHPS allows contextualisation of the individual within their household, and allows researchers to consider the effects of household level exposures and interactions with other household members, on individuals. The BHPS therefore reflects the complex and dynamic nature of reality, in which individuals are subject to exposures and influences at a hierarchy of interacting levels, which change continually through time. For this reason, the BHPS is ideally suited to the research aims of this thesis, which seeks to investigate the complex relationship between labour market status and psychological distress, and the ways in which this varies by place and through the lifecourse.

3.2 Defining the study sample

The longitudinal datasets used in this PhD project were constructed using Stata 10 software (StataCorp, 2007) by first defining cross-sectional samples for each wave, using BHPS cross-sectional datasets downloaded from the UK Data Archive (UKDA). The waves utilised in the analyses undertaken for this thesis depended upon data availability and methodological considerations related to the various use of lagged and advanced versions of exposure and outcome variables throughout the thesis. When BHPS data were initially acquired in 2008, only waves 1-17 were available. Wave 18 became available in June 2010, after analysis had been completed for chapters 3 and 4 of this thesis, but prior to the completion of analyses for chapters 5 and 6. Chapter 3 contains data from waves 1-17; Chapter 4 is based on data from waves 2-17; Chapter 5 contains data from waves 2-18; and Chapter 6 uses data from waves 2-

17. At the root of all final datasets used throughout the thesis however, was the creation of cross-sectional datasets for each wave, containing all of the variables of interest, and variables necessary for the derivation of further variables. Sample size diagrams detailing the initial sample size for the raw BHPS data and cuts made for the purposes of this PhD project are detailed Appendix 3.1. The varying original sample sizes for the raw versions of the BHPS waves are a result of both the addition of booster samples, and natural attrition. When the cross-sectional files had been created for each wave, these were appended to create a longitudinal dataset in long format. This process is detailed in Figure 3.1 which shows that an initial sample size of 128,872 observations (person-years) was achieved when waves 1-17 were appended, which increased to 135,469 with the addition of wave 18 in June 2010. These however were not the samples used in analyses. In order to ensure complete data for all of the variables of interest, these samples were further tailored. The sample used in chapters 3 and 4 was derived as described in Figure 3.2.

3.3 Variables and descriptive analysis

3.3.1 Performing descriptive analysis on longitudinal data

Simple descriptive tabulations and summaries cannot be used for panel data, since observations are nested within individuals over time and are not independent of one another. Description of longitudinal data requires the use of either repeated cross sections or methods specifically designed to describe panel data. Using longitudinal data as repeated cross sections loses the information about change within individuals over time whereas the methods outlined below exploit this valuable information. For this study, the *xt* suite of commands was used in Stata versions 10 and 11 (StataCorp, 2007; StataCorp, 2009). Initially, the data were *'xtset'* (wherein the time and panel identifiers are specified and the data are declared to be panel data). The *'xtsum'* (summarise panel data) command was used to describe numerical variables and the *'xttab'* (tabulation for panel data) command was used to describe categorical and binary variables. These descriptive *xt* commands decompose the descriptive statistics into 'overall', 'between' and 'within' categories. The overall category describes the data in terms of person-years, i.e. the total number of observations in the data, regardless of how they are clustered within individuals. These are the statistics which would be calculated if one was to use simple summarise and tabulate commands in Stata, which are not designed for use with panel data. The 'between' category describes how different individuals vary from one another, whilst the 'within' category describes how individuals change over time.

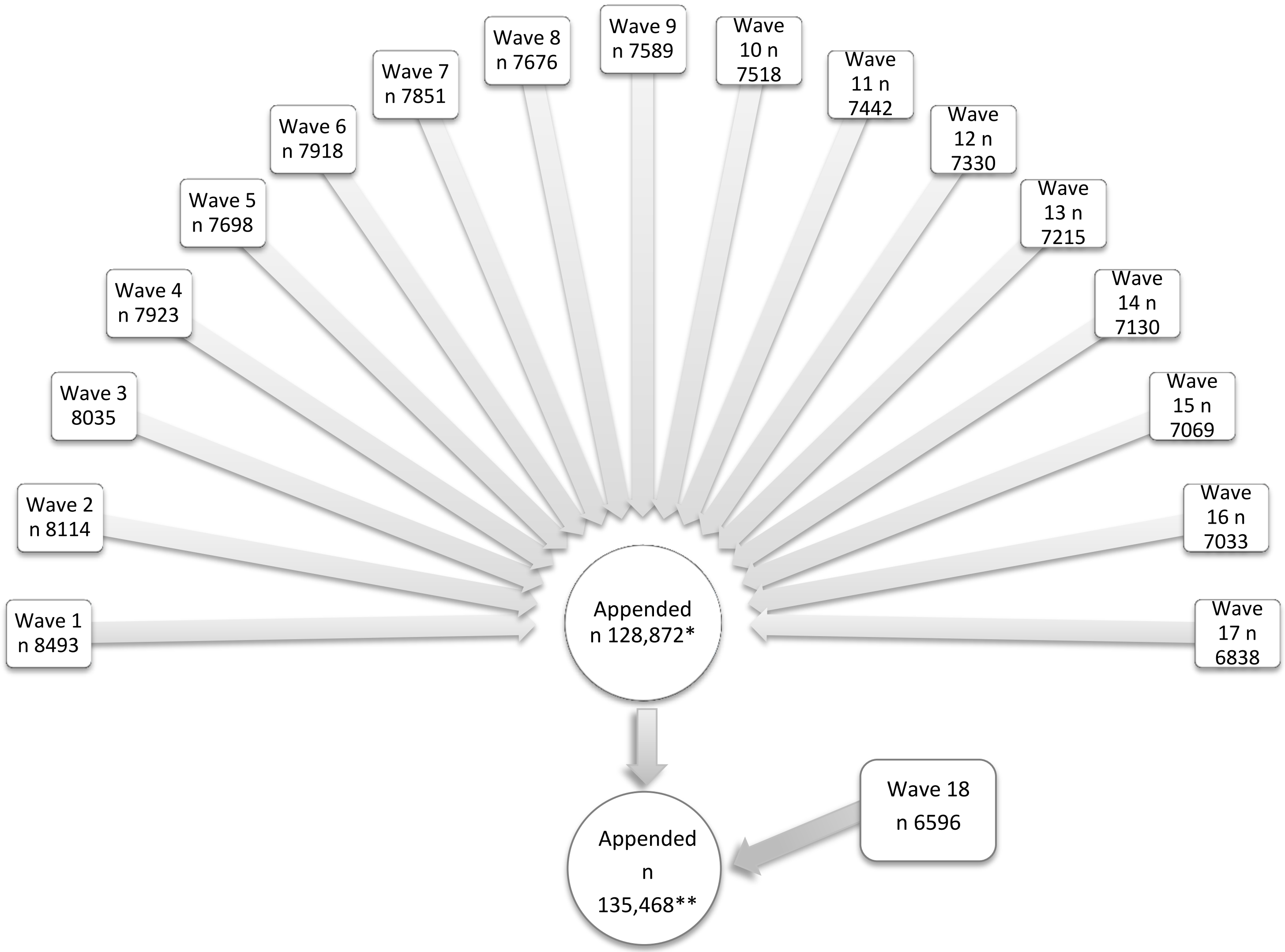

Figure 3.1 Flowchart showing derived sample size for each wave, combined to create a *longitudinal dataset from which the sample used in chapters 3 and 4 was derived, and to which wave 18 was added, providing the **longitudinal dataset from which the sample used in chapters 5 and 6 was derived. Derivation of cross-sectional samples is detailed in Appendix 3.

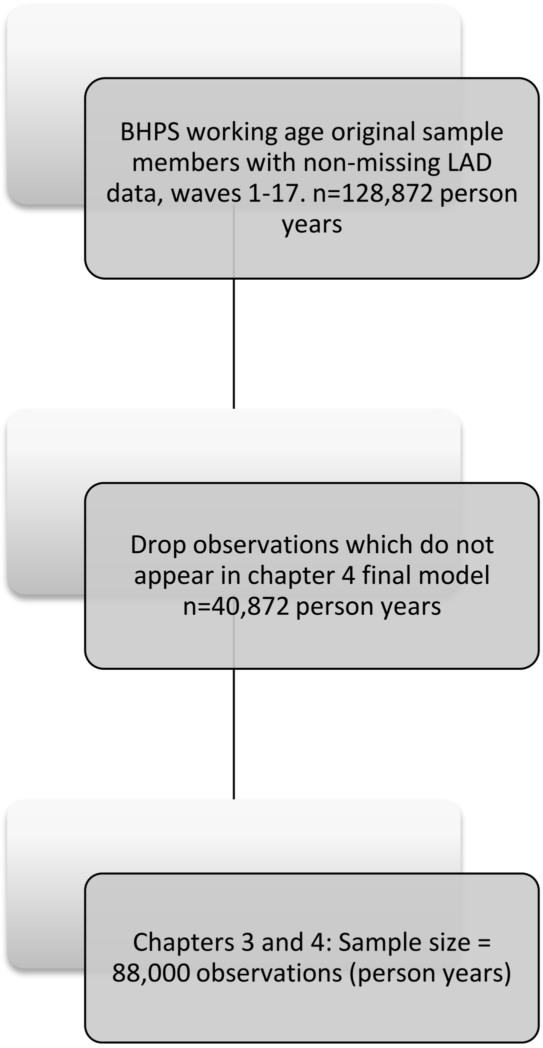

Figure 3.2 Flowchart to show how the longitudinal sample used in chapters 3 and 4 was derived from the initial longitudinal dataset

The *xtsum* command displays the total number of observation (N), the total number of separate respondents who contributed the data over time (n), and the average period of time over which an individual contributed data (T-bar). The command also calculates the following descriptive statistics. Firstly, the overall mean for the variable across all measurements on all respondents. Secondly, the standard deviation, split into three components: *overall*, across all measurements within all individuals; b*etween* **–** variation in the variable between different individuals, and; *within* **–** variation within one individual over time. The difference between the 'between' and 'within' standard deviation values describes the extent to which the variable varies over time. If the variable is time invariant (such as gender in this dataset), its 'within' standard deviation is 0. Thirdly, the range is calculated. Again, this is split into overall, between individual and within individual components. The minimum value for the 'within' category will commonly be a negative number. This does not mean that some measurements were negative (since this would often be impossible, depending on the scale of the variable). It means that some individuals deviated below their personal average for some of their measurements. Similarly, the maximum score for the 'within' category will commonly be greater than the maximum value for the variable (meaning that it would be impossible for someone to have varied this much from their average, even if this average was 0). The overall mean for the variable must be subtracted from this figure for interpretation, making if fall within the plausible range. The *xttab* command displays the total number of individuals who contributed data over time (n), and then tabulates the variable as described in Table 3.1 .

Table 3.1 The general form of the output provided by the 'xttab' Stata command, for longitudinal descriptive analysis

	Overall (person-years)		Between individuals		Within individuals over time
	Freq.	Percent	Freq.	Percent	Percent
0	Total number of '0' responses	'0' responses as a proportion of total obs	Number of individuals who have *ever* responded '0'.	Proportion of n individuals who have *ever* responded '0'.	Conditional on an individual *ever* responding '0', the proportion of his/her other obs that are also '0'
1	Total number of '1' responses	'1' responses as a proportion of total obs	Number of individuals who have *ever* responded '1'.	Proportion of n individuals who have *ever* responded '1'.	Conditional on an individual *ever* responding '1', the proportion of his/her other obs that are also '1'
Total	N (total number of observations)	100	≥ n	≥ 100	Normalized between-weighted average of the 'within' percents (summarises the stability of the variable)

The higher the total for the within column is, the more stable measurements within individuals are over time. A time-invariant variable has a tabulation with 'within' percentages of 100. Descriptive analysis presented in this chapter was undertaken using methods suitable for the panel nature of the data. The total number of observations (N) for all variables was 88,000 (from waves 2-17 of the BHPS). These observations were collected over 11,452 individuals (n) who each contributed an average of 7.68 years to the longitudinal study. One thousand and thirty three individuals (9 percent) were present at all of the 16 waves used.

3.3.2 Outcome variables

3.3.2.1 The General Health Questionnaire (GHQ)

Developed by Goldberg as a screening tool for current depression/general non-psychotic psychiatric disorders (Goldberg, 1972, 1978), the GHQ measures the domains of depression, anxiety, somatic symptoms and social withdrawal (Jackson, 2007). The GHQ was originally developed as a 60-item instrument, but a range of shorter versions are available, using 30, 28 or 12 items. The questionnaire asks the respondent to assess how their health has been over the last few weeks, and to choose the most appropriate response for each of the questions. In the GHQ-12, six of the questions are positively phrased (e.g. *'Have you recently been able to concentrate on whatever you're doing?'*) and six are negatively phrased (e.g. *'Have you recently lost much sleep over worry?'*). Each item has four possible responses, typically *'not at all'*, *'no more than usual'*, *'rather more than usual' and 'much more than usual'*. These are coded 0-3 for the negatively phrased questions and reverse-coded for the positively phrased questions, so that '0' always represents the response least indicative of psychological distress. The full questionnaire can be found in Appendix 3.2. The most commonly used scoring approaches are the Likert-scaled method and the binary coding method. Using the former, total scores between 0 and 36 are possible for the GHQ-12, with higher scores indicating greater levels of psychological distress. In the binary scoring method, the two least symptomatic answers are scored 0 and the two most symptomatic answers are assigned a value of 1, giving a total score of between 0 and 12 for the GHQ-12. This is often used to create a binary caseness variable, typically using a cut-off point of three or more to indicate risk of psychiatric caseness. However, the GHQ is not designed to be a diagnostic tool. 'Psychiatric caseness' in this context indicates that if the respondent were to present to a clinician, it is likely s/he would receive psychiatric attention (Goodchild and Duncan-Jones, 1985). GHQ-12 was used as the outcome measure for this PhD project, as this is available in every wave of the BHPS. Chapters 4-6 utilised the Likert-scaled continuous version as the outcome variable in linear regression models. Chapter 4 also required the use a dichotomised caseness version of the binary coded scale, in logistic regression models.

3.3.2.2 GHQ-12 score

Table 3.2 describes the Likert-scaled continuous version of the GHQ-12 outcome, used as the outcome of interest in chapters 4-6. The overall and within statistics are calculated over 88,000 person-years of data. The between is calculated over 11,452 persons, and the average number of years a person was observed in the hours data is 7.68. Overall GHQ-12 scores varied between 0 and 36 (the full range of possible scores for the variable). Average GHQ-12 scores for each individual also varied between 0 and 36, as one would expect. GHQ-12 scores 'within' individuals over time varied between -10.77 and 39.10. When interpreting the 'within' maximum value, the global average GHQ-12 score (11.10) must be subtracted. This means that the maximum amount by which any individual deviated from their average score was 28 units. The 'between' and 'within' standard deviation values are both close to 4. This means that the variation in GHQ-12 scores across individuals was similar to that observed within one individual over time. Variation between individuals (4.11) was only slightly higher than variation within an individual over time (3.99).

Table 3.2 Longitudinal summary statistics for the Likert-scaled GHQ-12 score continuous outcome variable

	Mean	**Std. Dev.**	**Min**	**Max**	**Observations**
Overall	11.10	5.41	0	36	N = 88000
Between individuals		4.11	0	36	n = 11452
Within individuals		3.99	-10.77	39.1	T-bar = 7.68

Figure 3.3 shows the individual GHQ-12 score trajectories for a random sample of 12 individuals with varying degrees of data completeness. Most of the individuals had somewhat volatile trajectories. For example the individual in the first graph (personal ID 13486497) experienced GHQ-12 scores greater than 20 in three waves, and as low as 5 and 0 in other waves.

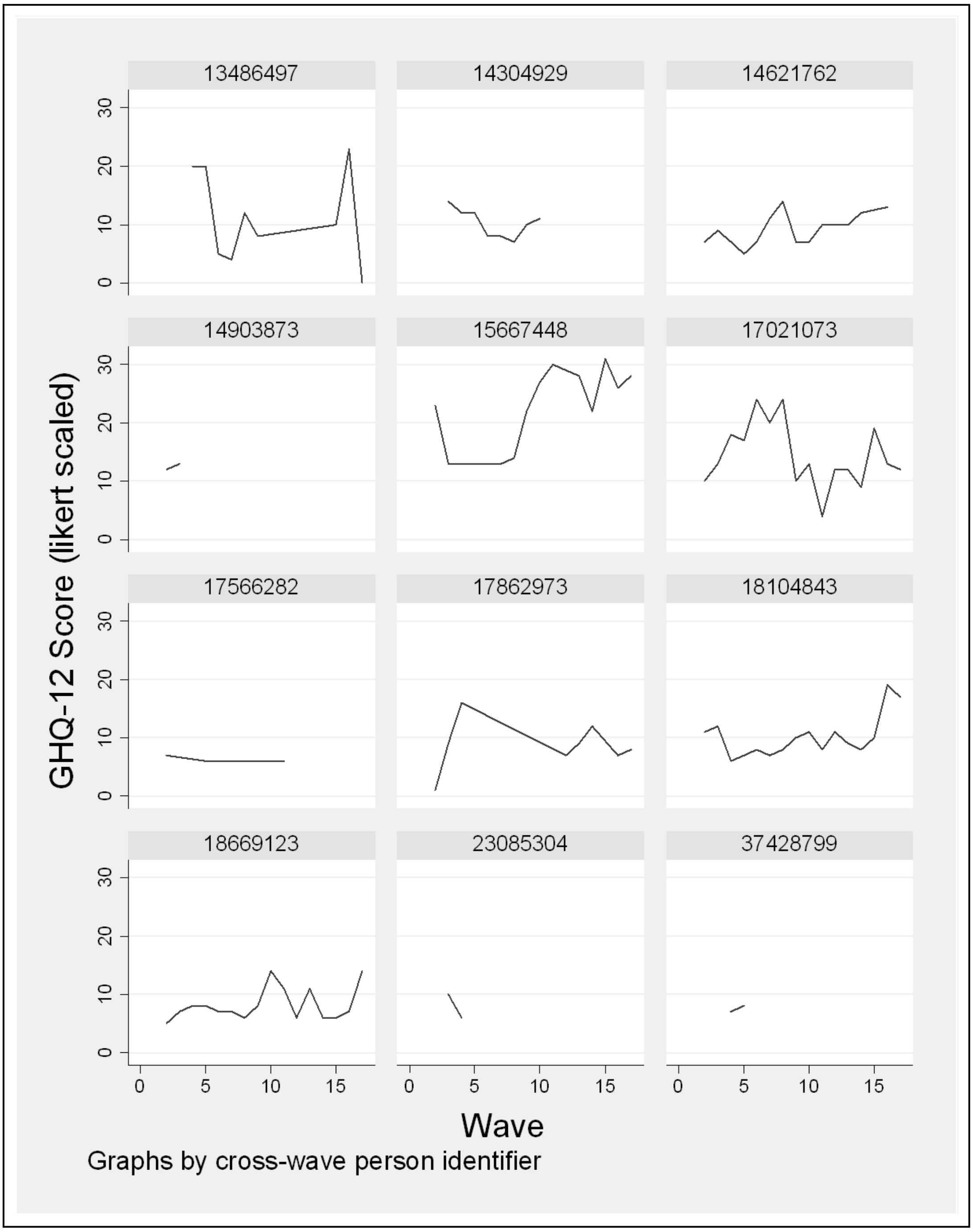

Figure 3.3 Individual GHQ-12 score trajectories for a random sample of 12 individuals from the sample

3.3.2.3 GHQ-12 caseness

Table 3.3 shows the prevalence of each score by wave for the binary scaled continuous version of the GHQ-12. This continuous version of the outcome was used to derive the binary caseness variable. A cut-off point of three or more was used to indicate caseness.

Table 3.3 Distribution of GHQ-12 scores through the sample, based on binary-scaled continuous GHQ-12 outcome variable

Wave	GHQ-12 Score	0	1	2	3	4	5	6	7	8	9	10	11	12	Total
2	**Freq.**	2,938	839	497	341	290	215	197	139	105	73	76	64	52	5,826
	Percent	50.43	14.40	8.53	5.85	4.98	3.69	3.38	2.39	1.80	1.25	1.30	1.10	0.89	100
3	**Freq.**	2,829	839	491	340	260	208	142	125	116	83	73	48	70	5,624
	Percent	50.3	14.92	8.73	6.05	4.62	3.70	2.52	2.22	2.06	1.48	1.30	0.85	1.24	100
4	**Freq.**	2,836	855	525	312	243	203	159	144	103	97	73	69	74	5,693
	Percent	49.82	15.02	9.22	5.48	4.27	3.57	2.79	2.53	1.81	1.70	1.28	1.21	1.30	100
5	**Freq.**	2,822	818	495	335	242	189	146	123	114	86	94	74	85	5,623
	Percent	50.19	14.55	8.80	5.96	4.30	3.36	2.60	2.19	2.03	1.53	1.67	1.32	1.51	100
6	**Freq.**	2,940	797	471	374	264	199	176	123	111	100	93	77	88	5,813
	Percent	50.58	13.71	8.10	6.43	4.54	3.42	3.03	2.12	1.91	1.72	1.60	1.32	1.51	100
7	**Freq.**	3,021	873	488	338	231	213	165	141	111	100	77	72	111	5,941
	Percent	50.85	14.69	8.21	5.69	3.89	3.59	2.78	2.37	1.87	1.68	1.30	1.21	1.87	100
8	**Freq.**	3,077	822	463	347	236	191	147	126	113	96	92	76	95	5,881
	Percent	52.32	13.98	7.87	5.90	4.01	3.25	2.50	2.14	1.92	1.63	1.56	1.29	1.62	100
9	**Freq.**	3,235	780	410	288	205	172	158	124	91	92	78	74	96	5,803
	Percent	55.75	13.44	7.07	4.96	3.53	2.96	2.72	2.14	1.57	1.59	1.34	1.28	1.65	100
10	**Freq.**	2,982	757	481	307	243	192	149	125	105	85	95	80	114	5,715
	Percent	52.18	13.25	8.42	5.37	4.25	3.36	2.61	2.19	1.84	1.49	1.66	1.40	1.99	100
11	**Freq.**	2,900	762	450	310	243	179	157	118	103	88	73	85	91	5,559
	Percent	52.17	13.71	8.09	5.58	4.37	3.22	2.82	2.12	1.85	1.58	1.31	1.53	1.64	100
12	**Freq.**	2,871	736	417	278	207	159	152	129	108	86	78	76	95	5,392
	Percent	53.25	13.65	7.73	5.16	3.84	2.95	2.82	2.39	2.00	1.59	1.45	1.41	1.76	100
13	**Freq.**	2,956	636	408	264	172	187	138	113	101	84	62	64	88	5,273
	Percent	56.06	12.06	7.74	5.01	3.26	3.55	2.62	2.14	1.92	1.59	1.18	1.21	1.67	100
14	**Freq.**	2,843	661	381	232	170	143	130	107	86	74	81	65	85	5,058
	Percent	56.21	13.07	7.53	4.59	3.36	2.83	2.57	2.12	1.70	1.46	1.60	1.29	1.68	100
15	**Freq.**	2,705	683	376	281	210	165	126	109	117	82	72	71	89	5,086
	Percent	53.19	13.43	7.39	5.52	4.13	3.24	2.48	2.14	2.30	1.61	1.42	1.40	1.75	100
16	**Freq.**	2,604	656	406	260	204	175	114	104	90	74	74	70	95	4,926
	Percent	52.86	13.32	8.24	5.28	4.14	3.55	2.31	2.11	1.83	1.50	1.50	1.42	1.93	100
17	**Freq.**	2,602	626	360	264	170	156	118	97	91	67	79	72	85	4,787
	Percent	54.36	13.08	7.52	5.51	3.55	3.26	2.47	2.03	1.90	1.40	1.65	1.50	1.78	100
	Total	46,161	12,140	7,119	4,871	3,590	2,946	2,374	1,947	1,665	1,367	1,270	1,137	1,413	88,000
	Percent	52.46	13.80	8.09	5.54	4.08	3.35	2.70	2.21	1.89	1.55	1.44	1.29	1.61	100

Table 3.4 describes the distribution of the GHQ-12 caseness binary outcome variable across the dataset, used as an outcome of interest in chapter 4. Twenty-two thousand, five hundred and eighty of the total 88,000 observations were cases (around a quarter of the total). Seven thousand and ten respondents (61 percent of the total number of respondents, n) had *ever* been a GHQ-12 case at any wave during their participation in the survey. This column adds up to more than 11,452 and greater than 100 percent because many respondents contribute to being a case and a non-case in different waves of the study. The 'within' column describes the fraction of time an individual has been a GHQ-12 case or not. Conditional on an individual having *ever* been a case, 43 percent of their other GHQ-12 caseness responses in other waves were also likely to be 'case'.

Table 3.4 Longitudinal descriptive analysis of GHQ-12 caseness variable

GHQ-12 Caseness	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Not Case	65420	74.34	10610	92.65	79.35
Case	22580	25.66	7010	61.21	43.27
Total	88000	100	17620	153.86	64.99

3.3.3 Key Exposure Variable: Labour market status

Labour market status was used as the key exposure variable of interest in the analyses presented in chapters 4-6. The 10-category 'current economic activity' (*wJBSTAT*) BHPS variable was used as the basis for the final five-category labour market status variable used throughout. It was split into four categories: employed; unemployed; other inactive; and permanently sick. The employed group was initially formed of the 'employed', 'self-employed' and 'maternity leave' groups from the original variable. It was decided that those on maternity leave were experiencing a temporary break from the labour market and therefore they were classified as employed rather than 'other inactive'. Two further BHPS variables were also used to create the 'employed' category: *'worked in the past week'*; and *'didn't work in the past week but has a job'*. Those who did not report being employed but nonetheless had undertaken paid work in the past week were classified as 'employed'. Those who did not report being employed but indicated that they had a job despite not working in the past week were also classified as employed. There were a small number of people in each wave who were 'waiting for a job'. Some of these had reported being 'employed' but others had not. It was decided that these individuals would be classed as 'employed' for the purposes of the study, as the literature on the psychological effects of joblessness emphasises the desolation and loss of traction that an uncertain future brings. This would not be as acute for those who are currently jobless, but who have secured employment to begin in the future. The 'employed' category derived from these three variables was then split, according to whether the respondent had reported feeling satisfaction with their level of job security or not. The 'job security' question in the 'job satisfaction' series was used. This variable has a 1-7 scale, where 1 represents *'not satisfied at all'* with job security and 7 means *'completely satisfied'*. This variable was dichotomised at the mid-point and used to split the employed individuals into 'securely employed' and 'insecurely employed' categories. Those cases which had missing data for the job security variable were dropped as part of the sample definition outlined in Figure 3.2. The unemployed and permanently sick categories from the original 'current economic activity' variable were used in the final variable. The 5 remaining 'current economic activity' categories were collapsed into a single 'other inactive' category, to describe those who were economically inactive but not permanently sick. This category comprised the following groups: the retired, full-time students, those engaged in home and family care, those in government training schemes and 'other'. For the regression models presented in chapters 4-6, the securely employed category was omitted as the referent category, since this represents the expected optimal category for psychological wellbeing.

Table 3.5 describes the distribution of the derived labour market status variable across the sample. Sixty-seven percent of the total 88,000 responses over 16 years were securely employed, with a further 10 percent insecurely employed. Employment was the most common labour market status across the dataset. Eighty-two percent of the 11,452 participants in the study had been securely employed in at least one wave. Secure employment was the most stable category: for those who had ever reported being securely employed, 77 percent of their other responses were also 'securely employed'. Insecure employment affected 34 percent of the participants in at least one wave, but this was a less stable category, with only 27 percent of their other responses also being 'insecurely employed'. Just 3130 responses out of 88,000 reported unemployment, with 15.7 percent of participants ever having reported it in at least one wave. As might be expected, unemployment was not a particularly stable status. For those who reported unemployment in at least one wave, 29.9 percent of their other labour market status observations were also unemployment. This was a lower level of stability than all of the other categories besides insecure employment, which was at a similar level. Other inactivity and permanent sickness were more stable statuses than unemployment or insecure employment, but less stable than secure employment.

Table 3.5 Longitudinal descriptive analysis for derived key exposure variable: Labour Market Status

Labour market status (n=11452)	**Overall**		**Between**		**Within**
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Securely Employed	58915	66.95	9419	82.25	77.20
Insecurely Employed	8900	10.11	3921	34.24	27.45
Unemployed	3130	3.56	1792	15.65	29.87
Other Inactive	13778	15.66	4212	36.78	50.91
Permanently Sick	3277	3.72	832	7.27	51.04
Total	88000	100	20176	176.18	56.76

'Other' inactivity was the second most prevalent status (15.7 percent of the total number of observations), and 36.8 percent of respondents had reported being other inactive in at least one wave. For these individuals, around half of their other labour market status responses in other waves were also 'other inactive'. Permanent sickness accounted for just 3.7 percent of the total observations and just 832 individuals reported being out of the labour force due to sickness in at least one wave. For these respondents, around half of their other labour market status responses were also 'permanently sick'. The total for the within-individuals column is 56.8 percent, showing that there was more churning within this variable than there was in the GHQ-12 caseness variable, for example. Most of the stability which did exist in this variable was driven by the majority securely employed group, who experienced high levels of stability compared to the other categories, especially the unemployed and insecurely employed.

3.3.4 Confounders

The following variables were conceptualised as factors which may confound the association between labour market status and psychological distress. This is explored in chapter 4. A confounding factor is associated with both exposure and outcome and yet is not on the hypothesised causal pathway (Kirkwood and Sterne, 2003). Failure to adequately control for the effects of such variables can result in confounding bias.

3.3.4.1 Age

Age was isolated as a covariate of interest, and used in chapters 4-5 as a continuous variable alongside a square term for age, centred at their means. The square term was added because age does not have a linear relationship with the GHQ-12 outcome. Age has been found to be a major confounding factor in a number of studies on the relationship between unemployment and mental health (Rowley and Feather, 1987; Warr and Jackson, 1984). This is explored further in section 4.1 and in chapter 6. The mean age across all observations was 39, with the minimum and maximum ages 16 and 65, reflecting the working-age inclusion criteria for the sample.

3.3.4.2 Gender

The BHPS 'sex' variable was used in the dataset. This was conceptualised as gender rather than sex, since it is hypothesised that the socially constructed gender norms and roles associated with masculinity and femininity may affect the relationship between labour market participation and GHQ-12, rather than the biological characteristics of sex. This binary variable was coded as follows: Men = 0; Women = 1. Since gender was a time-invariant variable in this dataset, the 'within' percentages are 100 and the total for the 'between' column is 100 percent (i.e. no individual had changed their gender throughout the study). As shown in Table 3.6, forty-nine percent of the individuals in the sample were male and 51 percent were female. These figures differ slightly from the proportions in the 'overall' column, since men may have been slightly more likely to drop out of the study than women.

Table 3.6 Gender distribution within the study sample

	Overall		Between		Within
Gender	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
Men	42773	48.61	5633	49.19	100
Women	45227	51.39	5819	50.81	100
Total	88000	100	11452	100	100

3.3.4.3 Educational attainment

Clark and Oswald (1994) reported that educational level is associated with employment status and security of employment, and highly educated individuals show more distress than others. It can therefore be conceptualised as a possible confounder of the relationship between labour market status and minor psychiatric morbidity. The 'highest academic qualification' BHPS variable was used to measure educational attainment. The original variable had 7 categories (higher degree, first degree, HND/NHC/Teaching qualification, A-level, O-level, CSE, none of these). The top three categories were collapsed into one 'higher education' category and the 'O-level' and 'CSE' categories were combined to create a 4-category variable (Table 3.7). For the regression models, the 'higher education' category was omitted as the referent category, as this was assumed to be the most advantaged category.

Table 3.7 Highest academic qualification variable

Category	Description
1	Higher Education (referent)
2	A-Levels
3	O-Levels/CSEs
4	None of the above

This variable was very stable compared to the labour market status and GHQ-12 caseness variables. This was not surprising because most people undertook educational qualifications as teenagers and young adults, and then generally ceased acquiring qualifications as they aged. As shown in Table 3.8, 24.5 percent of individuals reported having no qualifications in at least one wave of the survey. For this group, 97 percent of their other responses were also 'none of the above'. This was the most stable group and shows that those with no qualifications were least likely to attain further qualifications during their participation in the BHPS. It also reflects the fact that those with no qualifications were likely to be older (with an overall mean age of 49 compared to the general overall mean age of 39).

Table 3.8 Longitudinal descriptive analysis of educational attainment

	Overall		Between		Within
Highest academic qualification	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
Higher degree or teaching qualification	18602	21.14	2490	21.74	86.78
A level	19337	21.97	3124	27.28	82.77
O level/GCSE	31286	35.55	4658	40.67	85.52
None of the above	18775	21.34	2810	24.54	96.87
Total	88000	100	13082	114.23	87.54

3.3.4.4 Physical health status

The notion that physical health condition could confound the relationship between employment status and mental health is repeatedly discussed in the literature (Winefield, 1995). The BHPS contains two general self-rated health variables which are available at the majority of waves: 'health limits daily activities' *(wHLLT)* which is present in all but two waves; and 'health status over the last 12 months' *(wHLSTAT)* which is present in all but one wave. The use of either variable was problematic because of the missing data and because neither question separates physical from mental health. In order to avoid over-adjustment, it was necessary to use a variable which isolated overall physical health condition. The BHPS contains a series of binary 'health problem' variables which are available at all waves. The respondent is asked if they have any health problems related to a series of 12 categories (Figure 3.4). The two mental health categories (depression/anxiety and substance abuse) were excluded and a binary variable was derived, to indicate whether the respondent had 'no physical health problem' or 'one or more physical health problems' (from the list shown in Figure 3.4.

"Do you have any of the health problems or disabilities listed?"

- Problems or disability connected with: arms, legs, hands, feet, back, or neck (including arthritis and rheumatism)
- Difficulty in seeing (other than needing glasses to read normal size print)
- Difficulty in hearing
- Skin conditions/allergies
- Chest/breathing problems, asthma, bronchitis
- Heart/blood pressure or blood circulation problems
- Stomach/liver/kidneys
- Diabetes
- Epilepsy
- Migraine or frequent headaches
- Other

Figure 3.4 Physical health conditions included in the derivation of a binary variable to summarise physical health status

Table 3.9 shows the high prevalence of suffering from one or more physical health problems, across the sample. Fifty-one percent of all responses were cases and 73.5 percent of respondents had suffered from a physical health problem in at least one wave of the study. Of these individuals, 68 percent of their responses at other waves also indicated that they suffered from a physical health problem.

Table 3.9 Longitudinal descriptive analysis of derived binary physical health status variable

Presence of a physical health problem	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
No physical health problems	42698	48.52	8187	71.49	69.82
Suffers from ≥1 physical health problem	45302	51.48	8419	73.52	68.13
Total	88000	100	16606	145.01	68.96

3.3.4.5 Spousal factors

Several studies have found that marital status significantly affects individuals' psychological wellbeing and acts as a measure of social support (Bortner and Hultsch, 1976; Lowenthal *et al.*, 1975; Troll, 1982). Marital status is also significantly associated with labour market status. Therefore a 3-category marital status variable (Table 3.10) was used as a covariate in this PhD research, based on collapsing categories in the original BHPS marital status variable. In addition, two further spousal variables were derived: spouse's GHQ-12 caseness; and a variable for whether the spouse was jobless or working. The 'spouse GHQ-12 caseness' variable consisted of the referent category ('spouse not a GHQ-12 case') and two further categories: 'spouse is a GHQ-12 case' and 'no spouse' (Table 3.11). Similarly, the spousal joblessness variable contained the following three categories: 'spouse employed' (referent category); 'spouse jobless'; and 'no spouse' (Table 3.12). These two further spouse-related variables were included because the supposed positive effects of the presence of a spouse on psychological wellbeing may not hold if the spouse is exposed to joblessness, or is an MPM case.

Table 3.10 Marital status variable

Category	Description
0	Married or cohabiting
1	Divorced, widowed or separated
2	Never married or cohabiting

Table 3.11 Spousal GHQ-12 caseness variable

Category	Description
0	Spouse not a GHQ-12 case
1	Spouse a GHQ-12 case
2	No spouse

Table 3.12 Spousal employment status variable

Category	Description
0	Spouse not employed
1	Spouse employed
2	No spouse

Table 3.13 shows the distribution of marital status across the sample and over time. This variable was relatively stable, with the majority of people staying in the same category for the majority of their time in the study. The most prevalent and stable status was 'married/cohabiting'. This accounted for 69 percent of the total observations for the variable.

Table 3.13 Longitudinal descriptive analysis of marital status

	Overall		Between		Within
Marital status	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
Married/Cohabiting	60483	68.73	8084	70.59	86.96
Widowed/Divorced/Separated	8322	9.46	1670	14.58	63.18
Never Married	19195	21.81	4095	35.76	82.23
Total	88000	100	13849	120.93	82.69

Table 3.14 shows that having an employed spouse was the most prevalent status, and that 61 percent of individuals had given this response at least once. It was also a stable status, with 79 percent of these participants' other responses being the same. Having no spouse was also a stable status, although less prevalent. Thirty-two percent of observations were in this category and around half of all participants reported having no spouse in at least one wave. Twenty-nine percent of individuals reported having a jobless spouse in at least one wave, accounting for 14.4 percent of the total number of observations for the variable. This was the least stable status.

Table 3.14 Longitudinal descriptive analysis of spousal job status

Spousal job status	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Spouse jobless	12647	14.37	3321	29.00	50.70
Spouse employed	47580	54.07	6976	60.92	76.12
No spouse	27773	31.56	5657	49.40	78.80
Total	88000	100	15954	139.31	71.78

Table 3.15 shows that having a spouse who suffered MPM was the least prevalent status, accounting for 17 percent of all observations. Whilst 42.5 percent of respondents reported having a spouse who was a GHQ-12 case in at least one wave, this was a comparatively unstable status, since only 36 percent of their other responses indicated that their spouse was a GHQ-12 case. The majority of respondents had a spouse who was not a GHQ-12 case, since 65 percent had indicated that they fell into this category in at least one wave, and 70 percent of their other responses were the same. The most stable category was those with no spouse.

Table 3.15 Longitudinal descriptive analysis of spousal GHQ-12 caseness

Spousal GHQ-12 caseness	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Spouse not GHQ-12 case	45333	51.51	7477	65.29	69.98
Spouse is GHQ-12 case	14894	16.93	4864	42.47	36.21
No spouse	27773	31.56	5657	49.40	78.80
Total	88000	100	17998	157.16	63.63

3.3.4.6 Labour market status stability indicators

The BHPS contains a series of variables pertaining to the respondent's labour market status over the 12 months preceding the interview. Number of weeks in unemployment and inactivity and number of spells of unemployment and inactivity are four such variables. Owing to extensive coding problems for the 'number of weeks' variables in the BHPS, the two variables relating to spells of joblessness in the past year were used. These were dichotomised to create two variables which indicate whether the respondent had experienced one or more spell of unemployment or inactivity since their last interview (see Table 3.16 and Table 3.17).

Table 3.16 Binary variable indicating one or more unemployment spell in the past year

Category	Description
0	No unemployed spells in 12 months preceding interview
1	1+ unemployed spells in 12 months preceding interview

Table 3.17 Binary variable indicating one or more inactivity spell in the past year

Category	Description
0	No inactive spells in 12 months preceding interview
1	1+ inactive spells in 12 months preceding interview

As shown in Table 3.18, 52 percent of the individuals in the sample had experienced 1 or more spells of inactivity in the 12 months preceding a BHPS interview. Just over half of the other responses for this group also indicated that they had experienced 1 or more spells of inactivity between two BHPS interviews. Eighty-five percent of respondents reported having no spells of inactivity in the 12 months preceding an interview and this group were far more stable, with 83 percent of their other observations for this variable showing the same.

Table 3.18 Longitudinal descriptive analysis of those reporting economic inactivity spells in the past year

Economic Inactivity spells in past year	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
No inactivity	66625	75.71	9780	85.4	83.35
1+ inactive spells	21375	24.29	5949	51.95	55.47
Total	88000	100	15729	137.35	72.81

Table 3.19 shows that unemployment occurred in the 12 months preceding any interview for just 27.5 percent of individuals. This was an unstable category, since only 33.4 percent of their other observations for the variable also indicated one or more spells of unemployment in the 12 months prior to an interview. This variable was very stable, driven by the vast majority of people who had recorded ‘no unemployment spells in the past year’ for the majority of their responses.

Table 3.19 Longitudinal descriptive analysis: those reporting unemployment spells in the past year

Unemployment spells in past year	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
No unemployment	81655	92.79	11088	96.82	93.8
1+ spells of unemployment	6345	7.21	3154	27.54	33.35
Total	88000	100	14242	124.36	80.41

3.3.4.7 Region

The government office region (GOR) variable was used to classify which broad geographical area the respondent resided in at the time of interview. For the regression models presented in chapter 4, the coefficients/odds ratios for the regional variable were compared to the grand mean for the whole variable, instead of to an omitted category. This was achieved using the 'xi3' command in Stata, with the 'e.varname' effect coding option specified. This approach was judged to be more intuitive and sensible than comparing the regions to an omitted region. Table 3.20 shows that the region variable was stable, indicating that most individuals did not move between government office regions during their time in the BHPS. The least stable regions were London and the south of England. Scotland was the most stable GOR category, with 96 percent of observations for those who had ever reported dwelling in Scotland, also being Scotland. This is probably due to the vast size of the Scottish GOR, and to Scotland's status as a nation rather than simply an administrative region.

Table 3.20 Distribution of sample by Government Office Region of residence, over time.

Government Office Region	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
London	7879	8.95	1315	11.48	84.43
South East	17371	19.74	2477	21.63	88.68
South West	8014	9.11	1167	10.19	88.68
East of England	3577	4.06	545	4.76	84.75
East Midlands	8059	9.16	1166	10.18	87.98
West Midlands	7481	8.50	1102	9.62	91.23
North West	9574	10.88	1334	11.65	92.20
Yorks & Humber	8357	9.50	1200	10.48	91.25
North East	5590	6.35	753	6.58	92.75
Wales	4631	5.26	653	5.70	91.85
Scotland	7467	8.49	1038	9.06	95.76
Total	88000	100	12750	111.33	89.82

3.3.4.8 Percentage annual GDP Growth

Annual percentage GDP growth figures were obtained from the ONS website to use as a measure of national economic performance. This measure is used to define recession (two successive quarters of GDP contraction) and the business cycle. GDP growth was used as a continuous variable in the models. Over the period spanned by the BHPS, two recessions have occurred (Figure 3.5). The first took place between 1991 and 1992 and the second in 2008.

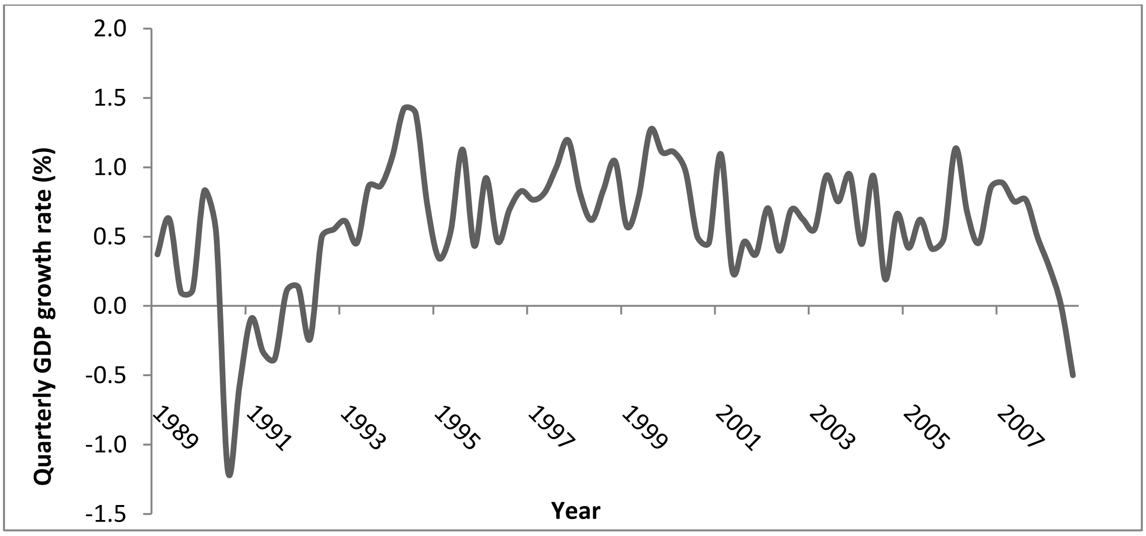

Figure 3.5 Percentage GDP growth rate by quarter. Q1 1989 to Q3 2008. ONS Time Series Data.

Using ONS statistics, each observation was assigned a value corresponding to the annual percentage GDP growth in the year of the wave. The longitudinal summary statistics for this variable are presented in Table 3.21.

Table 3.21 Longitudinal descriptive summary statistics for percentage annual GDP growth

Percentage annual GDP growth

	Mean	Std. Dev.	Min	Max	Observations
overall	2.69	0.91	0.30	4.40	N = 88000
between		0.64	0.30	4.40	n = 11452
within		0.86	0.02	4.81	T-bar = 7.68

3.3.4.9 Social Housing Tenure

Social housing tenure is thought to be a potential confounding factor in the relationship between labour market status and MPM. Social housing tenure is conceptualised as a confounder for the purposes of this study, since it is thought social housing tenure is not necessarily on the causal pathway between joblessness and MPM. It is likely that residing in deprived social housing reduces an individual's chances of finding work, through prejudiced attitudes of potential employers, joblessness becoming socially normed in neighbourhoods of high worklessness (Clark, 2003) and a lack of access to a wide range of jobs resulting from marginalised urban locations. It is also thought that residing in social housing can be a cause of MPM, over and above the effects of joblessness. A question on housing ownership or tenure status is asked at each wave of the BHPS. The original variable consists of 8 categories but for the purposes of this PhD project, was dichotomised into an indicator of whether the respondent lived in social housing or not (Table 3.22). The original categories for 'local authority rented' and 'housing association rented' were combined into a category which indicated social housing. The remaining 6 categories which cover home ownership and private sector renting were collapsed into a single category indicating that the respondent did not live in social housing.

Table 3.22 Binary variable indicating social housing tenure

Category	Description
0	Dwelling is owned outright, owned with mortgage, rented from employer, rented privately unfurnished, rented privately furnished, other rented.
1	Dwelling is rented from local authority or housing association

Table 3.23 shows that housing tenure status was a very stable variable. Fourteen percent of the total observations indicated local authority or housing association tenancy. Two thousand four hundred and forty individuals (21.3 percent) reported ever having resided in LA/HA rented accommodation and 74.4 percent of the other observations for individuals in this category also indicated social housing tenancy. Eighty-nine percent of individuals reported ever having lived in owned or privately rented accommodation, and for this category 94.9 percent of observations across all waves also indicated owned or privately rented housing. In the main, it seems that respondents remained in the same category of housing throughout their participation in the BHPS. However, it was less common for those who had ever reported residing on owned/privately rented accommodation to also have been in social housing at one or more waves of the study than vice versa.

Table 3.23 Longitudinal descriptive analysis for social housing tenure

Housing tenure	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Owned, privately rented	75479	85.77	10148	88.61	94.96
Local Authority/Housing Association Rented	12521	14.23	2440	21.31	74.41
Total	88000	100	12588	109.92	90.98

3.3.5 Mediators

Mediating factors must be considered as distinct from confounders, as they are defined as being associated with both exposure and outcome but are thought to be on the causal pathway (Kirkwood and Sterne, 2003). The addition of hypothesised mediators to a regression model is not with the aim of 'controlling' for their effects, but to investigate the extent to which the relationship between exposure and outcome acts through the mediating factor.

3.3.5.1 Objective financial status indicators

Many studies have included measures of financial strain and financial worry as potential mediators of the relationship between labour market status and MPM, including both objective and subjective measures (Finlay-Jones and Eckhardt, 1984; Kessler *et al.* 1987*;* Payne and Hartley, 1987). Two objective measures of financial status were used: monthly household income; and saving from current income. Monthly income is available at the household level in the BHPS, and takes account not just of the individual's income, but that of other household members. This original variable was equivalised (using the OECD modified scale, Hagenaars *et al.,* 1994) in order to account for the household's size and composition and log-transformed. Descriptive summary statistics are shown in Table 3.24.

Table 3.24 Longitudinal descriptive summary statistics for equivalised monthly household income

	Mean	Std. Dev.	Min	Max	Observations
Overall	1489.51	1089.03	0	45,110.32	N = 88000
Between		860.82	0	15,066.88	n = 11452
Within		726.94	-11881.55	40,776.32	T-bar = 7.68

The second objective financial status variable used was a binary BHPS variable which indicates whether an individual saves from their current income. The question asks "*Do you save any amount of your income for example by putting something away now and then in a bank, building society or Post Office account other than to meet regular bills?*" It explicitly excludes bills but includes savings for holidays and life insurance. As shown in

Table 3.25, 55.4 percent of the total observations for the variable indicated that the respondent did not save from their current income, besides putting money aside for household bills etc. on a monthly basis. Eighty-five percent of individuals indicated that they did not save from their current income in at least one wave, and for these people, 68 percent of their other responses also indicated that they did not save. This variable was relatively unstable, since 72.5 percent of respondents had indicated that they did save from their current income in at least one wave.

Table 3.25 Longitudinal descriptive analysis: saving from current income

	Overall		Between		Within
Saves from current income	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
Does not save from current income	48717	55.36	9734	85.00	68.11
Does save from current income	39283	44.64	8296	72.44	58.13
Total	88000	100	18030	157.44	63.52

3.3.5.2 Subjective financial situation indicators

Financial status is also measured subjectively with three BHPS variables: financial situation; change in financial position in the last year; and financial expectations for year ahead. The current financial situation variable was measured using five ordered categories whilst the other two variables were measured using three categories (Table 3.26). For each of the three variables, the most positive category was omitted as the referent category. As shown in Table 3.27 the majority (67 percent) of responses for subjective assessment of current financial situation across individuals and across time indicate that the respondent was *living comfortably* or *doing alright*. A further quarter of observations were in the *just about getting by* category. Just 5.8 percent of the total observations were *finding it quite difficult* responses, and a further 2.4 percent were *finding it very difficult* responses. This variable showed a great deal of instability, with individuals moving between categories across time. Of the 11,452 people in the sample, over half (56.6 percent) reported *living comfortably* in at least one wave.

Table 3.26 BHPS variables describing subjective assessment of current, past and future financial situation

Current financial situation	
1	Living comfortably
2	Doing alright
3	Just about getting by
4	Finding it quite difficult
5	Finding it very difficult
Current financial situation compared to one year ago	
1	Better off now than one year ago
2	Worse off now than one year ago
3	Same now as one year ago
Expectations for financial situation in 1 years' time, compared to now.	
1	Financial situation in 1 years' time will be better than now
2	Financial situation in 1 years' time will be worse than now
3	Financial situation in 1 years' time will be about the same as now

Of these individuals, 47.9 percent of their other responses were also *living comfortably*. Three-quarters of the respondents reported *doing alright* in at least one wave and similarly, around half of their other responses were also *doing alright*. Sixty-one percent of the sample reported *just about getting by* in at least one wave, but this group were marginally less stable, with 43 percent of their other responses also being *just about getting by* in other waves. The two negative responses were the least prevalent and the least stable. A quarter of respondents reported *finding it quite difficult* in at least one wave, but only around a quarter of their other responses were the same in other waves. Only 10.7 percent of individuals reported *finding it very difficult* in at least one wave and amongst this group, only 26.6 percent of their other responses were also *finding it very difficult*.

Table 3.28 and Table 3.29 show that the categories of subjective assessment of change and expectations of change in financial status were quite unstable. The most prevalent responses for the two variables were the categories which indicated that nothing had changed compared to one year ago and projecting one year ahead. Eighty percent of individuals indicated that their situation was the same as a year ago in at least one wave, and 83.2 percent of individuals expected their situation to be the same in one year's time in at least one wave. These categories were both the most stable of categories in their respective variables. For both categories, the most negative/pessimistic category was both the least prevalent and the least stable.

Table 3.27 Longitudinal descriptive analysis: current financial status

	Overall		**Between**		**Within**
Subjective assessment of current financial situation	**Freq.**	**Percent**	**Freq.**	**Percent**	**Percent**
Living comfortably	25162	28.59	6484	56.62	47.87
Doing alright	33836	38.45	8543	74.6	49.99
Just about getting by	21794	24.77	7005	61.17	42.75
Finding it quite difficult	5082	5.78	2811	24.55	26.57
Finding it very difficult	2126	2.42	1225	10.7	27.4
Total	88000	100	26068	227.63	43.93

Table 3.28 Longitudinal descriptive analysis: current compared to past financial status

Subjective assessment of current financial situation compared to one year ago	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Better off now	28585	32.48	8420	73.52	45.57
Worse off now	21021	23.89	7680	67.06	36.74
About the same	38394	43.63	9154	79.93	52.37
Total	88000	100	25254	220.52	45.35

Table 3.29 Longitudinal descriptive analysis: current compared to predicted future financial situation

Subjective assessment of current financial situation compared to predicted financial situation in 1 years' time	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Better than now	29609	33.65	8291	72.40	50.00
Worse than now	9367	10.64	4711	41.14	28.64
Same as now	49024	55.71	9531	83.23	62.51
Total	88000	100	22533	196.76	50.82

3.3.5.3 Substance abuse

Whilst substance abuse is not widely seen as a mediator of the relationship between labour market status and MPM, it was felt that this could be on the causal pathway between job loss or insecurity and MPM. It is significantly associated with both joblessness and with the MPM outcomes, and it has been shown that negative health behaviours including substance abuse commonly arise from job loss or prolonged joblessness (Bartley *et. al.* 2005). The substance abuse variable from the 'health problems' series of questions described above (section 3.3.4.4) was used. The question asked the respondent whether he/she has any 'alcohol or drug related problems'. This binary variable was coded as follows: 0 = No problems with alcohol or drugs mentioned; 1= problems with alcohol or drugs. Table 3.30 shows that only 386 (0.4 percent) of all observations for this variable were cases. Only 184 respondents (1.6 percent) reported having problems with drugs or alcohol in one or more waves of the study. This was quite an unstable status, as only a third of their other responses also indicated problems with substance abuse. Bias could be inherent in these statistics, since those with substance abuse problems are at high risk of dropping out of the study intermittently or permanently, due to related illness, chaotic lifestyle or mortality.

Table 3.30 Longitudinal descriptive analysis for substance abuse

Problems with alcohol/drugs?	**Overall**		**Between**		**Within**
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
None mentioned	87614	99.56	11436	99.86	99.61
Problems with alcohol/drugs	386	0.44	184	1.61	32.64
Total	88000	100	11620	101.47	98.55

3.4 Summary

The descriptive analysis presented in this chapter confirms that minor psychiatric morbidity is a prevalent condition and a significant public health issue. A quarter of all GHQ-12 observations could be classified as cases of minor psychiatric morbidity, and 61 percent of respondents in the sample had experienced MPM at some point during their involvement with the survey. These analyses also indicate that whilst the majority of individuals remained in secure employment for the majority of waves, less advantaged labour market positions were fairly widespread over time. Job insecurity affected a third of individuals at some point during their time in the study. Reflecting the buoyant macroeconomic conditions which characterised much of the era from which the observations were taken, unemployment was comparatively rare, accounting for 3.6 percent of all observations and affecting 16 percent of individuals on one or more occasions. Permanent sickness was similarly rare, accounting for 3.7 percent of observations and affecting half as many people as unemployment, over time. To what extent does exclusion from secure employment predict MPM caseness and elevated GHQ-12 scores in the BHPS and what role do social, economic and other factors play in this relationship? These questions are addressed in the following chapter.

3.5 Appendices

Appendix 3.1 Flowcharts showing sample derivation for cross-sectional files for waves 1-18 (Figures A3.1-A3.18).

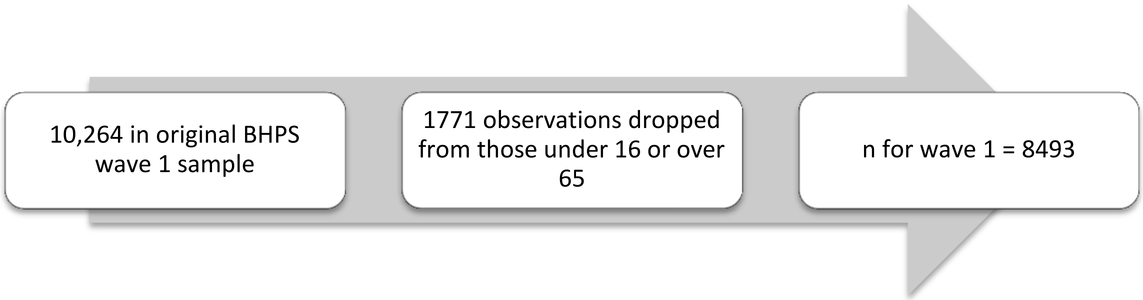

Figure A3.1 Flowchart showing sample derivation for wave 1 cross-sectional file

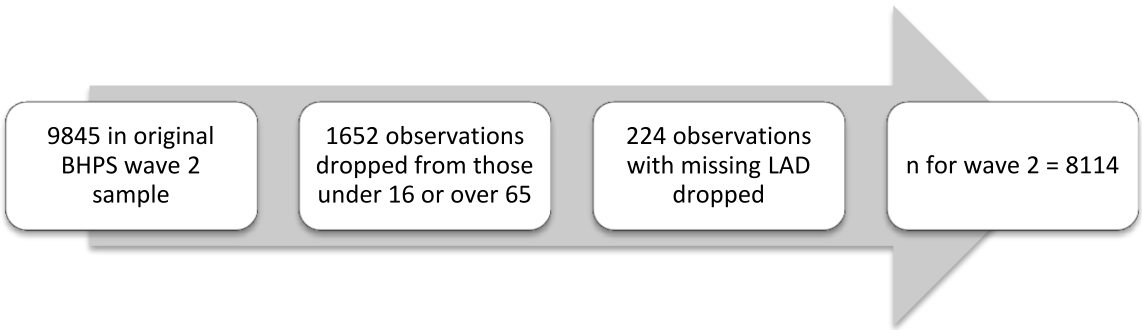

Figure A3.1 Flowchart showing sample derivation for wave 2 cross-sectional file

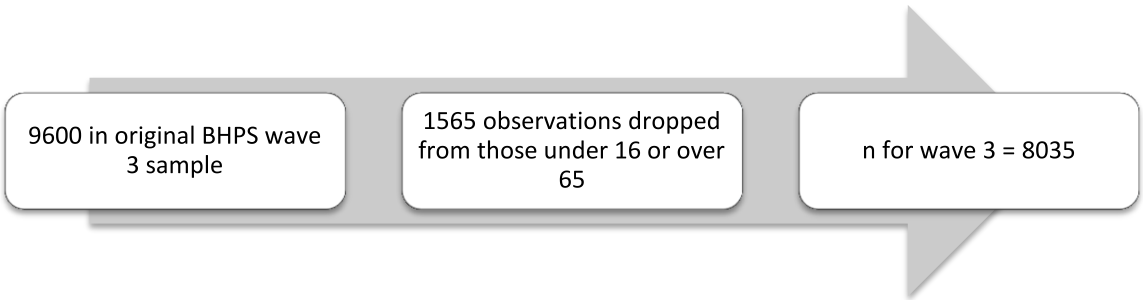

Figure A3.1 Flowchart showing sample derivation for wave 3 cross-sectional file

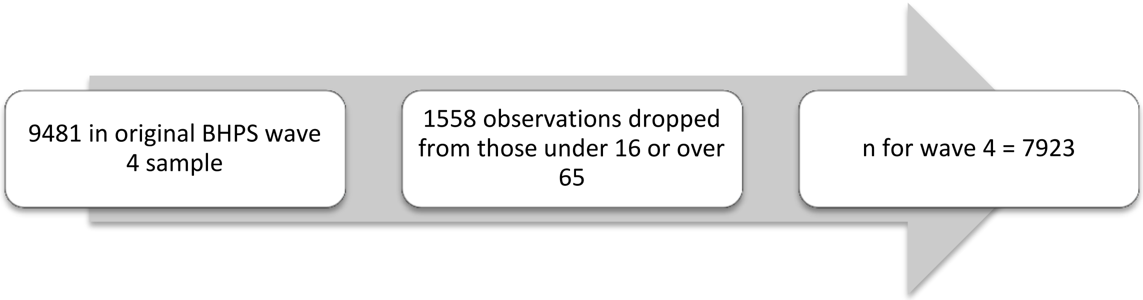

Figure A3.1 Flowchart showing sample derivation for wave 4 cross-sectional file

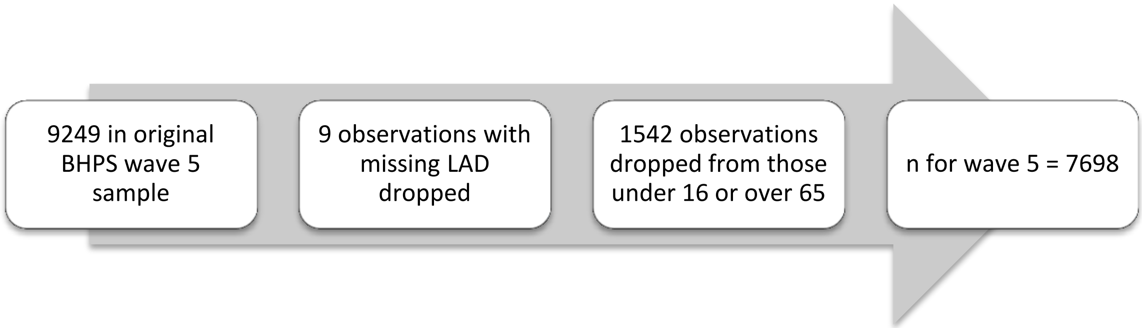

Figure A3.1 Flowchart showing sample derivation for wave 5 cross-sectional file

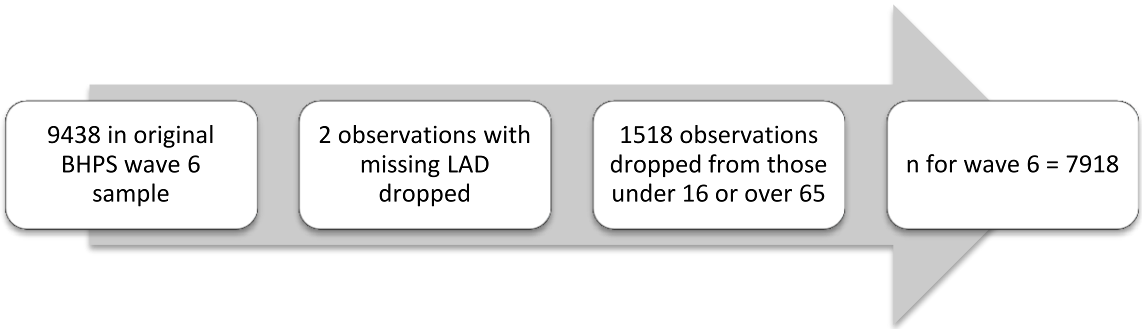

Figure A3.1 Flowchart showing sample derivation for wave 6 cross-sectional file

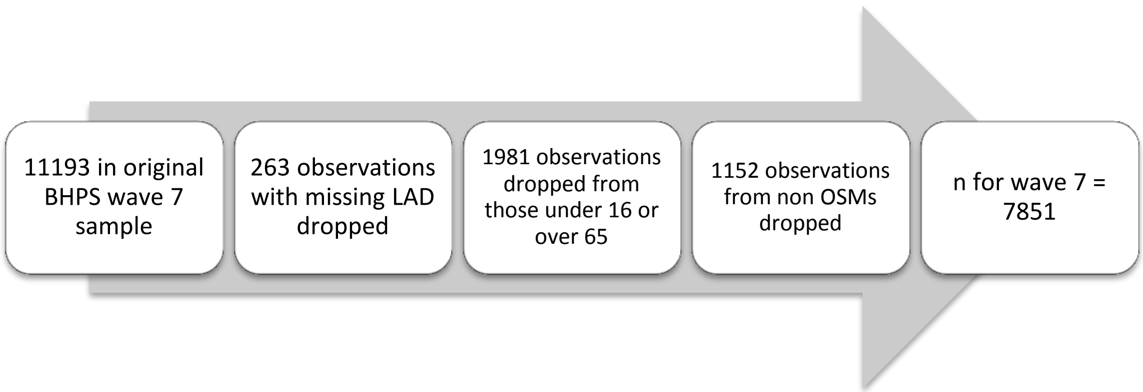

Figure A3.1 Flowchart showing sample derivation for wave 7 cross-sectional file

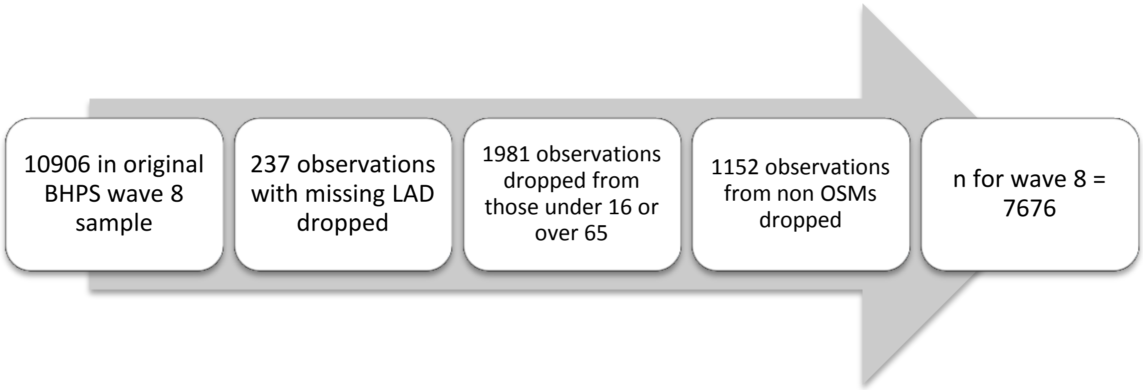

Figure A3.1 Flowchart showing sample derivation for wave 8 cross-sectional file

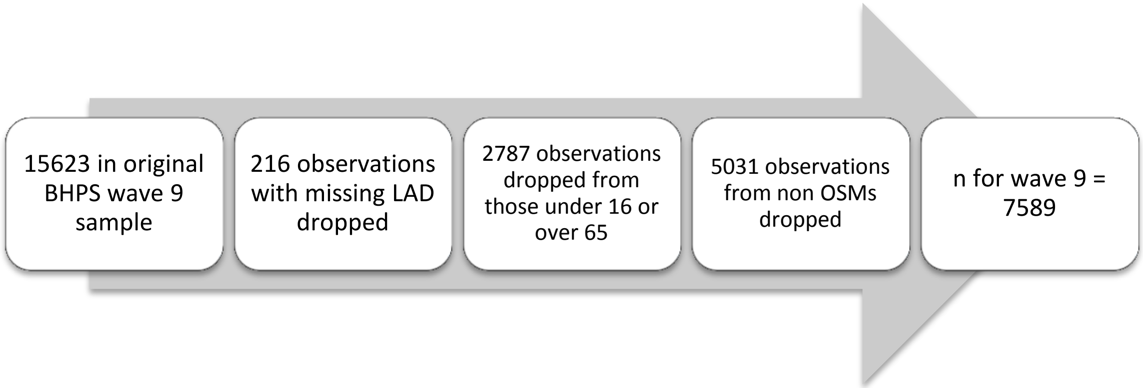

Figure A3.1 Flowchart showing sample derivation for wave 9 cross-sectional file

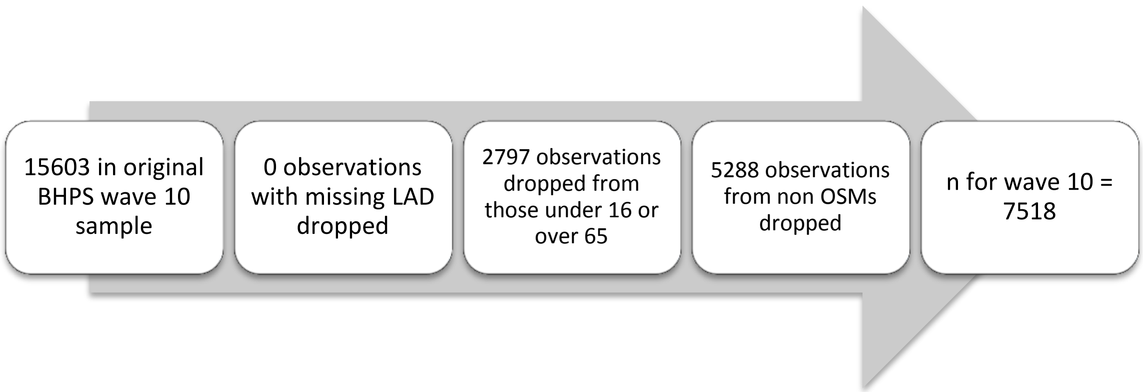

Figure A3.1 Flowchart showing sample derivation for wave 10 cross-sectional file

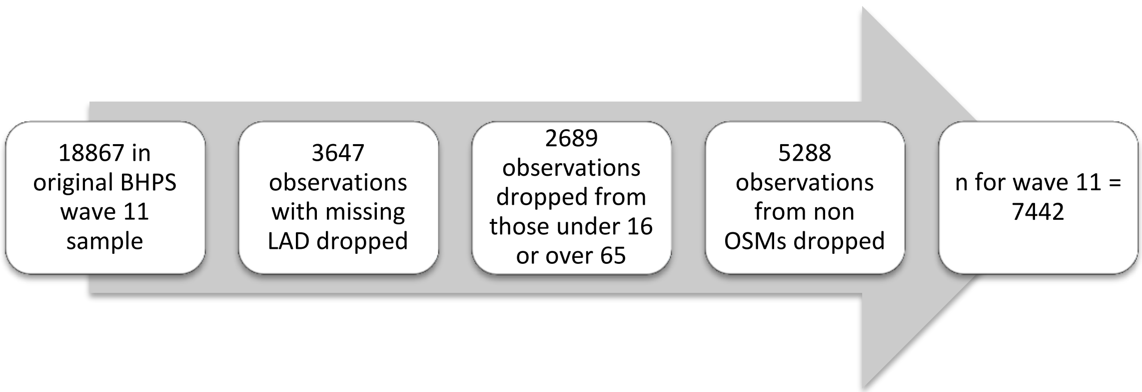

Figure A3.1 Flowchart showing sample derivation for wave 11 cross-sectional file

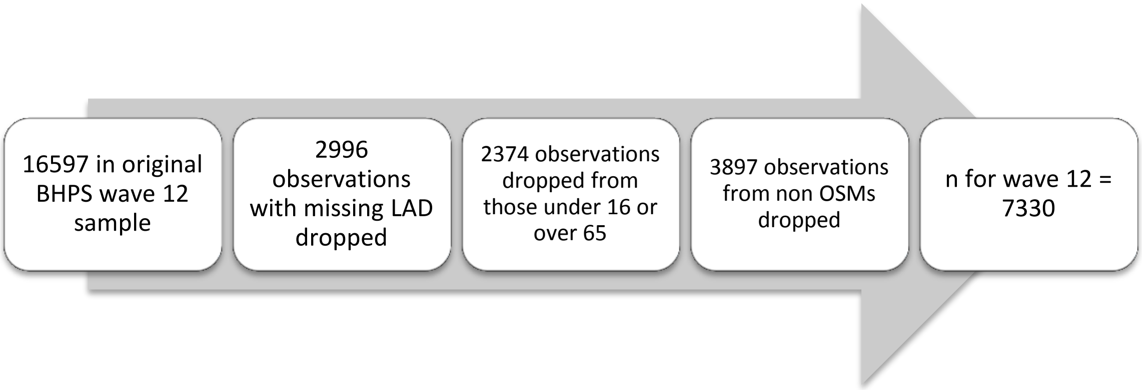

Figure A3.1 Flowchart showing sample derivation for wave 12 cross-sectional file

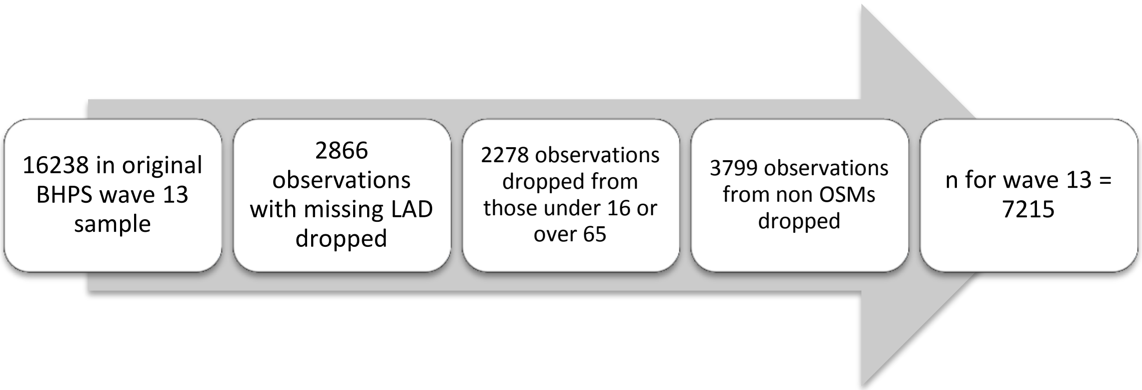

Figure A3.1 Flowchart showing sample derivation for wave 13 cross-sectional file

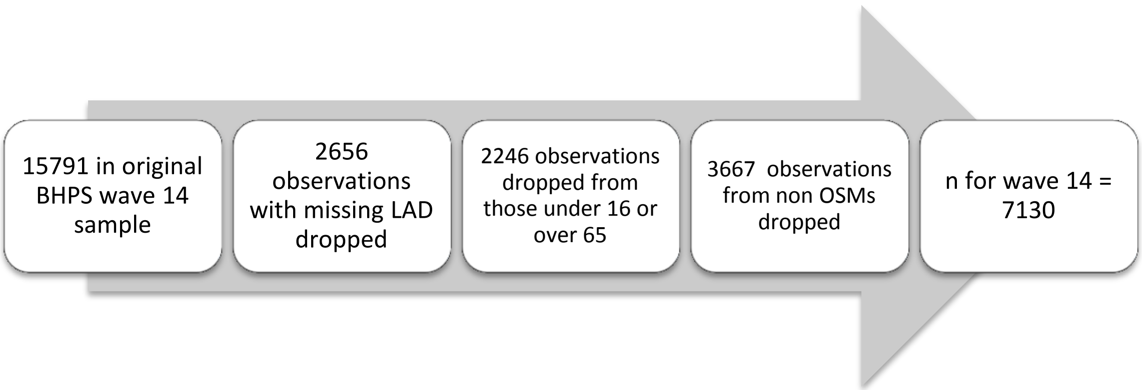

Figure A3.1 Flowchart showing sample derivation for wave 14 cross-sectional file

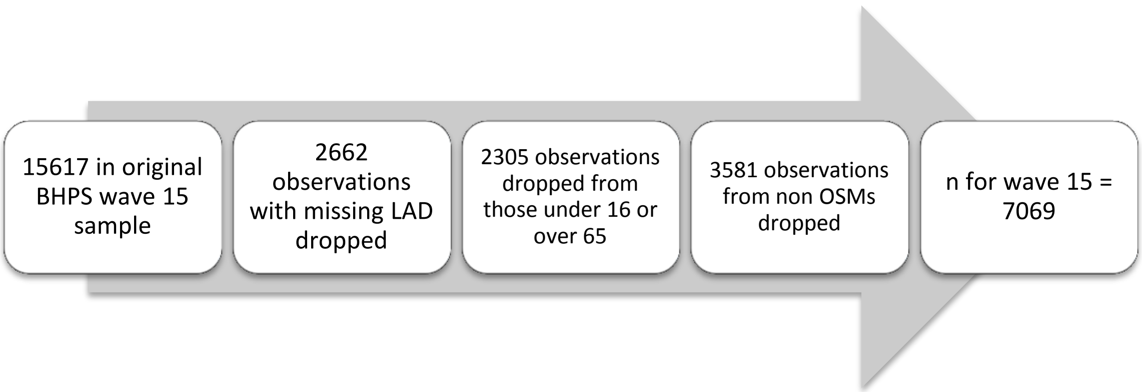

Figure A3.1 Flowchart showing sample derivation for wave 15 cross-sectional file

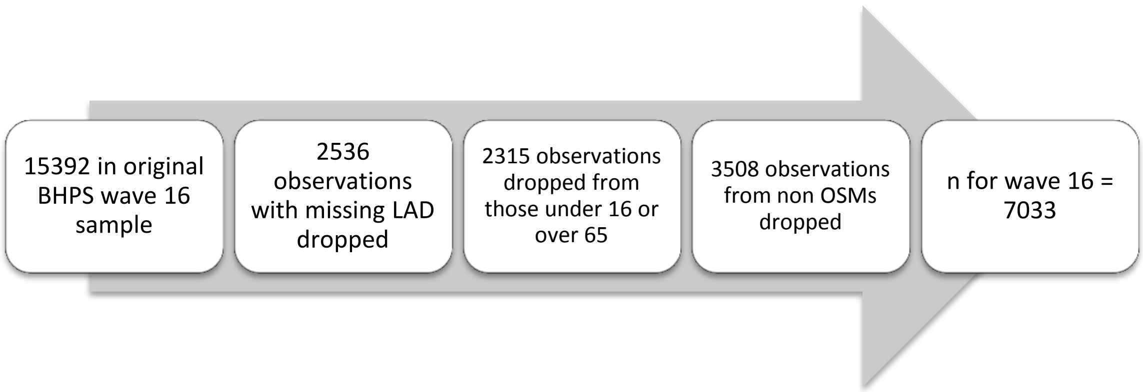

Figure A3.1 Flowchart showing sample derivation for wave 16 cross-sectional file

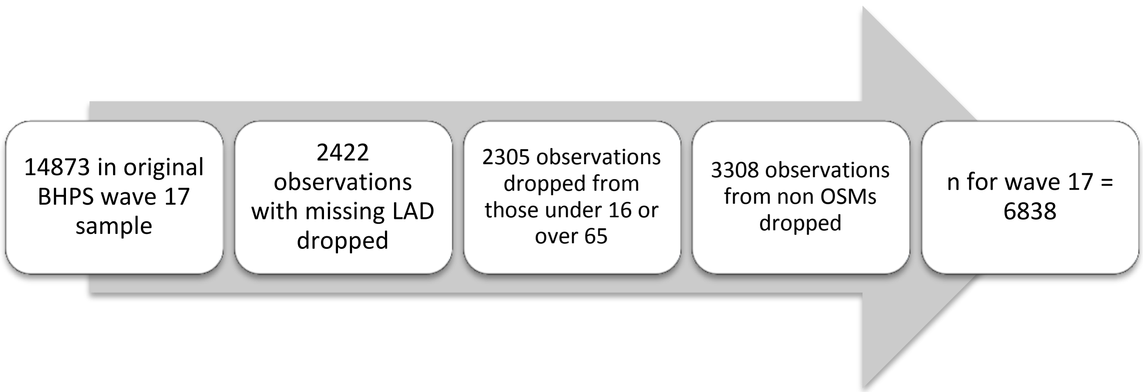

Figure A3.1 Flowchart showing sample derivation for wave 17 cross-sectional file

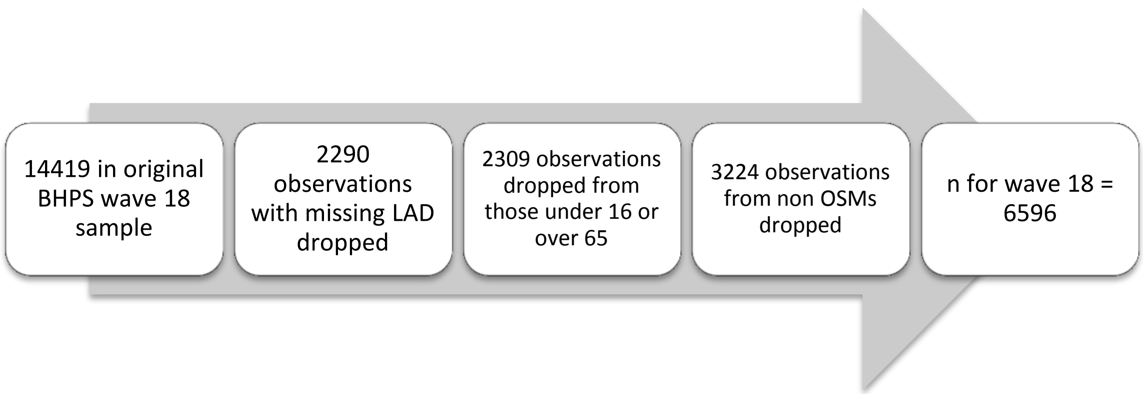

Figure A3.1 Flowchart showing sample derivation for wave 18 cross-sectional file

Appendix 3.2 *The 12 item General Health Questionnaire. Goldberg, 1978.*

Chapter 4

Investigating the Relationship between Labour Market Status and Minor Psychiatric Morbidity

4 Investigating the relationship between Labour Market Status and Minor Psychiatric Morbidity

4.1 Introduction

Existing evidence suggests that the link between joblessness and minor psychiatric morbidity (MPM) is likely to be causal, but that many complex processes are at play. This chapter seeks to contribute to the field by assessing the relationship between labour market status and MPM across the business cycle, looking at the effects of insecure employment, permanent sickness and other economic inactivity as well as unemployment. This chapter will also attempt to uncover the mechanisms at work in the relationship between labour market status and psychological wellbeing, and the ways in which other factors, related to both exposure and outcome, contribute to and confound the association. This chapter will also seek to assess the extent to which the relationship between labour market status and MPM varies by gender.

The literature generally supports the hypothesis that age modifies the relationship between unemployment and psychological wellbeing, and that a curvilinear association is observed, with larger effect sizes for those in mid-life compared to those in early or later working life (Daniel, 1974; Eisenberg and Lazarsfeld, 1938; Hepworth, 1980). This is explored in more detail in section 6.1. It is noted across the literature that joblessness appears to disproportionately affect male psychological wellbeing, despite the elevated prevalence of MPM generally observed amongst women. McFayden (1995) argues that in Western societies masculine identity is intrinsically bound up with having a job, and is therefore threatened by unemployment. In contrast, Karsten and Moser (2009) point out that women have access to alternative acceptable social roles outside the formal labour market and therefore may be less susceptible to the negative psychosocial effects of joblessness. Leana and Feldman (1991) propose a material explanation, stating that jobless women who cohabit with a man tend to receive a higher level of financial support than a non-working man would if his female partner were the lone wage-earner, as a result of the gender pay gap. It is expected therefore that a significant gender difference in the relationship between labour market status and psychological wellbeing will be apparent in this study, and that secure employment will be more protective for men than for women.

Väänänen *et al.* (2005) identify spouses as key providers of social support. The presence of a spouse has been shown to ameliorate the negative effects of joblessness by providing both emotional support (Atkinson *et al.,* 1986; Bolton and Oatley, 1987) and financial stability in their capacity as another potential wage earner (Gore, 1987). Whilst many studies adjust for the presence of a spouse when assessing the effect of labour market status on MPM, it is clearly important to specify the employment status of the spouse. The effects of cohabiting with a jobless partner are likely to vary by gender. An unemployed woman cohabiting with a jobless male spouse will have access to no extra financial support and may also derive less social support if her partner also suffers the negative psychological effects of joblessness. It is also possible that the norming of joblessness within a household may reduce the psychological burden on both jobless partners. In addition to the spouse's employment status, it may also be important to assess spousal psychological distress. In a systematic review, Meyler *et al.* (2007) concluded that there is overwhelming evidence for concordance of depressive symptoms and distress within couples, as well as general support for wellbeing concordance. Taking a dyadic methodological approach to a sample of elderly couples, Goodman and Shippy (2002) found that when one spouse was depressed, the other spouse was likely to also experience depression. The authors concluded that their results support a hypothesis of emotional contagion. It is therefore important to control for the potential effects of spousal psychological distress and joblessness on the individual. This is not attempted in the majority of studies on the effects of labour market status on psychological distress, but it is important to recognise that individuals are subject to influences at many levels, including within the household. The panel nature of the BHPS allows exploitation of household-level information such as these spousal factors.

The duration of time spent in a disadvantaged labour market status is identified as an important factor in determining the extent to which that labour market status is predictive of psychological distress. Jackson and Warr (1984) suggested that a linear relationship between increasing duration of unemployment and worsening psychological distress could be expected, as jobseekers accumulate discouraging experiences, and financial pressures intensify as savings are drained. However, a non-linear relationship has also been proposed, in which a final stage of adaptation to joblessness limits any further decline in psychological wellbeing beyond a certain point (Eisenberg and Lazarsfeld, 1938; Winegardner *et al.* 1984). Using multilevel modelling, Booker and Sacker (2011) found that previously employed individuals in the BHPS adapted to unemployment with each spell they experienced. In contrast, it was found that previously economically inactive individuals became increasingly sensitised to worsening psychological wellbeing with each attempt to re-enter the labour force. The authors suggest that those who transitioned between employment and unemployment remained active in the labour market, and therefore gained more experiences of finding a job, reducing their level of anxiety so that the next time they became unemployed, they had adapted somewhat. However, previously economically inactive individuals may have become very anxious when entering the labour market, increasing their level of sensitisation.

To what extent is the relationship between joblessness and MPM mediated by financial factors? Clearly the decline in income normally associated with job loss is likely to have some direct impact on psychological wellbeing. Jones argued that income is the key determinant of psychological health following job loss (Jones, 1991-1992). Hobfoll *et al.* (1996) point out that income determines access to necessities such as healthy food and secure housing, as well as social and leisure resources. It is therefore expected that a proportion of the association between labour market status and MPM will be indirect, acting through the effects of low income. However, the psychosocial pathways outlined by Jahoda (1981)**,** Warr (1985) and Fryer (1986) suggest that this is not the whole story. In addition to objective measures of financial status, subjective assessments of financial situation have been found to correlate highly with MPM (Ullah, 1990). The two concepts do not entirely capture the same dimensions. Vinokur *et al. (1996)* found a correlation of 0.4 between objectively and subjectively measured financial status, indicating that different individuals with a given level of financial security assess their situation differently, according to financial obligations or a difference in perspective. Many studies have reported a strong and negative association between perceived financial hardship and psychological wellbeing during unemployment (Creed and Macintyre, 2001; Vinokur and Schul, 2002). Additionally, Ullah (1990) found that perceived financial status was more strongly associated with psychological wellbeing than objectively measured financial status. Clearly there are grounds for concern regarding reverse causality in the relationship between psychological wellbeing and perceived financial hardship. An individual suffering high levels of psychological distress is more likely to view all domains of their life with a pessimistic outlook.

To date, a strong association between labour market status and MPM has been established. However, this research has often failed to distinguish between different forms of joblessness and is characterised by an overemphasis on registered unemployment. Whilst the effect of labour market status on MPM is thought to vary by gender, too few studies have taken a detailed look at the ways in which men and women differ with respect to labour market status and MPM. The results presented in this chapter elucidate the mechanisms and causal pathways operating in this complex relationship and allow conclusions to be made separately by gender, and for each labour market status category.

4.1.1 Research Question

To what extent does being insecurely employed, unemployed, permanently sick or economically inactive predict MPM (compared to being securely employed), controlling for the effects of potential confounding factors, and exploring the factors which might mediate the relationship?

4.1.2 Objectives

1. To ascertain the extent to which labour market status is associated with MPM in the BHPS.
2. To refine this by effectively taking into account the possibility that some individuals may become distressed first and then lose their job as a consequence.
3. To ascertain which theoretically-linked groups of potential confounding factors attenuate the relationship between labour market status and MPM, and to what degree.
4. To ascertain the extent to which certain factors mediate the relationship between labour market status and MPM.
5. To repeat the above in the following stages, in order to investigate possible gender differences in the relationship between labour market status and unpack potential differences between average GHQ-12 score and GHQ-12 caseness outcomes.

4.1.3 Hypotheses

1. Being in a labour market status other than secure employment predicts higher levels of minor psychiatric morbidity (for both caseness and GHQ-12 score outcome measures). The literature consistently shows that secure employment is the most protective labour market status for psychological wellbeing (Jahoda, 1981, 1982; Warr, 1985).
2. This effect will be seen for both genders but secure employment will be comparatively more protective for men, as theorised by MacFadyn (1985), Karsten and Moser (2009) and others.
3. Adjusting for potential confounders will attenuate the association between labour market status and MPM to some degree, but a significant independent association will remain.
4. The effect of joblessness on MPM will be mediated in part by household income and financial status, since the material disadvantages associated with joblessness are

expected to have some negative effect on MPM (Hobfoll *et al.* 1996). However, the association will not be entirely attenuated, since much of the relationship between labour market status and MPM is thought to operate via psychosocial pathways (Jahoda, 1981, 1982; Warr, 1985).

4.2 Methods

4.2.1 Defining the analysis sample

The final sample used for the modelling was constructed as described in section 3.2, by excluding non-working age respondents (below age 16 and above age 65) and all respondents who were not BHPS original sample members. The final regression model was run initially, and respondents who were left out of the final model were then dropped from the sample. The final sample therefore contained working-age original sample members who had complete data for all of the variables outlined in section 3.3, in at least two consecutive waves of the BHPS. Because of the inclusion of the lagged GHQ-12 score variable, all data from wave 1 (1991) was dropped, since no preceding wave exists. The final sample size is presented in Figure 4.1.

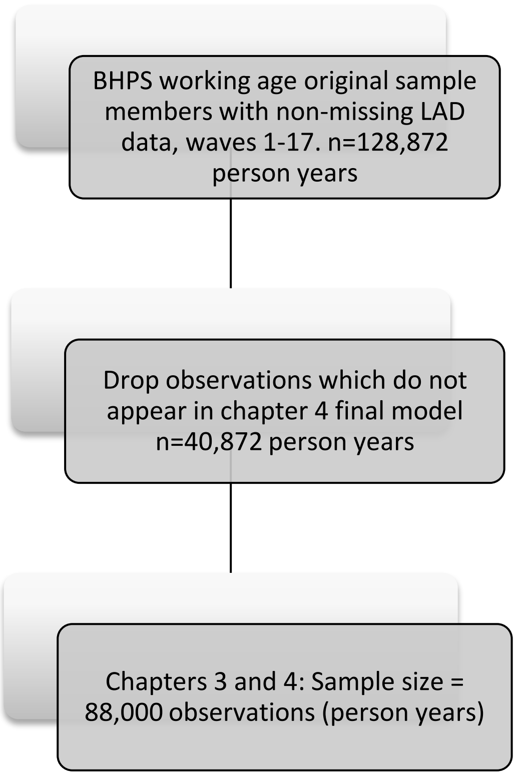

Figure 4.1 Flowchart showing derivation of sample used in chapters 3 and 4

4.2.2 Variables

The variables outlined in section 3.3 were used for the analysis presented in this chapter. Both versions of the GHQ-12 outcome variable described in section 3.3.2.1 were used: GHQ-12 score using the Likert-scaled variable; and MPM prevalence, using a caseness cut-off of ≥3 on the 1-12 scored GHQ-12 variable (Goldberg *et al.,* 1997). The key exposure variable, labour market status, was derived as described in section 3.3.3 and used throughout the models presented in this chapter. The range of hypothesised confounding and mediating covariates described in sections 3.3.4 and 3.3.5 were also used in this chapter. In addition to these variables, a lagged version of the Likert-scaled GHQ-12 score from the previous wave was generated and used in this chapter. Table 4.1 shows the distribution across the total number of person-years for each category of the categorical and binary variables of interest in this chapter. Longitudinal descriptive analysis for each variable can be found in section 3.3. Table 4.2 details the strength and significance levels of the bivariate associations between the covariates and the GHQ-12 outcome variables. Regression coefficients and odds ratios were obtained using linear and logit random effects models, respectively.

Table 4.1 Descriptive analyses summary table for binary and categorical covariates (person-years of exposure).

Binary or Categorical Variable	**Categories**	**Person-years**	
		Frequency	**Percent**
Outcome: GHQ-12 Caseness	0 - Not case	65420	74.34
	1 - Case	22580	25.66
Key exposure: Labour market status	1 - Securely employed	58915	66.95
	2 - Insecurely employed	8900	10.11
	3 - Unemployed	3130	3.56
	4 - Other Inactive	13778	15.66
	5 - Permanently sick	3277	3.72
Gender	0 - Man	42773	48.61
	1 - Woman	45227	51.39
Highest academic qualification	1 - Higher education	18602	21.14
	2 - A levels	19337	21.97
	3 - O level/GCSE	31286	35.55
	4 - None of the above	18775	21.34
Presence of a physical health problem	0 - No physical health problems	42698	48.52
	1 - Suffers from ≥1 phys. health prob.	45302	51.48
Marital Status	1 - Married or cohabiting	60483	68.73
	2 -Widowed, divorced or separated	8322	9.46
	3 - Never married	19195	21.81
Spousal job status	0 - Spouse jobless	12647	14.37
	1 - Spouse employed	47580	54.07
	2 - No spouse	27773	31.56

Spousal GHQ-12 caseness status	0 - Spouse not a case	45333	51.51
	1 - Spouse is a case	14894	16.93
	2 - No spouse	27773	31.56
Economic Inactivity spells in past year	0 - No inactivity	66625	75.71
	1 - ≥1 inactive spells	21375	24.29
Unemployment spells in past year	0 - No unemployment	81655	92.79
	1 - ≥1 spells of unemployment	6345	7.21
Housing tenure	1 - Owned, privately rented	75479	85.77
	2 - LA/HA Rented	12521	14.23
Government Office Region	1 - London	7879	8.95
	2 - South East	17371	19.74
	3 - South West	8014	9.11
	4 - East of England	3577	4.06
	5 - East Midlands	8059	9.16
	6 - West Midlands	7481	8.50
	7 - North West	9574	10.88
	8 - Yorks & Humber	8357	9.50
	9 - North East	5590	6.35
	10 - Wales	4631	5.26
	11 - Scotland	7467	8.49
Problems with alcohol or drugs	0 - None mentioned	87614	99.56
	1 - Problems with alcohol or drugs	386	0.44
Saving from current income	0 - Does not save from current income	48717	55.36
	1 - Does save from current income	39283	44.64
Subjective assessment of current financial situation	1 - Living comfortably	25162	28.59
	2 - Doing alright	33836	38.45
	3 - Just about getting by	21794	24.77
	4 - Finding it quite difficult	5082	5.78
	5 - Finding it very difficult	2126	2.42
Subjective assessment of current financial situation compared to one year ago	1 - Better off now	28585	32.48
	2 - Worse off now	21021	23.89
	3 - About the same	38394	43.63
Subjective assessment of current financial situation compared to predicted situation in 1 years' time	1 - Better off now	29609	33.65
	2 - Worse off now	9367	10.64
	3 - About the same	49024	55.71
Total (for each variable)		88000	100

Table 4.2 Table showing bivariate associations between hypothesised confounders/mediators, and the key exposure and outcome variables used in the models. Grey italics denote non statistical significance (p>0.05)

Variable	**Category**	**Association with outcome: bivariate logit and linear random effects models and chi-squared tests**					**Bivariate association with Labour Market Status exposure: χ^2 p-value**
		GHQ-12 caseness:		**GHQ-12 score:**		**Bivariate association with GHQ-12 caseness: χ^2 p-value**	
		Odds Ratio	**p-value**	**Coefficient**	**p-value**		
Gender (0.Male omitted)	0 - Male (ref)	1		0			
	1 - Female	1.935	<0.001	1.417	<0.001	<0.001	<0.001
Age		0.994	<0.001	0.023	<0.001		
Highest academic qualification	1 - Higher education (ref)	1		0			
	2 - A levels	*0.931*	*0.133*	-0.183	0.033	<0.001	<0.001
	3 - O level/GCSE	*0.935*	*0.145*	*0.042*	*0.621*		
	4 - None of the above	*1.051*	*0.347*	0.766	<0.001		
Phys. Health Problem	0 - No physical health problems (ref)	1		0			
	1 - ≥1 phys health problem	1.602	<0.001	0.893	<0.001	<0.001	<0.001
Marital Statu	1 - Married or cohabiting (ref)	1		0			
	2 -Widowed/divorced/separated	1.710	<0.001	1.303	<0.001	<0.001	<0.001
	3 - Never married	*1.032*	*0.353*	-0.446	<0.001		
Spousal Joblessness (1. omitted)	0 - Spouse Jobless	1.117	0.002	0.214	<0.001	<0.001	<0.001
	1 - Spouse employed (ref)	1		0			
	2 - No Spouse	1.275	<0.001	0.215	<0.001		
Spousal GHQ-12 Caseness	0 - Spouse not GHQ-12 case (ref)	1		0			
	1 - Spouse GHQ-12 case	2.058	<0.001	1.439	<0.001	<0.001	<0.001
	2 - No Spouse	1.539	<0.001	0.564	<0.001		

Inactive spells	0 - No inactive spells (ref)	1		0			
	1 - One or more inactive spells	1.256	<0.001	0.268	<0.001	<0.001	<0.001
Unemployed spells	0 - No unemployed spells (ref)	1		0			
	1 - One or more unemployed spells	1.359	<0.001	0.268	<0.001	<0.001	<0.001
Social housing tenure	0 - Not social housing tenant (ref)			0			
	1 - Social housing tenant	1.319	<0.001	0.582	<0.001	<0.001	<0.001
Percent Annual GDP growth		*0.987*	*0.188*	*0.030*	*0.067*		
Government Office Region (compared to grand mean)	1 - London	1.142	0.008	*-0.004*	*0.963*	<0.001	<0.001
	2 - South East	*0.919*	*0.177*	*0.070*	*0.547*		
	3 - South West	0.752	<0.001	*-0.273*	*0.054*		
	4 - East of England	0.777	0.010	*-0.152*	*0.403*		
	5 - East Midlands	*0.872*	*0.074*	*-0.054*	*0.709*		
	6 - West Midlands	*0.887*	*0.129*	*0.061*	*0.681*		
	7 - North West	*0.920*	*0.260*	*0.029*	*0.836*		
	8 - Yorks & Humber	0.794	0.003	*-0.039*	*0.789*		
	9 - North East	*0.871*	*0.117*	*0.103*	*0.543*		
	10 - Wales	*1.176*	*0.074*	0.489	0.005		
	11 - Scotland	0.743	<0.001	*-0.185*	*0.228*		
Substance abuse – problems with alcohol or drugs	0 - None mentioned (ref)	1		0			
	1 - Problems with alcohol or drugs	3.954	<0.001	3.694	<0.001	<0.001	<0.001
Log Equivalised Household Income		0.844	<0.001	-0.243	<0.001		
Saves from current income	0 - Does not save from current income	0.756	<0.001	-0.595	<0.001	<0.001	<0.001
	1 - Saves from current income (ref)	1		0			

Current financial situation	1 - Living comfortably (ref)	1		0			
	2 - Doing alright	1.223	<0.001	0.504	<0.001	<0.001	<0.001
	3 - Just about getting by	2.088	<0.001	1.638	<0.001		
	4 - Finding it quite difficult	4.655	<0.001	3.515	<0.001		
	5 - Finding it very difficult	9.403	<0.001	5.672	<0.001		
Financial situation now, compared to one year ago	1 - Better off now (ref)	1		0			
	2 - Worse off now	2.519	<0.001	2.164	<0.001	<0.001	<0.001
	3 - About the same	1.127	<0.001	0.692	<0.001		
Expectation for financial situation in one years' time, compared to now	1 - Better than now (ref)	1		0			
	2 - Worse off now	1.563	<0.001	1.051	<0.001	<0.001	<0.001
	3 - About the same	0.903	<0.001	0.167	<0.001		

4.2.3 Random Effects Models

When analysing longitudinal data, it is crucial to recognise that repeated measurements on the same individuals may be more alike than comparing observations between individuals. The observations made at different times are likely to be clustered within individuals and therefore an inherently hierarchical data structure is present. Pooling the observations and using, for example, ordinary least squares regression would result in biased estimates. In order to take account of this, random effects models were used. Random effects models are also known as variance components models. These models partition the variance into 'between' and 'within' effects. The 'between' effects refer to the variation in the outcome attributable to between cluster differences (i.e. between individuals); whereas the 'within' effects refer to the variation in the outcome attributable to within cluster differences (i.e. over repeated measures within individuals). For the linear outcome, the linear random effects command *xtreg* was used in Stata v10. This can be described as a matrix weighted average of the fixed-effects (within) and the between-effects. For the binary outcome, the logit version, *xtlogit*, was used with the *'or'* (odds ratio) option specified.

The modelling strategy and composition of each model is outlined in Figure 4.2. After the crude association between labour market status and GHQ-12 outcome was determined (model 1), a second model with just age, age-squared and gender was run in order to reveal any confounding effects of these covariates. Thirdly, an autoregressive model was run, in which each respondent's GHQ-12 outcome at the current wave was regressed onto their GHQ-12 score from the preceding wave, with age, age-squared and gender in the model as further covariates. This was added in order to take account of an individual's tendency towards generally higher or lower than average GHQ-12 scores over time.

The model series shown in Figure 4.2 was run for the following types of models:

1. Linear random effects
    a. Unstratified
    b. Gender stratified: men only
    c. Gender stratified: women only
2. Logit random effects
    a. Unstratified
    b. Gender stratified: men only
    c. Gender stratified: women only

Hypothesised confounder

Hypothesised mediator

Model 1:	GHQ-12	LM Status						
Model 2:	GHQ-12	LM Status	Gender*	Age & age^2				
Model 3:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12			
Model 4:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Educational attainment		
Model 5:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Physical health status		
Model 6:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Marital status	Spousal GHQ-12 caseness	Spousal joblessness
Model 7:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	1+ Unemployment spells past yr	1+ Inactivity spells past yr	
Model 8:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Social housing tenure		
Model 9:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Region		
Model 10:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Annual % GDP growth		
Model 11:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Substance abuse		
Model 12:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	log equivalised household income	Saves from current income?	
Model 13:	GHQ-12	LM Status	Gender*	Age & age^2	Lagged GHQ-12	Financial situation	FS last year	FS 1 yr ahead

Model 14 (Final Model): All of the confounders and mediators above were added together into a final model

Figure 4.2 General form for the 2 unstratified series of 14 regression models run in chapter 4. Series was run using GHQ-12 score outcome in linear random effects models, and with GHQ-12 caseness outcome for logit random effects models. *The series was repeated with gender stratification for both linear and logit models, excluding the 'gender' covariate.

The models were built up and run as described in the following equations. The subscripts 'i' and 'j' denote individuals (level 2) and occasions of measurement (level 1), respectively.

For the linear random effects models:

Model 1: $y_{ij} = \beta_0 + \beta_1\text{INSECURE} + \beta_2\text{UNEMP} + \beta_3\text{OI} + \beta_4\text{SICK} + \varepsilon_i + u_{ij}$

Model 2: As above plus $+ \beta_5\text{GENDER} + \beta_6\text{AGE} + \beta_7\text{AGE}^2$

Models 3-14: As (2) plus $\sum_{n=6}^{N} \beta_n x_{nij}$

For the logit random effects models:

Model 1: logit $(P(y_i=1|y_i\text{-}1) = \beta_0 + \beta_1\text{INSECURE} + \beta_2\text{UNEMP} + \beta_3\text{OI} + \beta_4\text{SICK} + u_{ij}$

Model 2: As above plus $+ \beta_5\text{GENDER} + \beta_6\text{AGE} + \beta_7\text{AGE}^2$

Models 3-14: As (2) plus $\sum_{n=6}^{N} \beta_n x_{nij}$

Where:

INSECURE = Insecurely Employed

UNEMP = Unemployed

OI = Other Inactive

SICK = Permanently Sick

$\mathbf{y_{ij}}$ **=** Outcome for individual 'i' at occasion 'j'

$\boldsymbol{\beta_0}$ **=** Intercept

$\boldsymbol{\varepsilon_i}$ **=** Within-individual residual (i.e. the level 1 random effect)

$\mathbf{u_{ij}}$ **=** Between-individual residual (i.e. the level 2 random effect)

$\boldsymbol{x_{nij}}$ **=** Further covariates, outlined in Figure 4.2 (i.e. fixed effects).

4.3 Results

Results from the unstratified and gender-stratified linear and logit random effects models series are shown in Figures 4.3 to 4.8 and with full details of the coefficients in Appendices 4.1 to 4.6.

4.3.1 Model 1: The crude association between labour market status and MPM

Bivariate models were run to show the crude association between labour market status and the GHQ-12 outcome. The results for the unstratified linear random effects model show that those in insecure employment, unemployment, other inactivity or permanent sickness tended to have higher GHQ-12 scores than those in secure employment. This is most apparent for the permanently sick category, who had GHQ-12 scores 3.85 units higher than the securely employed. The insecurely employed had GHQ-12 scores 1.30 units higher than their securely employed counterparts, while the other inactive showed the lowest level of difference from the referent group, with a crude coefficient of 0.50. All coefficients were significantly different from the omitted category ($p<0.001$). The same pattern was observed in the results from the unstratified logit random effects model with the binary GHQ-12 caseness outcome. Again, the permanently sick showed the largest difference from the securely employed referent category, being 4.5 times more likely to suffer MPM. The other inactive group showed the least difference from the securely employed, and only around 35 percent more likely to be GHQ-12 cases (OR=1.35). The unemployed and insecurely employed were also significantly more likely to suffer MPM than the referent group (OR=2.95 and OR=1.97 respectively). All odds ratios were highly statistically significant ($p<0.001$). The high average GHQ-12 scores and higher MPM prevalence among the permanently sick are expected, since affective disorders make up a high proportion of the morbidity among those on incapacity benefits, and many physical conditions are known to increase the risk of anxiety or depression. The fact that both the linear and logit models showed that insecure employment and joblessness are associated with poorer psychological wellbeing shows that the effects were not just limited to those with scores which were above or around the caseness cut-off point. The effects are also shown by the linear model, which is most greatly influenced by the middle section of the Likert-scaled GHQ-12 score distribution.

A significant interaction was observed between sex and labour market status which justified stratification of the models. Stratification of the bivariate linear random effects model by gender showed that insecure employment, unemployment and permanent sickness were associated with greater psychological distress for men than for women. Insecurely employed men had GHQ-12 scores 1.56 units higher than securely employed men, compared to a coefficient of 0.98 for the females-only model. However whilst insecure employment was worse for men than women, when compared to the securely employed, the female insecure group had a higher average GHQ-12 score which was above the threshold of 12 (Goldberg *et al.* 1997) for poor psychological wellbeing (12.34 for insecurely employed women compared to 11.44 for their male counterparts). This probably reflects the higher GHQ-12 scores among the female population generally. For the unemployed, the coefficients were more similar (2.06 for men and 1.99 for women). Again, the average GHQ-12 score for the female unemployed group was higher than for the unemployed male group. In the males-only linear model, the coefficient for the other inactive group was not statistically significant, whereas a statistically significant coefficient of 0.54 ($p<0.001$) was observed in the females-only model, probably owing to a larger sample size for other inactive women. Gender stratification of the bivariate logit random effects model showed a similar pattern for the binary outcome. Insecurely employed males were 2.6 times more likely to be MPM cases than securely employed males, compared to a corresponding odds ratio of 1.52 for women. The effect was also greater for men in the unemployed category, with unemployed men 3 times more likely to be MPM cases compared to an odds ratio of 2.35 for the females-only model. Unlike the linear stratified model, the logit model shows that other inactive males were significantly more likely to be MPM cases than securely employed males (OR=1.11), but that the effect was greater for the corresponding females (OR=1.27). Whilst significantly different to the referent category, these effect sizes for both inactive males and females are very small. The largest gulf between male and female odds ratios was for the permanently sick group, where males were 6 times more likely to be MPM cases than securely employed men, compared to a corresponding odds ratio of 3.43 for permanently sick women.

The crude models show a strong association between labour market status and both GHQ-12 outcomes, and indicate that both MPM prevalence and GHQ-12 score were higher among the insecurely employed and the jobless, compared to those in secure employment. This has also been shown for men and women separately. The differences between the coefficients in the crude models were all statistically significant ($p<0.05$), as tested by the Wald test. The following series of models controls for the effects of different sets of variables hypothesised to act as confounders or mediators in the association between labour market status and GHQ-12.

4.3.2 Model 2: Adding age and gender

The first multivariate linear and logit random effects models were run with just age, an age-squared term and gender added as covariates (M2). For both the unstratified linear and logit models, the coefficients and odds ratios increased for all four labour market status categories, showing that when controlling for the effects of age and gender, being insecurely employed or jobless was associated with even poorer mental health outcomes than shown by the unadjusted models. This pattern was largely the same for the gender-stratified versions of the linear and logit models, with coefficients and odds ratios for M2 marginally higher than the corresponding estimates for the crude models.

4.3.3 Model 3: Basic Autoregressive model controlling for age, gender and lagged GHQ-12 score from previous wave

The second multivariate linear and logit random effects models saw lagged GHQ-12 score from the previous wave added to age and gender as covariates (M3). GHQ-12 score from the previous wave was added to the model in order to control for individuals' propensities towards psychological wellbeing or distress, and therefore to allow a focus on change in mental health status. For the unstratified linear model, the addition of lagged GHQ-12 score had mixed effects on the coefficients for the different labour market status categories. The coefficient for the insecurely employed group increased slightly to 1.34 (compared to 1.31 for M2 and 1.30 for the bivariate model). The coefficient for the other inactive group also remained higher than in the crude model (0.52). However, the association between unemployment and GHQ-12 score was attenuated somewhat by the addition of lagged GHQ-12 score (1.75 compared to a coefficient of 2.15 in M2). The same pattern was seen for the permanently sick group, who had GHQ-12 scores 3.17 units higher than the securely employed in M3, compared to a coefficient of 3.88 in M2. Gender stratification showed that the association between labour market status and GHQ-12 score was attenuated in all labour market status categories for men and in all but the insecurely employed category for women. The effect of adding lagged GHQ-12 score to the logit model did not have similarly mixed effects. For all of the labour market status categories, the addition of lagged GHQ-12 score attenuated the association between labour market status and MPM caseness, although not by a great amount. The odds ratios for the insecurely employed and other inactive categories were only marginally smaller than in M2. However, the odds ratio for the permanently sick group decreased from 5.02 in M2 to 3.79 with adjustment for lagged GHQ-12 score. This indicates that there was a greater degree of long-term MPM among the permanently sick. This pattern of attenuation was also apparent across the gender stratified logit autoregressive models, with the exception of the male other inactive group. Coefficients and odds ratios for all of the M3 models were highly statistically significant ($p<0.001$). Postestimation testing (using the Wald test) showed that with the exception of the insecurely employed and unemployed categories in the males-only logit model, the differences between the coefficients for the labour market status categories within each of the models were statistically significant ($p<0.05$).

Further adjustment for mediating and confounding factors was achieved using a series of models. All models were constructed by adding thematically linked variables to the set of basic covariates in M3 (age, gender and lagged GHQ-12). The models are described below.

4.3.4 Model 4: Adding educational attainment to the basic autoregressive model as a hypothesised confounder

The addition of educational attainment to the linear random effects model had very little effect on the relationship between labour market status and GHQ-12 score. This was also true for the logit model with the caseness outcome. The females-only linear model showed slight attenuation of the association between labour market status and GHQ-12 score for the unemployed, other inactive categories and permanently sick categories, but this was not the case in the males-only linear model or either of the gender-stratified logit models. The results of M4 suggest that there was little confounding by educational attainment.

4.3.5 Model 5: Adding confounding physical health condition to the basic autoregressive model

The presence of a physical health condition was hypothesised as a potential confounder of the association between labour market status and MPM, since it was associated with all categories of joblessness, and is also a well-established predictor of anxiety and depression. The addition of this variable to the linear model however, attenuated the association between labour market status categories and GHQ-12 score by less than 0.05 units, with the exception of the permanently sick category, which was attenuated by only 0.26 units. The addition of a physical health condition indicator had similarly little effect on the unstratified logit model and the gender-stratified linear and logit models. For the unstratified logit model, the association between permanent sickness and poor mental health was attenuated somewhat, but there was little change for the insecurely employed and other inactive categories. The results for M5 show that there was a small confounding effect of physical health found mainly for the permanently sick category, and to a lesser extent for the unemployed category, but no confounding effect for the insecurely employed or other inactive groups.

4.3.6 Model 6: Adding confounding spousal factors to the basic autoregressive model

Variables relating to spouses were added to the models as potential confounders. The presence of a spouse suffering MPM and/or joblessness could have had a negative effect on the MPM of the respondent, and was also associated with labour market status. The addition of these factors attenuated the relationship between labour market status and MPM by only a very small degree in the unstratified and gender-stratified linear and logit models. In the unstratified logit model, the addition of spousal factors resulted in an odds ratio decrease from 2.4 in M3 to 2.3 in M6 for the unemployed group. The permanently sick group in M6 were 3.6 times more likely to be a GHQ-12 case than the securely employed, compared to an odds ratio of 3.8 in M3. Postestimation testing (using the Wald test) showed that the differences between the coefficients for the labour market status categories within each of the models were statistically significant ($p<0.05$). The results of this model show that spousal factors had a small confounding effect for the unemployed and permanently sick groups, but barely any effect on the insecurely employed and other inactive groups.

4.3.7 Model 7: Adding confounding labour market status stability variables to the basic autoregressive model

In order to examine the effects of repeated spells of joblessness throughout the year preceding the interview for each wave, variables were added to the models which indicate whether the individual had experienced one or more spells of joblessness since that last questionnaire, over and above any current spell of joblessness. Two binary variables were added: one indicating spells of unemployment, and the other indicating spells of economic inactivity. The addition of these variables to the unstratified and gender-stratified linear models increased the coefficients for all of the labour market status categories. For example, in the unstratified model, the coefficient for the unemployed group increased from 1.75 in M3 to 2.22 in M7. These results are consistent with those of Booker and Sacker (2011) as they indicate that the effects on MPM are greater for the first spell of joblessness. In contrast, controlling for spells of joblessness in the past year had essentially no effect on the corresponding unstratified and gender-stratified logit models.

4.3.8 Model 8: Adding social housing tenure to the basic autoregressive model as a potential confounder

A binary variable which indicates whether the respondent dwelt in social housing (i.e. local authority or housing association tenancy) was added to the basic autoregressive model as a hypothesised confounder of the relationship between labour market status and MPM. The addition of the variable had no general effect on the coefficients or odds ratios for the labour market status categories in the gender-stratified or unstratified linear and logit models.

4.3.9 Model 9: Adding region to the basic autoregressive model as a potential confounder

Government Office Region (GOR) was added to the model as a hypothesised confounder of the relationship between labour market status and MPM. It is recognised that unemployment and permanent sickness are geographically patterned, and that areas with high concentrations of workless inhabitants map onto areas with poor overall health outcomes. The addition of the GOR identifier to the basic autoregressive model had no significant effect on the coefficients or odds ratios for the labour market status categories in the gender-stratified or unstratified linear and logit models. This is potentially because GOR is not the theoretically appropriate geographical scale at which to consider area effects as confounders. In addition, any area effects are best understood using a three level multilevel framework. This will be addressed in chapter 5.

4.3.10 Model 10: Adding macroeconomic condition to the basic autoregressive model as a potential confounder

Annual percentage change in GDP growth was added to M3 as an indicator of national economic performance and therefore as a hypothesised confounder of the relationship between labour market status and MPM. The addition of this variable had no significant effect on the coefficients or odds ratios for the labour market status categories in the gender-stratified or unstratified linear and logit models. This suggests that there is no confounding effect of macroeconomic conditions which can be picked up through the use of annual percentage GDP growth as an indicator of national macroeconomic conditions.

4.3.11 Model 11: Adding substance abuse to the basic autoregressive model as a hypothesised mediator

The addition of a binary measure of substance abuse did not produce change in the regression coefficients or odds ratios for either the unstratified or gender-stratified linear or logit models.

4.3.12 Model 12: Adding mediating objective financial situation to the basic autoregressive model

Two objective measures of financial situation were added to the basic autoregressive linear random effects model: log equivalised household income and a binary indictor of whether the respondent saved from their current income. In the unstratified linear model and logit models, the association between labour market status and MPM was attenuated somewhat for each of the jobless categories. For example, for the unemployed group, the coefficient reduced from 1.75 in M3 to 1.47 in M12. Similarly, the odds ratio decreased from 2.4 to 2.2 in the corresponding logit model. The same pattern was evident in the stratified linear and logit models for both genders. Controlling for household income and the individual's ability to save from their current income appeared to attenuate the effect of joblessness on MPM to some extent, but had no effect on the association between insecure employment and the outcome.

4.3.13 Model 13: Adding mediating subjective financial situation to the basic autoregressive model

Three subjective financial situation variables were added to the autoregressive models. These were: (a) financial situation; (b) change in financial position in the last year; and (c) financial expectations for year ahead. The association between labour market status and MPM was attenuated to some degree in the gender-stratified and unstratified linear and logit models. A greater degree of attenuation was observed for M13 than for any of the preceding models. In both the linear and logit unstratified models, the greatest degree of attenuation was seen for the unemployed group. Compared to the securely employed, unemployed individuals had GHQ-12 scores 1.47 units higher and were 1.5 times more likely to be an MPM case. This compares to a coefficient of 2.12 and an odds ratio of 2.41 in the M3 models. The addition of subjective financial status variables also affected the results for the permanently sick, with the odds ratio for this group dropping from 3.8 in M3 to 3.0 in M13. The same pattern of attenuation was observed for the unemployed and permanently sick categories in the gender-stratified models. Controlling for subjective financial situation also attenuated the association between insecure employment and MPM, although not to the same degree as for unemployment and permanent sickness. Compared to the securely employed, the insecurely employed had GHQ-12 scores 1.0 units higher, and were 1.7 times more likely to be cases. This compares to a coefficient of 1.3 and an odds ratio of 1.9 in M3. Similar levels of attenuation were seen in the gender-stratified models for the insecurely employed group.

Results for the 'other inactive' group did not follow the same pattern as those for the other labour market status categories in M13. Controlling for subjective financial situation completely attenuated the association between other inactivity and GHQ-12 score, as the unstratified coefficient decreased from a highly significant 0.52 in M3 to a non-significant 0.06 ($p=0.203$) in M13. The same occurred in the gender-stratified linear models. In the unstratified logit model, the association between 'other' inactivity and MPM caseness was not eliminated, but decreased substantially from 1.32 ($p<0.001$) in M3 to just 1.09 ($p=0.01$) in M13. Stratification of the logit model by gender showed the same pattern as the linear model, with the odds ratio for the other inactive group becoming non-significant for both men and women. Postestimation testing (using the Wald test) showed that with the exception of the insecurely employed and unemployed categories in the females-only logit model, the differences between the coefficients for the labour market status categories within each of the models were statistically significant ($p<0.05$). Owing to the subjective nature of these variables, it is likely that an individual's GHQ-12 score could influence their perception of their financial status in a reversal of the hypothesised direction of causality. It is important, therefore, to recognise this as a potential limitation of these results.

4.3.14 Model 14: The fully adjusted final model

All of the above hypothesised confounding and mediating factors were added to the final model. The final unstratified and gender-stratified linear and logit models all show that labour market status was associated with increased GHQ-12 score and caseness prevalence, after controlling for all of the covariates. Compared to secure employment, being insecurely employed, unemployed, permanently sick or other inactive was predictive of having poorer mental health. The association was attenuated to some degree by adjusting for covariates, but still remained. Differences exist between the six versions of the final model, with regards to the different labour market status categories. In the unstratified linear model, when holding other factors constant, the permanently sick group had the worst mental health, with GHQ-12 scores 2.4 units higher than the securely employed. This was followed by the unemployed group, whose GHQ-12 scores were 1.6 units higher than the referent category. The insecurely employed group had worse mental health than the other inactive group (with coefficients of 1.4 and 1.2 respectively), but fared better than the unemployed and the permanently sick. Postestimation testing (using the Wald test) showed that the differences between the coefficients for the labour market status categories within each of the models were statistically significant ($p<0.05$).

This pattern differed from that observed in the logit model with the caseness outcome. The permanently sick group were still at greatest risk for poor mental health (OR=2.9) but the insecurely employed group were the second worst affected. The insecurely employed were 1.71 times more likely to be MPM cases than the securely employed, compared to an odds ratio of 1.68 for the unemployed and 1.17 for the other inactive. However, the gender-stratified logit model shows that the odds ratio for the insecurely employed was only higher than that of the unemployed for men, and not for women. It must be noted though, that postestimation testing using the Wald test showed that the odds ratios for the insecurely employed and unemployed categories were not significantly different from one another in the unstratified final logit model or either of the gender-stratified final logit models. Insecurely employed men were 2.05 times more likely to be a GHQ-12 case than securely employed men, compared to an odds ratio of 1.78 for unemployed men. Insecurely employed women were only 1.37 times more likely to be GHQ-12 cases than securely employed women, compared to an odds ratio of 1.63 for unemployed women. In the males-only linear and logit final models, the effects of ‘other’ inactivity on MPM were completely attenuated, with the coefficient and odds ratio non-significant. This was not the case for the females-only models or the unstratified models, in which the coefficients and odds ratios for the other inactive were small but significant. A gap between men and women was apparent for the insecurely employed and permanently sick groups. The gender-stratified logit models show that insecurely employed males were 2 times more likely to be a MPM case than their securely employed counterparts, whilst insecurely employed women were only 1.4 times more likely to be a case than securely employed women. Similarly, permanently sick men were 3.7 times more likely to be a GHQ-12 case than securely employed men, compared to a corresponding odds ratio of 2.4 for permanently sick women. Aside from the exception stated above, for the insecurely employed and unemployed categories in all three of the logit models, postestimation Wald testing has shown that the differences between the coefficients for the labour market status categories within each of the final models were statistically significant ($p<0.05$).

4.3.15 Summary

After controlling for sociodemographic factors, lagged GHQ-12 score, and physical health, insecure employment, unemployment, permanent sickness and other inactivity were still associated with both higher GHQ-12 scores and higher GHQ-12 caseness prevalence. The relationship was partly but not entirely mediated by substance abuse, spousal factors, labour market status stability, objective and subjectively measured financial situation, geographical region and social housing tenure. All other factors being equal, among men insecure employment was as harmful to mental health as unemployment, and insecure employment and permanent sickness were associated with much higher levels of MPM in men than in women.

4.3.16 Between and within individual effects

The bivariate unstratified linear random effects model had an overall R^2 value of 0.04, meaning that only 4 percent of the total variance in GHQ-12 score could be explained by labour market status alone. The R^2 value was largely unaffected by the addition of age and gender (M2) but increased dramatically to 0.25 with the addition of lagged GHQ-12 score (M3). This figure then remained between 0.25 and 0.26 throughout models 3-8 and 10-11. The addition of subjective financial status variables increased explanatory power slightly to 0.28 in model 9 and in the final model R^2 increased further to 0.29. This means that approximately thirty percent of the total variance in GHQ-12 scores could be explained by the variables in the final model, but that most of this was due to the lagged GHQ-12 variable.

The addition of the lagged GHQ-12 variable also had a substantial impact on the intra-class correlation coefficient (ICC) of the models. For the crude model the ICC was 0.36, meaning that 36 percent of the total variance in GHQ-12 scores was attributable to between-individual factors. This decreased to 0.023 in M3 (the basic autoregressive model) and then remained fairly constant across models 3-8 and 10-11. The ICC increased slightly to 0.027 in M13 and the final model. This reduction in the proportion of the total unexplained variance in the outcome attributable to between-individual factors with the addition of lagged GHQ-12 was expected, since the lagged variable was added in order to control for clustering of similar GHQ-12 scores within individuals.

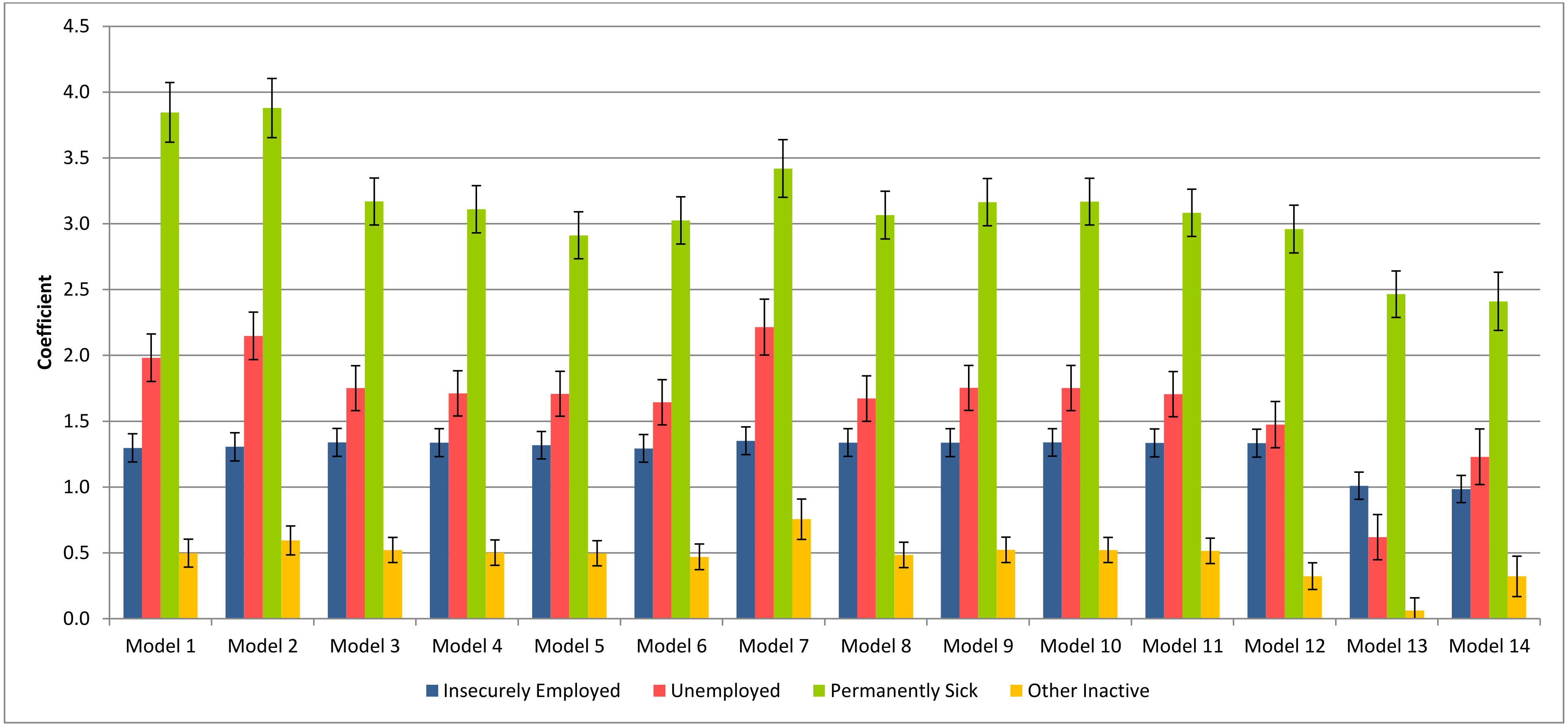

Figure 4.3 Unstratified linear random effects model: the relationship between labour market status and GHQ-12 score

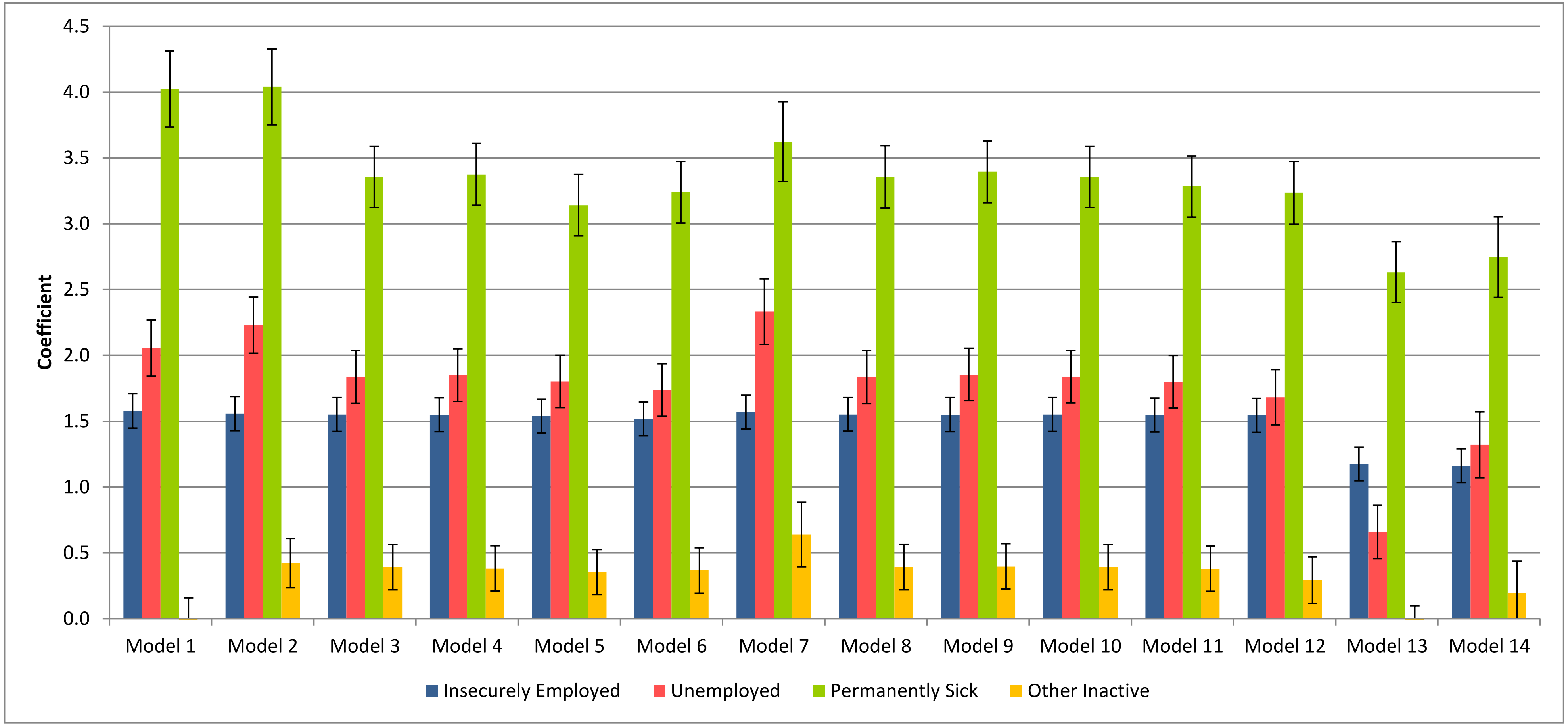

Figure 4.4 Gender-stratified (males only) linear random effects models: the relationship between labour market status and GHQ-12 score

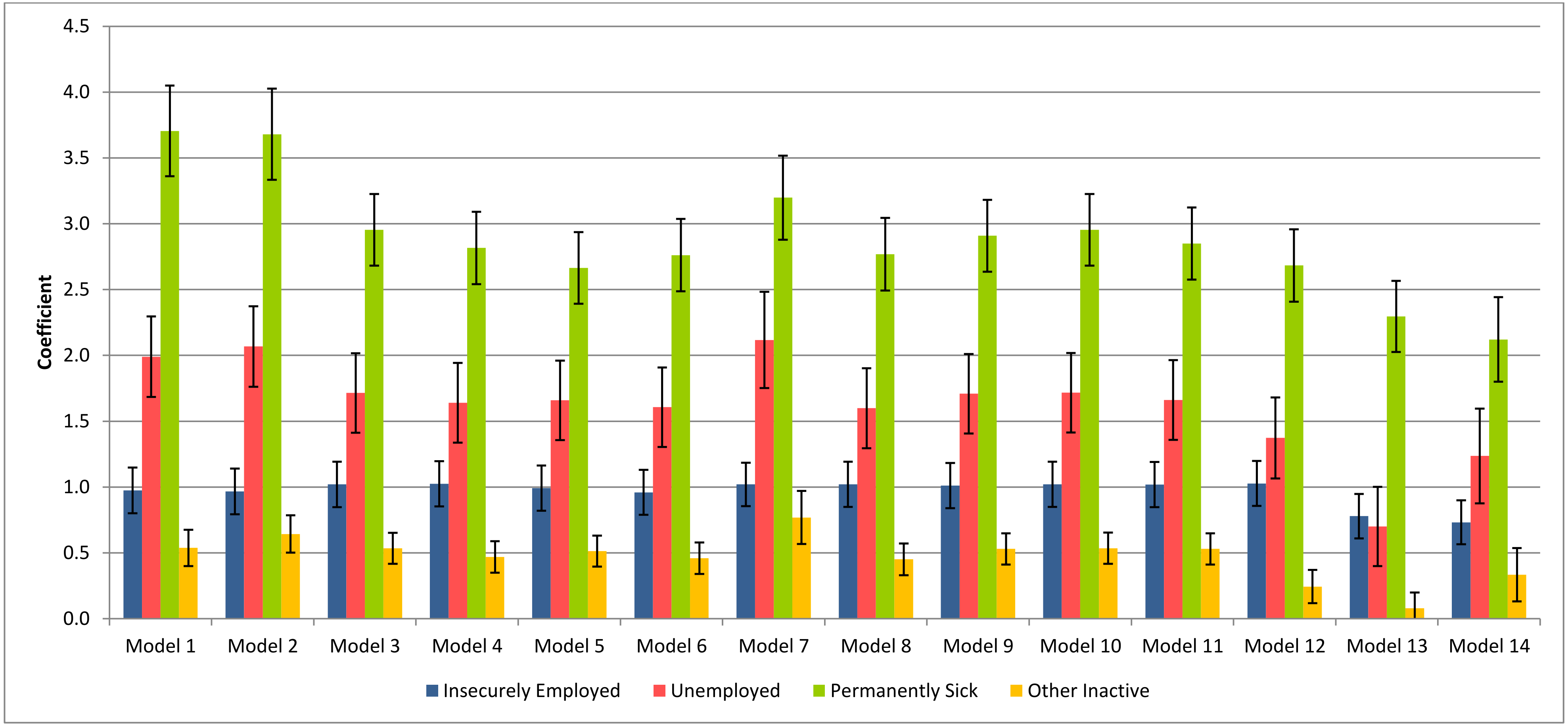

Figure 4.5 Gender-stratified (females only) linear random effects models: the relationship between labour market status and GHQ-12 score

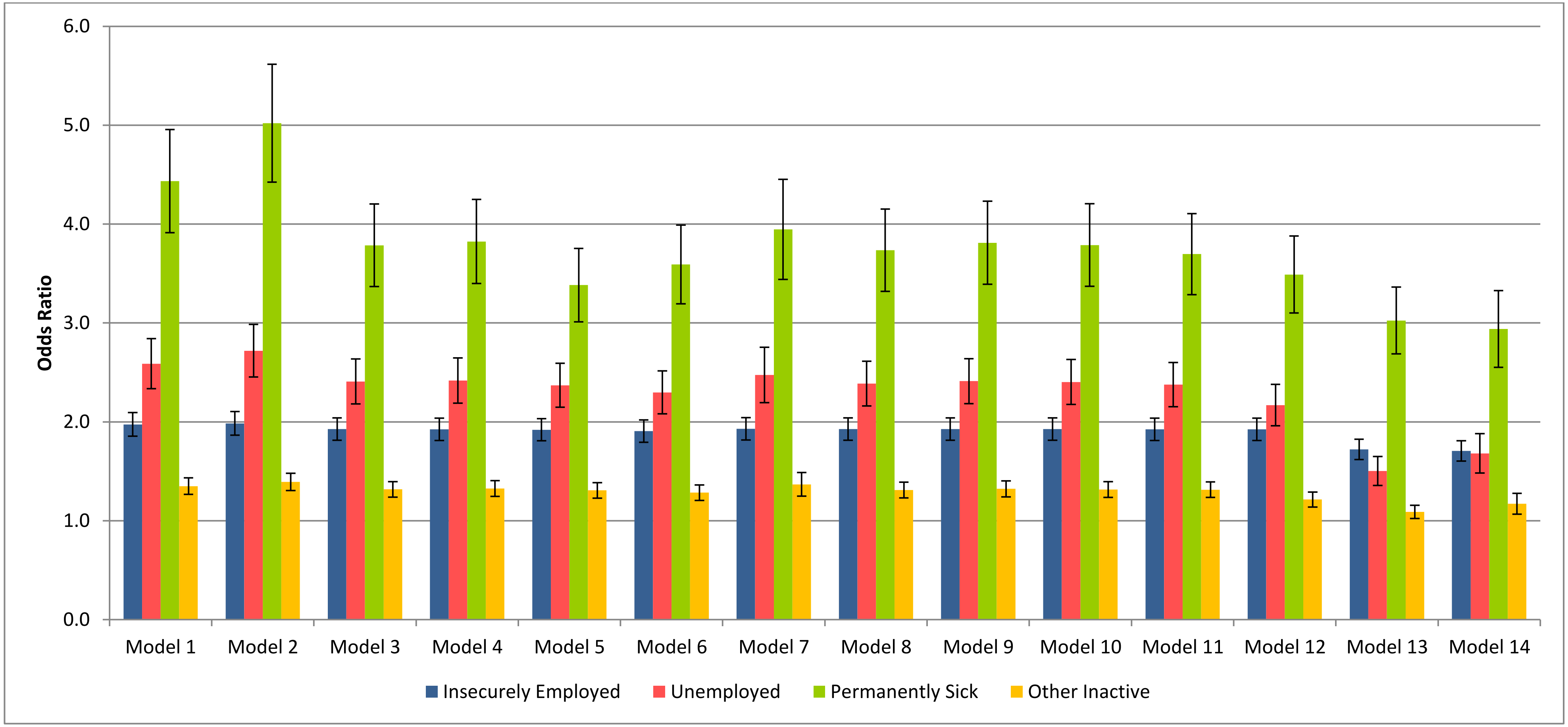

Figure 4.6 Unstratified random effects logit model: the relationship between labour market status and GHQ-12 caseness

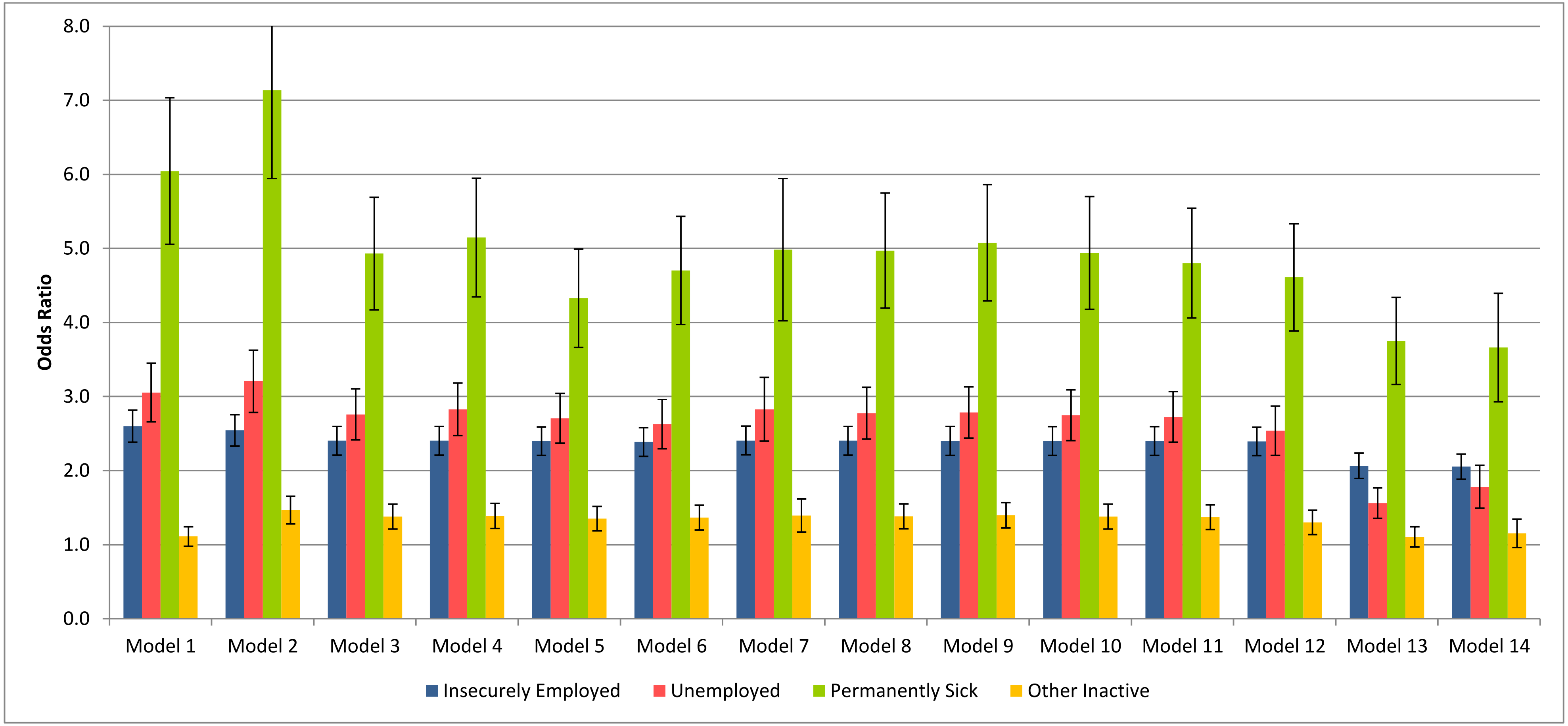

Figure 4.7 Gender-stratified (males only) random effects logit models: the relationship between labour market status and GHQ-12 caseness

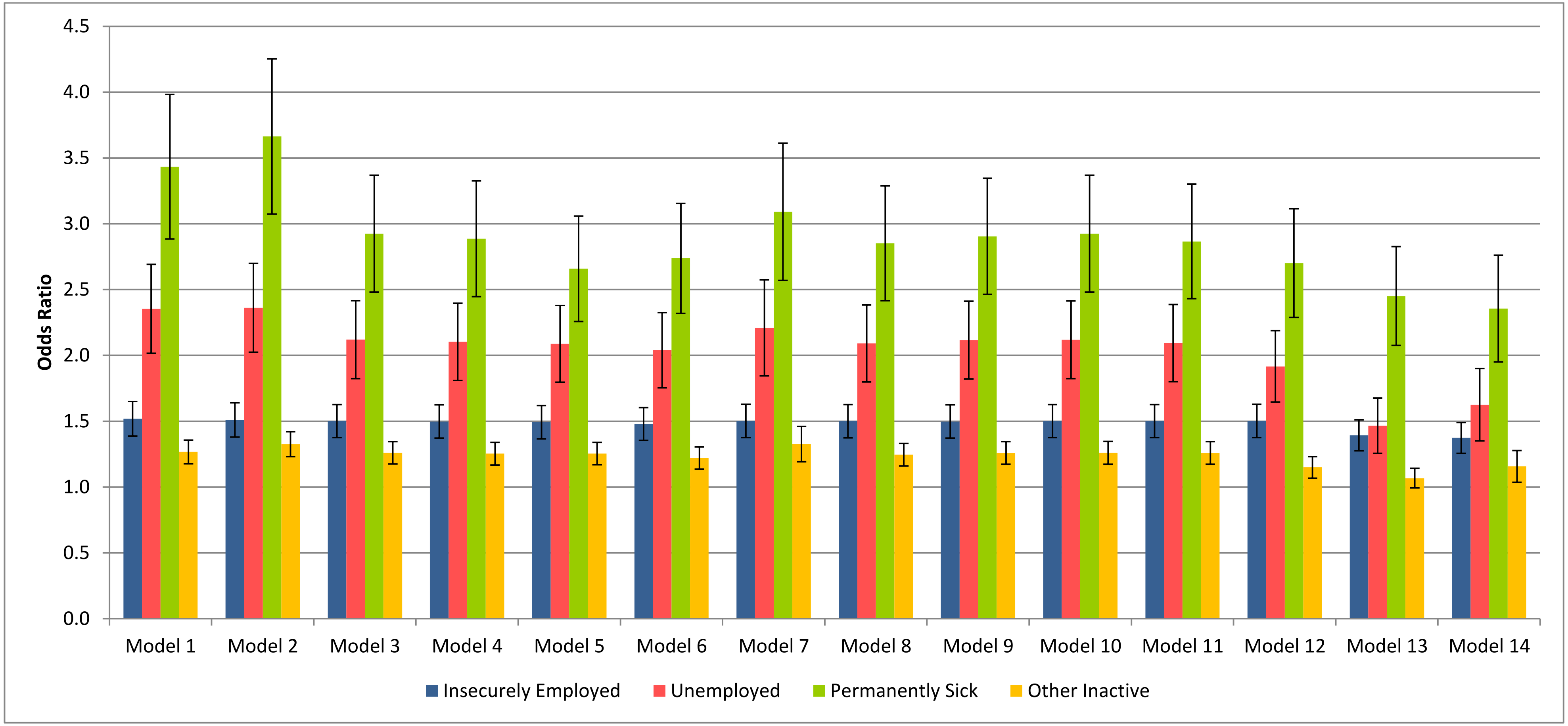

Figure 4.8 Gender-stratified (females only) random effects logit models: the relationship between labour market status and GHQ-12 caseness

4.4 Discussion

The results show that for both the GHQ-12 caseness and GHQ-12 score outcomes, being jobless or insecurely employed was significantly worse for mental health than being securely employed. This applied to both men and women, held true despite adjustment for a wide range of hypothesised confounding factors and could not be explained by financial status or household income differences. This supports the hypotheses and the majority of previous studies on unemployment and adds important new findings on the effects of job insecurity. It is not surprising that the permanently sick category are likely to have higher GHQ-12 scores and are at higher risk of MPM, compared to all of the other labour market status categories. Anxiety and depression are common reasons for why people are eligible to claim permanent sickness benefits and are unable to work. The association between permanent sickness and GHQ-12 outcome was attenuated to some degree in model 5, with adjustment for physical health status.

The use of two differently measured outcomes is valuable as it illuminates different elements of the relationship between labour market status and minor psychiatric morbidity. The normally-distributed Likert scaled linear outcome describes the experience of the average person and is driven by the mean of the distribution. Caseness describes the experiences of those who become depressed and/or recover and allows us to assess the level of clinically significant minor psychiatric morbidity associated with labour market status. Whilst in the main, the series of models for the two different outcome measures showed broadly the same patterns, there were some differences. In the unstratified and males-only final logit models, insecurely employed males were slightly more likely to be an MPM case than unemployed males. However, in the unstratified and males-only linear models, unemployment was a predictor of higher GHQ-12 scores than insecure employment was. For both outcome measures, the effects of being in a labour market status other than secure employment appeared worse for men than for women. Secure employment is the socially normal and expected role for men, and traditionally men have expected an unbroken run of secure employment throughout the whole of their working lives. Women's attachment to the labour market has always been more flexible, and a number of social roles are available to women with regards to labour market engagement (McMunn *et al*., 2006). Whilst the traditional homemaker role is becoming less prevalent, women have always had a socially acceptable alternative role to continuous employment. Similarly, it is generally more common for women to take part time work and to work in highly feminised sectors in which insecure contractual arrangements are common. This may lead women to perceive insecure employment as more normal, and therefore not to become distressed by it to the same degree as men. Despite the large increase in women working full time, there is still a cultural overhang of the traditional male-breadwinner family model (McMunn *et al.*, 2006). This may mean that many women in the period 1991-2007 did not define their identity by their work in the way that perhaps men did.

In summary, the analyses presented in this chapter support the first hypothesis that being in a labour market status other than secure employment predicts higher levels of MPM for both caseness and GHQ-12 score outcome measures. This is consistent with the wider literature, which generally shows that secure employment is the most protective labour market status for psychological wellbeing. The analyses shown in this chapter also support the second hypothesis, that adjusting for potential confounders attenuates the association between labour market status and MPM to some degree, but a significant independent association remains. The third hypothesis is also supported, as the effects of joblessness on MPM were mediated to some extent by financial status variables, but that a strong independent association remained after income, savings and perceived financial situation had been taken into account. This supports Jahoda's (1981, 1982) and Warr's (1985) contention that much of the relationship between labour market status and MPM operates via psychosocial pathways.

4.4.1 Limitations

It is important to question the extent to which the 5-category exposure variable, labour market status, adequately captures the experiences of secure employment, insecure employment, unemployment, inactivity and permanent sickness. Owing to the nature of the question, we are measuring employment status at a set point in time – a snapshot within the year. Attempts have been made in this study to take account of intervening periods of unemployment and/or inactivity in the months since the previous wave's interview. However, adjusting for whether the individual had one or more spells of joblessness in the past 12 months is a fairly crude measure of their labour market status stability. Attempts were made to include a continuous measure of number of weeks unemployed/inactive since the last interview. However, owing to problems with the derivation of the relevant variables in the BHPS, this was not possible within the constraints of the study. Further work is needed on adequately taking into account periods of joblessness between interviews. A greater problem is posed by the lack of a measure of job security/insecurity in the months between interviews.

A subjective assessment of job security is more suitable than an objective measure (such as, contract type) theoretically, since this study is mainly concerned with how the personal experience of feeling insecure at work affects mental health. In the context of recession, many people employed under permanent contracts who formally have a secure employment contract may feel increasingly insecure in their role. They may have fears that the company will become insolvent or that their public sector department may be merged with another, resulting in effective demotion, for example (Ferrie *et al.*, 1995). These individuals would not be classed as insecurely employed if an objective measure such as contract type were used. However, whilst the subjective experience of insecurity is of paramount interest, there is a potential question over causality. An individual with a pessimistic outlook on life may be more likely to have a high GHQ-12 score. It is possible that an employment situation which may be considered reasonably secure by a more optimistic individual could be considered insecure by someone who is more risk averse and more likely to perceive threats in their environment. In addition, it is important to note that the variable used to derive the 'insecurely employed' category did not simply ask respondents to assess their level of job security, but asked instead the extent to which they were satisfied with their level of job security. *("I'm going to read out a list of various aspects of jobs, and after each one I'd like you to tell me from this card which number best describes how satisfied or dissatisfied you are with that particular aspect of your own present job: 4. Your job security").* Conceivably, a respondent could have reported a high level of satisfaction with their level of job security, despite being engaged in very insecure employment. This hypothetical respondent may be satisfied with a high level of job insecurity, as it may meet with their expectations or fulfil their wishes. However, as discussed above, it is the experience of unwanted perceived insecure employment which is of interest in this study.

The measure of physical health used (a binary variable indicating the presence of one or more physical health problems from a list of conditions) could be considered a fairly crude measure of the extent to which someone has a physical health condition which puts them at higher risk of psychological distress. A very broad definition of physical health was used and prevalence was very high. Long term limiting illness may theoretically have been a better variable to control for. However, it was impossible to achieve a limiting illness variable with data for all waves (since such questions were missed out in one or two waves), and which allowed mental health conditions to be isolated from physical health problems. Using a broader self-rated health question would have included mental health problems (probably largely anxiety and depression) and would have resulted in over-adjustment.

Whilst GDP growth is commonly used to measure the business cycle and define recession and expansion, the resumption of GDP growth following a period of contraction may still leave workers unemployed and factories closed. Economists argue that the margin of unused resources in the economy (i.e. the difference between actual and potential output) is a more sensitive indicator. The problem encountered by economists is that potential output is inherently difficult to measure since the notion of capacity is very hard to define, particularly in the service sector where hours worked are often not directly related to output. Economists have attempted to construct proxies for potential output (De Masi, 1997). One approach is to plot a smooth trend line through the fluctuating points of actual GDP, assuming that potential output evolves smoothly over time (Bean, 2010). A second approach combines measures of capital and available labour force (after correcting for any labour market frictions) with assumptions about the level of technology the workers will use to produce output (Bean, 2010). An alternative method uses measures of unused resources derived from surveys to draw inferences about the trends in potential output (Bean, 2010). The application and use of any of these methods is beyond the scope of this PhD thesis. However, it is important to acknowledge that the use of percentage annual GDP growth as a sole measure of macroeconomic performance and the business cycle is crude by the standards of economists. In addition, the effect that gross domestic product growth has on the fortunes of individual citizens is tempered by factors such as welfare policy.

The subjective financial status variables were the strongest predictors of the outcome and along with lagged GHQ-12 made the largest contribution towards the attenuation of risk between the crude and final models. However, their subjective nature poses a significant limitation. Those with an affective disorder may be more likely to perceive their financial situation in a pessimistic light. It is likely that reverse causality may be at play, as it is unclear whether a poor financial situation is at the root of poor mental health, or whether poor mental health causes the individual to interpret their financial situation more negatively. This is the inherent problem with using a subjective measure of financial status, and is similar to the issues raised over the use of a subjective measure of job security. It may be particularly problematic for the variable which asks the respondent how they expect their financial situation in one year's time will compare to their current situation. Respondents suffering from depression are more likely to have less hope for the future generally, and therefore may give a more pessimistic answer than a more objective projection may give.

The regions used in this model are Government Office Regions. These areas are much larger than local labour markets and have no particular theoretical basis in terms of regional economies. The next chapter will look in much greater detail at regions.

4.4.2 Strengths

The use of autoregressive modelling, with lagged GHQ-12 score added into the models as a covariate, allows preliminary suggestions to be made about the direction of causality. This is explored in more detail in chapter 6. A further strength of this research is the differentiation between secure and insecure employment, a distinction often overlooked in the literature but one which is of great importance in the post-Fordist labour market. In addition, economic inactivity is considered alongside registered unemployment. This study also allows separate conclusions to be drawn for each gender, using gender-stratified models. Many previous studies in the field concentrate only on men, so investigation into the effects of labour market status on the psychological wellbeing of women is much needed.

4.5 Conclusions

The results of the nested linear and logit random effects models presented in this chapter show that labour market status remained a significant predictor of MPM, after controlling for the effects of a range of potential confounding factors, and adjusting for the effects of a number of supposed mediators. The effects can be seen for both average GHQ-12 score, and MPM prevalence, showing that it is not just controlled by the centre of the distribution, and that it applies to both the clinically relevant cut-off point and the general population. The following chapters explore the extent to which these effects vary across space and through time.

4.6 Appendices

Appendix 4.1 Unstratified Random Effects Linear Model: Labour Market Status and GHQ-12 Caseness. (Regression coefficients with 95% confidence intervals in parentheses).

Labour Market Status (sec. emp. omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**1.30**	**1.31**	**1.34**	**1.34**	**1.32**	**1.29**	**1.35**	**1.34**	**1.34**	**1.34**	**1.34**	**1.33**	**1.01**	**0.99**
	(1.19-1.40)	(1.20-1.41)	(1.23-1.45)	(1.23-1.44)	(1.21-1.42)	(1.19-1.40)	(1.25-1.46)	(1.23-1.44)	(1.23-1.44)	(1.23-1.45)	(1.23-1.44)	(1.23-1.44)	(0.91-1.11)	(0.88-1.09)
Unemployed	**1.98**	**2.15**	**1.75**	**1.71**	**1.71**	**1.64**	**2.22**	**1.67**	**1.75**	**1.75**	**1.71**	**1.47**	**0.62**	**1.23**
	(1.80-2.16)	(1.99-2.33)	(1.58-1.92)	(1.54-1.88)	(1.54-1.88)	(1.47-1.82)	(2.00-2.43)	(1.50-1.85)	(1.58-1.92)	(1.58-1.92)	(1.53-1.88)	(1.30-1.65)	(0.45-0.79)	(1.02-1.44)
Perm. Sick	**3.85**	**3.88**	**3.17**	**3.11**	**2.91**	**3.03**	**3.42**	**3.07**	**3.16**	**3.17**	**3.08**	**2.96**	**2.47**	**2.41**
	(3.62-4.07)	(3.65-4.10)	(2.99-3.35)	(2.93-3.29)	(2.73-3.09)	(2.85-3.20)	(3.20-3.64)	(2.88-3.25)	(2.96-3.34)	(2.99-3.35)	(2.90-3.26)	(2.78-3.14)	(2.29-2.64)	(2.19-2.63)
Other Inactive	**0.50**	**0.59**	**0.52**	**0.50**	**0.50**	**0.47**	**0.76**	**0.48**	**0.52**	**0.52**	**0.52**	**0.32**	***0.06***	**0.32**
	(0.39-0.60)	(0.48-0.71)	(0.42-0.62)	(0.41-0.60)	(0.40-0.59)	(0.37-0.57)	(0.60-0.91)	(0.39-0.58)	0.43-0.62)	(0.43-0.62)	(0.42-0.61)	(0.22-0.42)	*(-0.03-0.16)*	(0.17-0.47)

Appendix 4.2 Stratified Random Effects Linear Models (men only): Labour Market Status and GHQ-12 Caseness. (Regression coefficients with 95% confidence intervals in parentheses).

Labour Market Status (sec. emp. omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**1.58**	**1.56**	**1.55**	**1.55**	**1.54**	**1.52**	**1.57**	**1.55**	**1.55**	**1.55**	**1.55**	**1.55**	**1.18**	**1.16**
	(1.47-1.71)	(1.43-1.70)	(1.42-1.68)	(1.42-1.68)	(1.41-1.67)	(1.39-1.65)	(1.44-1.70)	(1.42-1.68)	(1.42-1.68)	(1.42-1.68)	(1.42-1.68)	(1.42-1.67)	(1.05-1.30)	(1.03-1.29)
Unemployed	**2.06**	**2.23**	**1.84**	**1.85**	**1.80**	**1.74**	**2.33**	**1.84**	**1.86**	**1.84**	**1.80**	**1.68**	**0.66**	**1.32**
	(1.84-2.27)	(2.02-2.44)	(1.84-2.04)	(1.65-2.05)	(1.60-2.00)	(1.54-1.94)	(2.08-2.58)	(1.63-2.04)	(1.66-2.06)	(1.60-2.00)	(1.60-2.00)	(1.47-1.89)	(0.46-0.86)	(1.07-1.60)
Perm. Sick	**4.02**	**4.04**	**3.36**	**3.38**	**3.14**	**3.24**	**3.62**	**3.36**	**3.40**	**3.36**	**3.28**	**3.24**	**2.63**	**2.75**
	(3.74-4.31)	(3.75-4.33)	(3.36-3.56)	(3.14-3.61)	(2.91-3.38)	(3.24-3.47)	(3.32-3.93)	(3.12-3.59)	(3.16-3.63)	(3.12-3.59)	(3.05-3.52)	(3.00-3.47)	(2.40-2.87)	(2.44-3.05)
Other Inactive	***-0.02***	**0.42**	**0.39**	**0.38**	**0.35**	**0.37**	**0.64**	**0.39**	**0.40**	**0.39**	**0.38**	**0.29**	***-0.07***	***0.20***
	(-0.19-0.16)	(0.24-0.61)	(0.22-0.56)	(0.21-0.56)	(0.18-0.53)	(0.19-0.54)	(0.39-0.88)	(0.22-0.56)	(0.23-0.57)	(0.22-0.56)	(0.21-0.55)	(0.12-0.47)	*(-0.24-0.10)*	*(-0.05-0.44)*

Appendix 4.3 Unstratified Random Effects Logit Models: Labour Market Status and GHQ-12 Caseness. (Odds ratios with 95% confidence intervals in parentheses).

Labour Market Status (securely employed omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**1.97** (1.86-2.10)	**1.98** (1.86-2.11)	**1.93** (1.82-2.05)	**1.93** (1.81-2.05)	**1.92** (1.80-2.04)	**1.91** (1.79-2.03)	**1.93** (1.82-2.05)	**1.93** (1.81-2.05)	**1.93** (1.81-2.05)	**1.93** (1.81-2.05)	**1.93** (1.81-2.05)	**1.92** (1.81-2.04)	**1.72** (1.62-1.83)	**1.71** (1.60-1.81)
Unemployed	**2.59** (2.34-2.87)	**2.72** (2.45-3.01)	**2.41** (2.18-2.66)	**2.42** (2.19-2.67)	**2.37** (2.15-2.62)	**2.30** (2.08-2.54)	**2.47** (2.19-2.79)	**2.39** (2.16-2.64)	**2.41** (2.19-2.66)	**2.40** (2.18-2.65)	**2.38** (2.15-2.62)	**2.17** (1.96-2.40)	**1.50** (1.36-1.67)	**1.68** (1.48-1.91)
Perm. Sick	**4.44** (3.91-5.03)	**5.02** (4.43-5.70)	**3.79** (3.37-4.25)	**3.82** (3.40-4.30)	**3.38** (3.01-3.80)	**3.59** (3.19-4.04)	**3.95** (3.44-4.53)	**3.74** (3.32-4.20)	**3.81** (3.39-4.28)	**3.79** (3.37-4.26)	**3.70** (3.29-4.15)	**3.49** (3.10-3.93)	**3.03** (2.69-3.41)	**2.94** (2.55-3.39)
Other Inactive	**1.35** (1.27-1.44)	**1.39** (1.31-1.49)	**1.32** (1.24-1.40)	**1.33** (1.25-1.41)	**1.31** (1.23-1.39)	**1.28** (1.21-1.37)	**1.37** (1.25-1.50)	**1.31** (1.23-1.39)	**1.32** (1.24-1.41)	**1.32** (1.24-1.40)	**1.31** (1.24-1.40)	**1.22** (1.14-1.30)	**1.09** (1.02-1.16)	**1.17** (1.07-1.29)

Appendix 4.4 Stratified Random Effects Linear Models (women only): Labour Market Status and GHQ-12 Caseness. (Regression coefficients with 95% confidence intervals in parentheses).

Labour Market Status (sec. emp. omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**0.98** (0.80-1.14)	**0.97** (0.79-1.14)	**1.02** (0.85-1.19)	**1.03** (0.85-1.20)	**0.99** (0.82-1.16)	**0.96** (0.79-1.31)	**1.02** (0.85-1.20)	**1.02** (0.85-1.19)	**1.01** (0.84-1.18)	**1.02** (0.85-1.19)	**1.02** (0.85-1.19)	**1.03** (0.86-1.20)	**0.78** (0.61-0.95)	**0.73** (0.56-0.90)
Unemployed	**1.99** (1.69-2.30)	**2.07** (1.76-2.37)	**1.72** (1.41-2.02)	**1.64** (1.34-1.94)	**1.66** (1.36-1.96)	**1.61** (1.31-1.91)	**2.12** (1.75-2.48)	**1.60** (1.30-1.90)	**1.71** (1.41-2.01)	**1.72** (1.42-2.02)	**1.66** (1.36-1.97)	**1.37** (1.07-1.68)	**0.70** (0.40-1.00)	**1.24** (0.88-1.60)
Perm. Sick	**3.71** (3.36-4.05)	**3.68** (3.33-4.03)	**2.95** (2.68-3.23)	**2.82** (2.54-3.09)	**2.66** (2.93-2.94)	**2.76** (2.49-3.04)	**3.20** (2.88-3.52)	**2.77** (2.50-3.05)	**2.91** (2.64-3.18)	**2.95** (2.68-3.23)	**2.85** (2.58-3.12)	**2.68** (2.41-2.30)	**2.30** (2.03-2.57)	**2.12** (1.80-2.44)
Other Inactive	**0.54** (0.40-0.68)	**0.64** (0.50-0.78)	**0.53** (0.42-0.65)	**0.47** (0.35-0.59)	**0.51** (0.40-0.63)	**0.46** (0.34-0.58)	**0.77** (0.57-0.97)	**0.45** (0.33-0.57)	**0.53** (0.41-0.65)	**0.54** (0.42-0.65)	**0.53** (0.41-0.65)	**0.24** (0.12-0.37)	0.08 (-0.04-0.20)	**0.33** (0.13-0.60)

Appendix 4.5 Stratified Random Effects Logit Models (men only): Labour Market Status and GHQ-12 Caseness. (Odds ratios with 95% confidence intervals in parentheses).

Labour Market Status (securely employed omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**2.60**	**2.54**	**2.40**	**2.40**	**2.40**	**2.39**	**2.41**	**2.40**	**2.40**	**2.40**	**2.40**	**2.39**	**2.07**	**2.05**
	(2.38-2.84)	(2.33-2.78)	(2.21-2.61)	(2.21-2.61)	(2.20-2.61)	(2.19-2.60)	(2.21-2.61)	(2.21-2.61)	(2.21-2.61)	(2.21-2.61)	(2.20-2.61)	(2.20-2.61)	(1.90-2.25)	(1.89-2.24)
Unemployed	**3.05**	**3.21**	**2.76**	**2.83**	**2.71**	**2.63**	**2.83**	**2.78**	**2.79**	**2.75**	**2.72**	**2.54**	**1.56**	**1.78**
	(2.66-3.51)	(2.79-3.69)	(2.42-3.15)	(2.47-3.23)	(2.37-3.09)	(2.30-3.01)	(2.40-3.34)	(2.43-3.18)	(2.44-3.18)	(2.41-3.14)	(2.38-3.11)	(2.21-2.92)	(1.35-1.80)	(1.49-2.13)
Perm. Sick	**6.05**	**7.14**	**4.93**	**5.15**	**4.33**	**4.70**	**4.98**	**4.97**	**5.08**	**4.94**	**4.80**	**4.61**	**3.75**	**3.66**
	(5.06-7.23)	(5.95-8.57)	(4.17-5.83)	(4.35-6.09)	(3.66-5.11)	(3.97-5.57)	(4.02-6.17)	(4.19-5.89)	(4.29-6.00)	(4.18-5.84)	(4.06-5.68)	(3.89-5.47)	3.16-4.45)	(2.93-4.58)
Other Inactive	1.11	**1.47**	**1.38**	**1.39**	**1.35**	**1.37**	**1.39**	**1.38**	**1.40**	**1.38**	**1.37**	**1.30**	*1.10*	1.15
	(0.98-1.26)	(1.28-1.68)	(1.21-1.57)	(1.22-1.58)	(1.19-1.54)	(1.20-1.56)	(1.17-1.66)	(1.21-1.57)	(1.23-1.59)	(1.21-1.57)	(1.20-1.56)	(1.14-1.49)	*(0.97-1.26)*	(0.96-1.38)

Appendix 4.6 Stratified Random Effects Logit Models (women only): Labour Market Status and GHQ-12 Caseness. (Odds ratios with 95% confidence intervals in parentheses).

Labour Market Status (securely employed omitted)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
Insecurely Employed	**1.52**	**1.51**	**1.50**	**1.50**	**1.49**	**1.48**	**1.50**	**1.50**	**1.50**	**1.50**	**1.50**	**1.50**	**1.39**	**1.37**
	(1.39-1.66)	(1.38-1.65)	(1.38-1.64)	(1.37-1.64)	(1.37-1.63)	(1.34-1.62)	(1.38-1.64)	(1.37-1.64)	(1.37-1.64)	(1.38-1.64)	(1.38-1.64)	(1.38-1.64)	(1.28-1.52)	(1.26-1.50)
Unemployed	**2.35**	**2.36**	**2.12**	**2.10**	**2.09**	**2.04**	**2.21**	**2.09**	**2.12**	**2.12**	**2.09**	**1.92**	**1.47**	**1.63**
	(2.02-2.75)	(2.02-2.76)	(1.82-2.46)	(1.81-2.44)	(1.80-1.35)	(1.75-2.37)	(1.85-2.64)	(1.80-2.43)	(1.82-2.46)	(1.82-2.46)	(1.80-2.43)	(1.65-2.23)	(1.26-1.71)	(1.35-1.96)
Perm. Sick	**3.43**	**3.66**	**2.93**	**2.89**	**2.66**	**2.74**	**3.09**	**2.85**	**2.90**	**2.93**	**2.87**	**2.70**	**2.45**	**2.36**
	(2.88-4.09)	(3.08-4.37)	(2.48-3.45)	(2.45-3.41)	(2.26-3.13)	(2.32-3.23)	(2.57-3.72)	(2.42-3.37)	(2.46-3.43)	(2.48-3.45)	(2.43-3.38)	(2.29-3.19)	(2.08-2.90)	(1.95-2.84)
Other Inactive	**1.27**	**1.33**	**1.26**	**1.25**	**1.26**	**1.22**	**1.33**	**1.25**	**1.26**	**1.26**	**1.26**	**1.15**	1.07	**1.16**
	(1.18-1.36)	(2.02-2.76)	(1.18-1.35)	(1.17-1.35)	(1.17-1.35)	(1.14-1.31)	(1.19-1.48)	(1.16-1.34)	(1.17-1.35)	(1.17-1.35)	(1.17-1.35)	(1.07-1.24)	(0.99-1.15)	**(1.04-1.29)**

Chapter 5

Investigating the Extent to which Area-Level Characteristics affect Minor Psychiatric Morbidity

5 Investigating the extent to which area-level characteristics of local labour markets affect Minor Psychiatric Morbidity outcomes

5.1 Introduction

It was shown in chapter 4 that being jobless or insecurely employed was significantly worse for mental health than being securely employed. This was found to apply to both men and women, and the complex nature of the relationship was unpacked using nested autoregressive random effects models. The strong association between labour market status and GHQ-12 score has been seen to withstand adjustment for a wide range of hypothesised confounding factors and could not be explained away by financial status or household income differences between the securely employed reference group and the insecurely employed or jobless groups. This chapter builds on the previous one by expanding the research question to consider the place in which individuals live, and the effect exposures at the area level may have on psychological wellbeing regardless of the individual experience of joblessness and job insecurity.

Since the early 1990s, a strong focus on the ways in which 'place', loosely defined as *"a process by which social, economic, and political relations produce meanings for and through particular spaces"* (Massey, 1994 p.154), contributes to and independently constitutes spatial variations in health outcomes, has been apparent in the fields of epidemiology and geography. A distinction between 'compositional' (individual characteristics, aggregated to area population level) and 'contextual' (indivisibly measurable at the area level) effects developed, in which these two dimensions were often set up as a mutually exclusive dichotomy (MacIntyre *et al.,* 2002). In reality the sociocultural milieu of a place and the characteristics of its inhabitants are mutually constitutive and the perceived distinction between contextual and compositional effects is more of a convenient construct than a reflection of reality. Multilevel modelling should therefore not be used purely to isolate and compare the proportion of unexplained variation in the outcome at the area versus individual levels, attributing the former to an indefinable contextual effect or place-based "*social miasma*" (Sloggett and Joshi, 1994. p.1470). Cummins *et al.* (2007) and others have called for a greater focus on the use of multilevel models to elucidate causal pathways and processes to explain the complex effects of place on health and the ways in which these are entangled with individual-level exposures. Rather than asking simply whether place 'matters', it is crucial to build models which attempt to define which specific characteristics of places matter, for which specific outcomes and with what hypothesised mechanisms.

This chapter is concerned with investigating the extent to which the unemployment rate of the area in which an individual lives affects their psychological wellbeing, and the extent to which this is dependent on their own labour market status. It seems intuitive that areas with high claimant count rates (CCR) probably have low demand for labour, resulting in greater competition for each job among the local unemployed and therefore engendering greater stress and anxiety levels within this group. However, this is not borne out by the evidence. Authors in the field of economics have suggested an alternative hypothesis that if one conceptualises unemployment as a 'social norm', the utility impact of an individual's own unemployment will be reduced by a higher level of contextual unemployment (Clark and Oswald, 1994; Clark, 2003; Powdthavee, 2006). In early work on the subject, Clark and Oswald noted a relationship between the regional rate of joblessness and the average unemployment related increase in GHQ-12 score. From calculation of utility gap figures, the authors suggested that unemployment is "*relatively more unpleasant the less there is of it"*, which in their research, was broadly the case in the South and East of England (Clark and Oswald, 1994 p.562). In later work using multivariate analysis of the BHPS, Clark (2003) showed that high ILO unemployment rates at the government office region level were associated with lower GHQ-12 scores among unemployed residents concluding, in a similar fashion to his earlier work, that *"unemployment hurts less the more there is of it around"* (Clark, 2003 p.326). In an extension to this work, Powdthavee concluded from multivariate analysis of South African data that *"it may be psychologically easier to be unemployed in a region with a high level of joblessness"* (Powdthavee, 2006 p.649). Similar findings have also been reported in the epidemiological literature. In an ecological study of England and Wales, Jackson and Warr (1987) found that GHQ-12 scores among the unemployed were significantly lower in areas of high unemployment and that this association withstood adjustment for a limited range of individual-level confounders. Platt and Kreitman (1990) found lower suicide and parasuicide rates among the unemployed in Edinburgh's areas of high unemployment, compared to the city's areas of low unemployment. These findings were corroborated by results from a similar study in Italy (Platt *et al.,* 1992).

Much of the evidence upon which the current consensus rests is ecological. Where multivariate analysis of individual level data has been used, there has been little attempt to introduce the methodological advantages of multilevel modelling to this research question. The investigation undertaken for this chapter will make an original contribution to our understanding of the complex interrelationships between the labour market participation characteristics of where we live, our own labour market status, and the many other factors in our lives which affect our psychological wellbeing through time. To the author's knowledge, no other studies have sought to adequately model the 'realistically complex' (Best *et al.,* 1996) longitudinal and spatial hierarchical structure of the BHPS in relation to this substantive research topic, in a UK setting.

In addition, previous research uses the concepts of 'unemployment' and 'joblessness' interchangeably, when it has been established that a more precise definition of labour market status is crucial. This overemphasis on registered unemployment as opposed to other forms of worklessness and insecure labour market engagement is typical of the literature overall. This research will distinguish between unemployment, permanent sickness and other inactivity, and will consider insecure employment as an important labour market status category in its own right. It is important to recognise that there may be differential effects of area-level unemployment rates on different forms of labour market participation.

5.1.1 Research Question

To what extent does area level claimant count rate affect minor psychiatric morbidity, independently of individual-level exposure to joblessness and insecure employment?

5.1.2 Objectives

1. Is there independent variation in GHQ-12 at the area level, after accounting for variation within and between individuals? Does 'place' superficially appear to matter?

2. Is area level claimant count rate associated with individual-level GHQ-12 score? Is this independent of individual-level confounding factors such as age, gender etc., and can it be explained by hypothesised mediating factors such as household income?

3. Is it more psychologically distressing to be unemployed in an area with a high claimant count rate, compared to an area with a low claimant count rate? What is the relationship with insecure employment, permanent sickness and other inactivity?

5.1.3 Hypotheses

1. There will be a small amount of independent variation in GHQ-12 scores at the area level. This will disappear once individual-level covariates such as age, gender etc. are accounted for.

2. Area level claimant count rate will have a small independent association with individual GHQ-12 score, but this will disappear once individual-level characteristics are adjusted for.

3. In line with findings from Clark and Oswald (1994), the effect of area level claimant count rate on GHQ-12 score will vary according to an individual's labour market status. Living in an area of low overall unemployment will be associated with higher levels of psychological distress among the unemployed than living in an area of high overall unemployment.

5.2 Methods

5.2.1 Defining geographical units and obtaining annual area-level variables

5.2.1.1 Travel-to-Work Areas

Arguably, the most theoretically appropriate geographical units for exploring the effects of characteristics of local labour markets on individual-level psychological distress are Travel-to-Work Areas (TTWA). These units are designed to encapsulate local labour markets. They are defined using the following criteria: (i) at least 75 percent of the resident economically active population must work in the area; and (ii) at least 75 percent of everyone working in the area must also live there. In 2007 there were 243 TTWAs in the United Kingdom (*http://www. statistics.gov.uk/geography/ttwa.asp*). During the 18 years of the BHPS study period used in this analysis (1992-2008), TTWAs have been redefined (*http://www.statistics.gov.uk/ geography/downloads/2001_TTWA_Methodology.pdf)*. The TTWA classifications issued in 1996 were based on data aggregated up from 1991 wards using 1991 census data. In 2007, a new TTWA classification was introduced, aggregated up from Lower Super Output Areas (LSOAs) using 2001 census data. It is important to note that 1991 wards and LSOAs are not equivalent and are not nested. Both versions of TTWA indicators are available with the BHPS from the UK Data Archive, allowing identification of which TTWA each respondent resided in at each wave, using either system or a combination of both. After acquiring TTWA indicators for all waves of the BHPS, it was necessary to ascertain the availability of TTWA-level variables such as claimant count rates, which describe the socioeconomic conditions of the areas over time. Unfortunately, it was not possible to acquire appropriate TTWA-level data for the years 1991-2004 from Nomis, National Statistics or any official source. This is because mid-year population estimates for TTWAs are no longer supported for historical data, prior to 2004 *(Nomis: Peter Dodds and Peter Henderson, personal correspondence 10/11/10 and 24/11/10).* Rates therefore cannot be calculated, rendering annual figures for indicators such as claimant count incomparable over time. The solution to this initial problem was to acquire either rates, or numerators and mid-year population estimates separately for the constituent lower-level geographical units (1991 census wards and LSOAs) and then aggregate up to TTWA-level using matching tables which show how wards/LSOAs were allocated to TTWAs under both TTWA systems. This solution proved to be problematic, since rates are not available for annual data between 1991 and 2001. This is because mid-year population estimates for 1991 wards are no longer available (aside from the census year itself, which falls just before the study period anyway). Therefore populations and hence rates cannot be aggregated up to create rates at the TTWA-1991 level. A second problem was that for the first few years of the new TTWA-2001 system, rates are not available from Nomis, so data would have to have been aggregated up from LSOAs using the experimental small-areas mid-year population statistics from ONS. Caution is advised when using these figures and it is doubtful whether the appropriate level of accuracy could be ensured. It was therefore decided that the practical barriers to using TTWAs rendered the preferred methodology impossible to achieve, given the parameters of a PhD project. In addition, it should be recognised that TTWAs have theoretical problems associated with their derivation, and are not a perfect solution in any case. It has been argued that TTWAs misrepresent local labour markets for the unemployed and lead to underestimation of unemployment in urban areas (Thomas, 1998; Webster and Turok, 1997).

5.2.1.2 Local Authority Districts

It was decided that the pre-2009 version of Local Authority Districts (LADs) would be used instead of TTWAs. This was a compromise between theoretical and practical concerns. Pre-2009 LADs are harmonised across the study period (1992-2008) and annual population data are supported. Being a widely-used geographical indicator, more data are available at this level than at other geographical levels. Whilst it cannot be argued that LADs represent isolated labour markets (especially within Greater London which is conceptualised as a single TTWA but comprised of a 33 LADs), or represent ‘neighbourhood’ owing to their relatively large size, it is felt that LADs are the only geographical unit at which the desired comparable data are available annually, over areas whose definitions do not change over time. The fact that their use has necessitated significant theoretical compromises underlines the need for more resources directed towards work on harmonisation of geographical data across space and time. Even using the most practically suitable geographical unit, it was only possible to find one area-level variable which vaguely characterised the local labour market and general socioeconomic profile of the area, for which comparable annual figures were available: Claimant Count Rate. Details of the LAD-area variables investigated and their coverage and comparability over the 18 year period are detailed in Appendix 5.1. Even though these were the best indicators available, there were still small gaps in coverage.

5.2.1.3 LAD-level variable: claimant count rate

It is important not to overstate the ability of LAD level claimant count rate to completely or accurately summarise the state of a local economy or labour market. It is a measure of the proportion of residents claiming unemployment benefits and therefore registered as unemployed. This may underestimate levels of unmet need for work, particularly among groups such as economically inactive women, which generally have higher LFS unemployment rates than their claimant count rate would predict (Machin, 2004). It also does not reflect hidden unemployment which may be prevalent amongst economically inactive and permanently sick groups in the area. In areas with high levels of economic inactivity, and potentially high hidden unemployment, the claimant count rate may significantly underestimate the burden of joblessness in the area.

5.2.2 Sample

The BHPS sample used for this study has the same basis as the sample used in chapters 3 and 4, although is different in two important ways: it includes data from wave 18 of the study (released in June, 2010); and it does not include observations from Scotland (since claimant count rates for Scottish LADs were found to be unavailable for the years 1992-1995). Aside from these important differences, the sample has the same basis as the sample defined in chapters 3 and 4 (see Figure 5.1). It consists of BHPS original sample members between the ages of 16-65, who have complete data for at least two consecutive waves of the BHPS. As in chapters 3 and 4, this was defined by running the final random effects model, including all hypothesised confounding and mediating variables, and then selecting only those observations used in the model, to be the final sample. This procedure was executed using the 'e(sample)' command in Stata, which is can be run after a regression model in order to cut the sample down to only those observations used in the model.

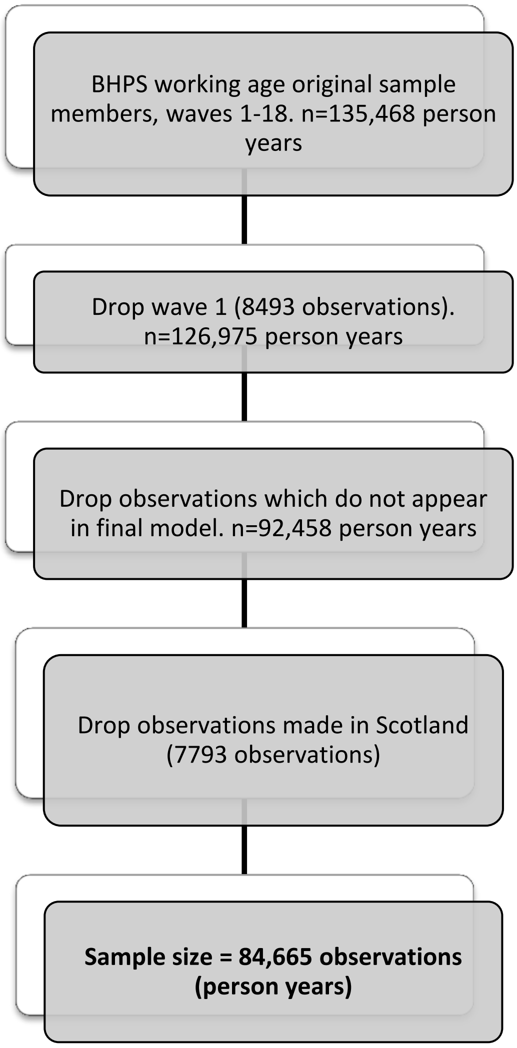

Figure 5.1 Flowchart to show sample size and definition

5.2.3 Variables

The outcome variable used in this chapter is the continuous Likert scaled GHQ-12 variable, described in Table 5.1. The GHQ-12 caseness outcome used in chapter 4 was not included as an outcome of interest in this or the following chapter, since there was little difference in the conclusions drawn from the parallel analyses on both continuous and caseness outcomes in chapter 4.

Table 5.1 Summary statistics for GHQ-12 score outcome, person-years of data, chapter 5 sample.

	Mean	Std. Dev.	Min	Max	Observations
Outcome: GHQ-12 score (0-36 Likert scaled)	11.11	5.41	0	36	N = 84665

A slight upward trend in GHQ-12 scores can be observed throughout the study (Figure 5.2) and a continuous wave variable is positively associated with GHQ-12 score in the data (coefficient: 0.02, 95% C.I: 0.01-0.02). It is therefore possible that 'panel conditioning' is present, in which participants become more comfortable with answering sensitive questions over time, and therefore give more accurate answers (Sturgis *et al.* 2009). However, based on comparison of the first seven waves of the study to cross-sectional data from the Health Survey for England, Pevalin found no evidence of retest effects and concluded that the GHQ-12 is consistent and reliable across repeated measures (Pevalin, 2000).

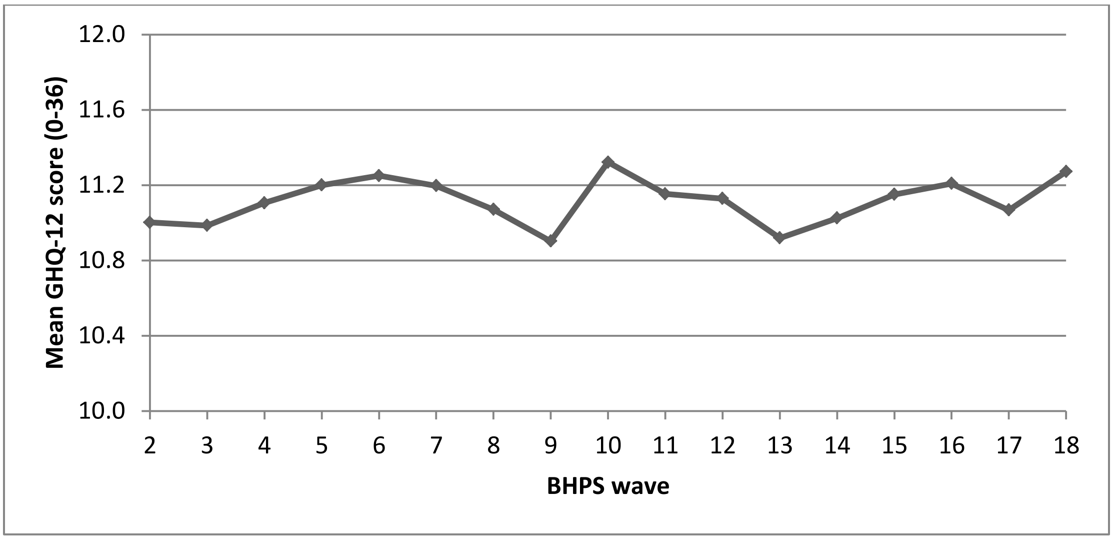

Figure 5.2 Mean GHQ-12 score (0-36 scored variable) by wave in the BHPS chapter 5 sample

The LAD-level claimant count rate variable used in this chapter also exhibits a long run trend throughout the period. Between 1992 and 2008, claimant count rates decreased across England and Wales (Figure 5.3). In order to avoid artifactual correlation between these two variables in the models, the GHQ-12 outcome variable was standardised to the grand mean and overall standard deviation for all person-years of data, and then rescaled. This standardisation is an attempt to remove differences in GHQ-12 scores over time which are independent of employment rates. This allows the models to show if there is a relationship between variability in claimant count rates over areas, and GHQ-12 scores.

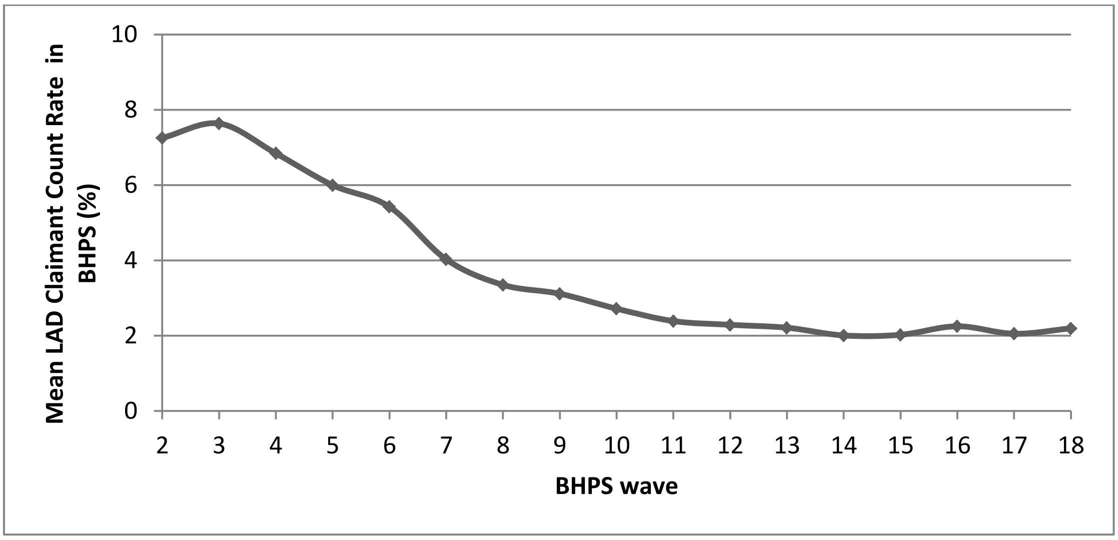

Figure 5.3 Mean LAD claimant count rate by wave, England and Wales

The individual labour market status variable used in this chapter is the five-category variable defined in section 3.3.3 and described in Table 5.2. The referent category is 'securely employed' and the remaining four categories are: insecurely employed, unemployed, permanently sick, and other inactive.

Table 5.2 Longitudinal summary statistics for labour market status

Labour Market Status	All person-years		Within individuals		Between individuals
	Frequency	**Percent**	**Frequency**	**Percent**	**Percent**
Securely Employed	56902	67.2	8837	82.6	77.1
Insecurely Employed	8467	10.0	3690	34.5	26.7
Unemployed	2988	3.5	1717	16.0	29.2
Perm Sick	2978	3.5	772	7.2	48.8
Other Inactive	13330	15.7	4008	37.5	50.6
Total	84665	100	19024	177.8	56.3

This chapter introduces a new key explanatory variable: LAD-level claimant count rate. As described above, this was downloaded from the Nomis website for each LAD at each time point, and used as a mean-centred continuous variable in the analysis (downloaded 27/01/11 from *www.nomisweb.co.uk*).

The chapter also uses a set of hypothesised confounding factors, drawn from the covariates explored in chapter 4 (Table 5.3). Detailed description of the selection, derivation and coding of these variables can be found in section 3.3.5.

Table 5.3 Hypothesised confounding covariates used in chapter 5 models

Variable	Properties
Age	Continuous, mean centred
Age-squared	Continuous, mean centred
Lagged GHQ-12 score from previous wave	Continuous, mean centred
Gender	Binary
Educational attainment	5 categories
1+ Unemployed spells in past year	Binary
1+ Physical health problem	Binary
Social housing tenure	Binary
Spousal joblessness	3 categories
Spousal GHQ-12 caseness	3 categories
Marital status	3 categories

5.2.4 Models

The hierarchical structure of the data is summarised in Figure 5.4. Occasions of measurement (level 1) are nested within individuals (level 2). If all individuals had lived in the same LAD throughout their participation in the study, then individuals would be perfectly nested within the higher LAD level (level 3). However, in reality individuals often move between areas and are therefore exposed to varying area level characteristics at different times. It is also important to recognise that areas change over time, and cannot be conceptualised has having static and unchanging characteristics which have the same effects on residents throughout the 18 year study period. Whilst some areas remain relatively unchanged over time, others have undergone dramatic improvement or decline over the past two decades, driven by processes such as gentrification or the after-effects of deindustrialisation.

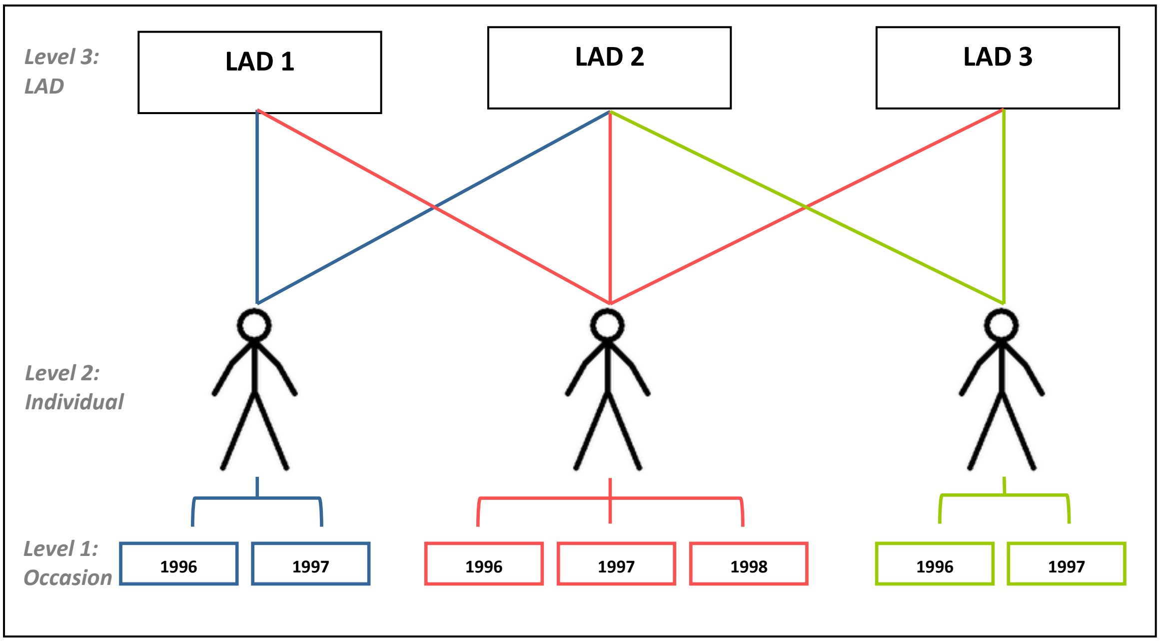

Figure 5.4 Diagram to summarise the complex hierarchical nature of the BHPS data

In order to adequately reflect the complexity of the hierarchical relationship in the sample, three complementary modelling approaches were used:

(i) Two-level random effects models

(ii) Two-level cross-sectional multilevel models for four selected waves

(iii) Three-level multiple membership multilevel models

For each of the model types, the following series of models were run, based on the models developed in chapter 4:

M_0. Null model

M_C. Crude model for the association between LAD Claimant Count Rate and GHQ-12 score.

M1. Labour market status and confounding covariates added to the crude model.

M2. Interaction between labour market status and LAD Claimant Count Rate added to M1

5.2.4.1 Two-level random effects models

In chapter 4, series of two-level random effects models were developed to explore the association between labour market status and GHQ-12 score after adjusting for confounding and mediating factors at the individual and occasion-specific levels. As the first stage in the investigation into the effects of area-level characteristics on GHQ-12 scores, the same methodology is used. The two-level random effects models allow repeated measurements to be clustered within the individuals to whom they pertain. For the purposes of this chapter, these models have been developed to include LAD-level variables at the ‘occasion’ level since they vary annually. All individuals who lived in the same LAD at the same wave will have the same values as one another for LAD-level variables. The structure of the data assumed by the two-level random effects models is outlined in Figure 5.5.

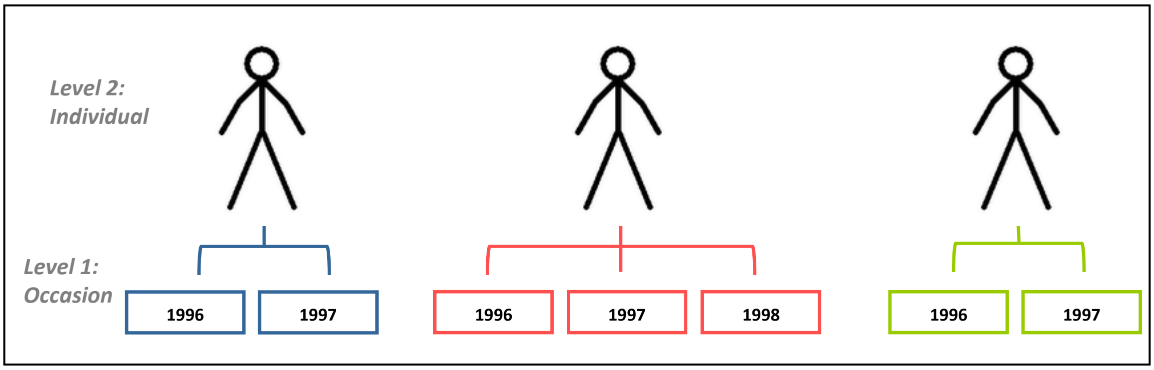

Figure 5.5 Diagram to summarise the hierarchy assumed by two-level random effects models

The fundamental limitation of using this method is that nesting of individuals within LADs has not been built into the structure, meaning that LADs are seen as independent and defined only by their claimant count rate. This method does not show whether area ‘matters’, only whether LAD annual claimant count is associated with GHQ-12 score. In addition to this theoretical consideration, failing to nest individuals within areas also means that standard errors are smaller than they would be if the clustering had been accounted for. The strengths of this method are that it allows LAD-level characteristics to change over time rather than characterising areas as static and unchanging. It also takes into account the clustering of repeated measures within individuals over time, and provides a longitudinal perspective.

5.2.4.1.1 Equations for nested series of two-level random effects models

The models were specified as shown in the following series of equations, with LAD Claimant Count Rate, age, age-squared and lagged GHQ-12 score centred on their grand means. The subscripts ‘i’ and ‘j’ denote the individual (level 2) and the occasion at which the measurement was taken (level 1), respectively.

(M_0) $y_{ij} = \beta_0 + u_i + e_{ij}$

(M_c) $y_{ij} = \beta_0 + \beta_1 LADClaimantCountRate_{ij} + u_i + e_{ij}$

(M1) $y_{ij} = \beta_{0ij} + \beta_1 LADClaimantCountRate_{ij} + \beta_2 Insecure_{ij} + \beta_3 Unemployed_{ij} + \beta_4 PermSick_{ij} + \beta_5 OtherInactive_{ij} + \beta_6 Age_{ij} + \beta_7 Age^2_{ij} + \beta_8 LaggedGHQ_{ij} + \beta_9 1{+}UnempSpells_{ij} + \beta_{10} A\text{-}Levels_{ij} + \beta_{11} GCSEs_{ij} + \beta_{12} NoQuals_{ij} + \beta_{13} PhysHealthProblem_{ij} + \beta_{14} SocialHousing_{ij} + \beta_{15} SpouseNoJob_{ij} + \beta_{16} SpouseGHQcase_{ij} + \beta_{17} NoSpouse_{ij} + \beta_{18} Married/Cohabiting_{ij} + \beta_{19} Divorced/Widowed/Separated_{ij} + \beta_{20} Never\ Mar/Cohab_{ij} + \beta_{21} Gender_j + u_i + e_{ij}$

(M2) $y_{ij} = \beta_{0ij} + \beta_1 LADClaimantCountRate_{ij} + \beta_2 Insecure_{ij} + \beta_3 Unemployed_{ij} + \beta_4 PermSick_{ij} + \beta_5 OtherInactive_{ij} + \beta_6 LADClaimantCountRate{*}Insecure_{ij} + \beta_7 LADClaimantCountRate{*}Unemployed_{ij} + \beta_8 LADClaimantCountRate{*}PermSick_{ij} + \beta_9 LADClaimantCountRate{*}OtherInactive_{ij} + \beta_{10} Age_{ij} + \beta_{11} Age^2_{ij} + \beta_{12} LaggedGHQ_{ij} + \beta_{13} 1{+}UnempSpells_{ij} + \beta_{14} A\text{-}Levels_{ij} + \beta_{15} GCSEs_{ij} + \beta_{16} NoQuals_{ij} + \beta_{17} PhysHealthProblem_{ij} + \beta_{18} SocialHousing_{ij} + \beta_{19} SpouseNoJob_{ij} + \beta_{20} SpouseGHQcase_{ij} + \beta_{21} NoSpouse_{ij} + \beta_{22} Married/Cohabiting_{ij} + \beta_{23} Divorced/Widowed/Separated_{ij} + \beta_{24} Never\ Mar/Cohab_{ij} + \beta_{25} Gender_j + u_i + e_{ij}$

Where:

$\mathbf{y_{ij}}$ = Outcome (GHQ-12 score) for individual i at occasion j.

$\boldsymbol{\beta_0}$ = Intercept

$\boldsymbol{\beta_1 - \beta_{25}}$ = Regression coefficients (i.e. fixed effects)

$\mathbf{u_i}$ = Between-individual error (i.e. the level 2 random effect)

$\mathbf{e_{ij}}$ = Within-individual error (i.e. the level 1 random effect)

5.2.4.2 Four Two-level Cross-Sectional Multilevel Models (1992, 1998, 2002, 2008)

In order to reflect both the nesting of individuals within LADs and the potential for characteristics of LADs to change over time, the next stage was to build two-level cross-sectional multilevel models for four selected waves of the BHPS. The four years (1992, 1998, 2002, and 2008) were chosen since they are all separated by six-year intervals and so span the entire period of available BHPS data. In addition, these four years represent snapshots into different national economic conditions. In 1992, the economy was officially out of recession but national unemployment was still high and economic conditions were uncertain. By 1998, the GDP growth rate had improved and national unemployment rates had decreased. In 2002 the UK was experiencing conditions of high and prolonged growth and prosperity, with low unemployment rates. By the autumn of 2008, when the BHPS interviews were undertaken, Lehman Brothers bank had collapsed and the UK was on the cusp of recession.

Figure 5.6 shows the structure of the data assumed by these two-level cross-sectional models. A limitation of this approach is that the longitudinal nature of the dataset is not exploited and it is therefore unwise to infer causality in any discussion about the relationship between GHQ-12 score and LAD claimant count rate or labour market status.

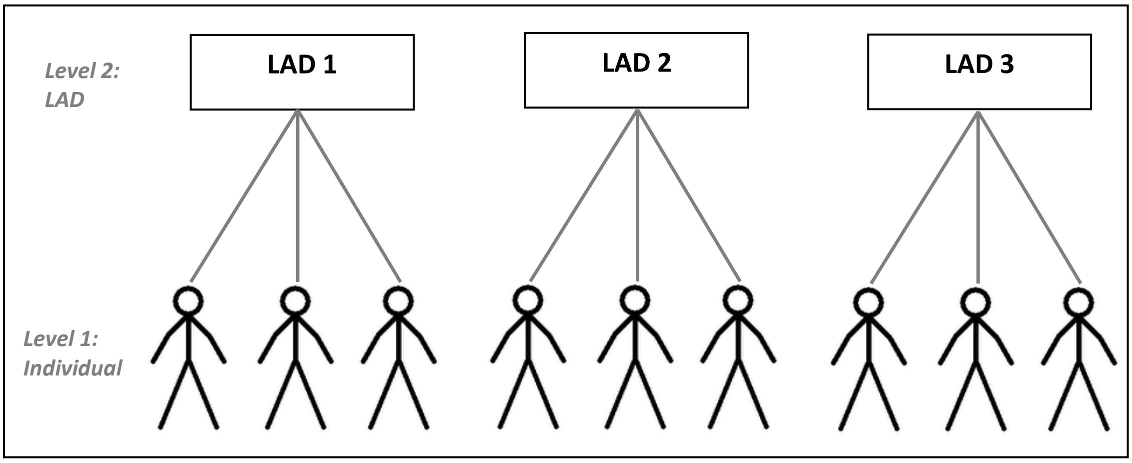

Figure 5.6 Diagram to summarise the hierarchical structure assumed by cross-sectional two-level multilevel models

Exclusion criteria were entered in MLwiN to limit the longitudinal dataset to each of the four waves, and four separate cross-sectional datasets were created. Each of these datasets contained working-age original BHPS sample members with complete information for all of the variables included in the final model (see Table 5.4 for sample size).

Table 5.4 Sample size by wave for cross-sectional models

Wave	n Individual	n LAD
1992	5258	231
1998	5388	321
2002	4930	322
2008	4185	329

Models were built up in stages using MLwiN 2.11 software (Rasbash *et al.*, 2009), and were run using the iterative generalised least squares (IGLS) algorithm which is described in detail by Goldstein (1986). Usually, cross-sectional BHPS probability weights would be used for any cross-sectional analysis of the BHPS, in order to render the sample representative of the initial

1991 British population. However, weights cannot be used with multivariate models in MLwiN v.2.11, and the entire weighting facility is considered experimental (MLwiN Help version 2.02.03, 'Weights'). Adding probability weights was attempted, but the software became unstable. It is important therefore, to treat the results of the cross-sectional models with some caution, although regression is considered reasonably robust in any case.

5.2.4.2.1 Equations for four series of cross-sectional two-level multilevel models

The models were specified as shown in the following series of equations, with LAD Claimant Count Rate, age, age-squared and lagged GHQ-12 score centred on their wave means. The 'i' and 'j' subscripts denote the LAD (level 2) and the individual within that LAD (level 1), respectively.

(M0) $y_{ij} = \beta_0 + u_i + e_{ij}$

(Mc) $y_{ij} = \beta_0 + \beta_1 \text{LADClaimantCountRate}_{ij} + u_i + e_{ij}$

(M1) $y_{ij} = \beta_{0ij} + \beta_1\text{LADClaimantCountRate}_{ij} + \beta_2\text{Insecure}_{ij} + \beta_3\text{Unemployed}_{ij} + \beta_4\text{PermSick}_{ij} + \beta_5\text{OtherInactive}_{ij} + \beta_6\text{Age}_{ij} + \beta_7\text{Age}^2_{ij} + \beta_8\text{LaggedGHQ}_{ij} + \beta_9 1\text{+UnempSpells}_{ij} + \beta_{10}\text{A-Levels}_{ij} + \beta_{11}\text{GCSEs}_{ij} + \beta_{12}\text{NoQuals}_{ij} + \beta_{13}\text{PhysHealthProblem}_{ij} + \beta_{14}\text{SocialHousing}_{ij} + \beta_{15}\text{SpouseNoJob}_{ij} + \beta_{16}\text{SpouseGHQcase}_{ij} + \beta_{17}\text{NoSpouse}_{ij} + \beta_{18}\text{Married/Cohabiting}_{ij} + \beta_{19}\text{Divorced/Widowed/Separated}_{ij} + \beta_{20}\text{Never Mar/Cohab}_{ij} + \beta_{21}\text{Gender}_j + u_i + e_{ij}$

(M2) $y_{ij} = \beta_{0ij} + \beta_1\text{LADClaimantCountRate}_{ij} + \beta_2\text{Insecure}_{ij} + \beta_3\text{Unemployed}_{ij} + \beta_4\text{PermSick}_{ij} + \beta_5\text{OtherInactive}_{ij} + \beta_6\text{LADClaimantCountRate*Insecure}_{ij} + \beta_7\text{LADClaimantCountRate*Unemployed}_{ij} + \beta_8\text{LADClaimantCountRate*PermSick}_{ij} + \beta_9\text{LADClaimantCountRate*OtherInactive}_{ij} + \beta_{10}\text{Age}_{ij} + \beta_{11}\text{Age}^2_{ij} + \beta_{12}\text{LaggedGHQ}_{ij} + \beta_{13}1\text{+UnempSpells}_{ij} + \beta_{14}\text{A-Levels}_{ij} + \beta_{15}\text{GCSEs}_{ij} + \beta_{16}\text{NoQuals}_{ij} + \beta_{17}\text{PhysHealthProblem}_{ij} + \beta_{18}\text{SocialHousing}_{ij} + \beta_{19}\text{SpouseNoJob}_{ij} + \beta_{20}\text{SpouseGHQcase}_{ij} + \beta_{21}\text{NoSpouse}_{ij} + \beta_{22}\text{Married/Cohabiting}_{ij} + \beta_{23}\text{Divorced/Widowed/Separated}_{ij} + \beta_{24}\text{Never Mar/Cohab}_{ij} + \beta_{25}\text{Gender}_j + u_i + e_{ij}$

Where:

$\mathbf{y_{ij}}$ = Outcome (GHQ-12 score) for LAD i at individual j.

$\boldsymbol{\beta_0}$ = Intercept

$\beta_1 - \beta_{25}$ = Regression coefficients (i.e. fixed effects)

u_i = Between-LAD residual (i.e. level 2 random effect)

e_{ij} = Within-LAD (between individuals) residual (i.e. level 1 random effect)

5.2.4.3 Three-level Multiple Membership Structure

In order to take account both of the longitudinal nature of the data, and of the fact that individuals move between LADs during the study, three-level multiple membership models were built using MLwiN v.2.11. Multiple membership models require the creation of a variable to describe the proportion of time each individual spent in each of the LADs s/he inhabited during the study. For example, if an individual was present for 6 waves of the study, and spent two of these waves in LAD 1 and the other four in LAD 2, a weight of 0.33 would be appropriated to observations collected during the LAD 1 era, and a weight of 0.66 would be applied to the remaining LAD 2 observations. The methodology is outlined in detail by its developers, Browne *et al.* (2002) and in the MCMC MLwiN user manual (Browne, 2009). The limitation with this method is that areas are conceptualised as having unchanging characteristics over time. An assumption is made that the effects of living in LAD 1 for four years between 1992 and 1996 would be the same as the effects of living in LAD 1 between 2002 and 2006. However, it is possible that LAD 1 has undergone processes of gentrification or of decline in the intervening decade. This limitation has been tackled to some extent by adding annual figures for LAD-level claimant count rate at level 1. The hierarchical structure assumed by the multiple membership models is outlined in Figure 5.7**.**

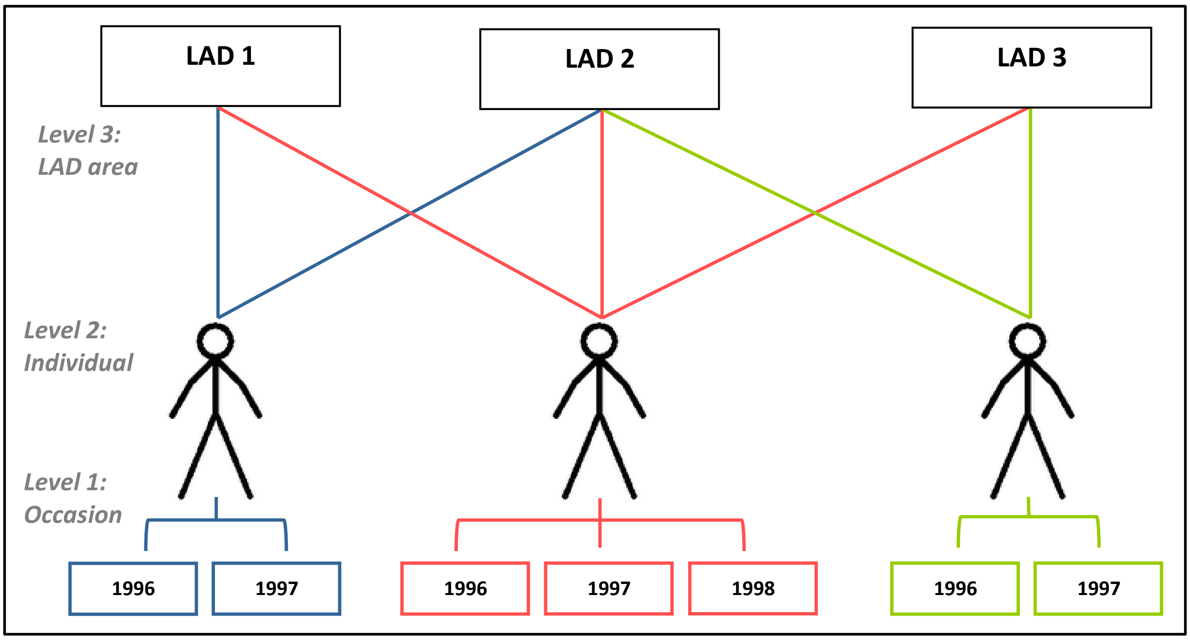

Figure 5.7 Diagram to summarise the hierarchical structure assumed by multiple membership three-level multilevel models

The weighting system was created in Stata 11, and the dataset was then imported into MLwiN v2.11. The data were then sorted on LAD, person ID and wave and the classification information was set. Starting values for the models were attained using Iterative Generalised Least Squares (IGLS) maximum likelihood estimation. This was then switched to Monte Carlo Markov Chain estimation (MCMC) and burnt-in for 500 simulations. The models were then monitored for 5000 simulations. The trace of all the estimates was assessed to check for good mixing, in which the chain did not trend or stick, creating a 'white noise' pattern which indicated that the equilibrium distribution had been reached (Jones, 2010). The Raftery-Lewis and Brooks-Draper prospective diagnostics were assessed to ensure that sufficient simulations had been performed (Raftery and Lewis, 1992; Brooks and Draper, 1999). On this basis, the MLwiN default of 5000 was deemed sufficient.

5.2.4.3.1 Equations for nested series of multiple membership multilevel models

The models were specified as shown in the following series of equations, with LAD Claimant Count Rate, age, age-squared and lagged GHQ-12 score centred on their grand means. The subscripts 'i', 'j' and 'k' denote LAD (level 3), individual (level 2) and occasion of measurement (level 1), respectively.

(M0) $y_{ijk} = \beta_0 + v_i + u_{ij} + e_{ijk}$

(Mc) $y_{ijk} = \beta_0 + \beta_1 \text{LADClaimantCountRate}_{ijk} + v_i + u_{ij} + e_{ijk}$

(M1) $y_{ijk} = \beta_0 + \beta_1 \text{LADClaimantCountRate}_{ijk} + \beta_2 \text{Insecure}_{ijk} + \beta_3 \text{Unemployed}_{ijk} + \beta_4 \text{PermSick}_{ijk} +$
$\beta_5 \text{OtherInactive}_{ijk} + \beta_6 \text{Age}_{ijk} + \beta_7 \text{Age}^2_{ijk} + \beta_8 \text{LaggedGHQ}_{ijk} + \beta_9 \text{1+UnempSpells}_{ijk} + \beta_{10} \text{A-Levels}_{ijk} +$
$\beta_{11} \text{GCSEs}_{ijk} + \beta_{12} \text{NoQuals}_{ijk} + \beta_{13} \text{PhysHealthProblem}_{ijk} + \beta_{14} \text{SocialHousing}_{ijk} + \beta_{15} \text{SpouseNoJob}_{ijk} +$
$\beta_{16} \text{SpouseGHQcase}_{ijk} + \beta_{17} \text{NoSpouse}_{ijk} + \beta_{18} \text{Married/Cohabiting}_{ijk} +$
$\beta_{19} \text{Divorced/Widowed/Separated}_{ijk} + \beta_{20} \text{Never Mar/Cohab}_{ijk} + \beta_{21} \text{Gender}_{ij} + v_i + u_{ij} + e_{ijk}$

(M2) $y_{ijk} = \beta_0 + \beta_1 \text{LADClaimantCountRate}_{ijk} + \beta_2 \text{Insecure}_{ijk} + \beta_3 \text{Unemployed}_{ijk} + \beta_4 \text{PermSick}_{ijk} +$
$\beta_5 \text{OtherInactive}_{ijk} + \beta_6 \text{LADClaimantCountRate*Insecure}_{ijk} +$
$\beta_7 \text{LADClaimantCountRate*Unemployed}_{ijk} + \beta_8 \text{LADClaimantCountRate*PermSick}_{ijk} +$
$\beta_9 \text{LADClaimantCountRate*OtherInactive}_{ijk} + \beta_{10} \text{Age}_{ijk} + \beta_{11} \text{Age}^2_{ijk} + \beta_{12} \text{LaggedGHQ}_{ijk} +$
$\beta_{13} \text{1+UnempSpells}_{ijk} + \beta_{14} \text{A-Levels}_{ijk} + \beta_{15} \text{GCSEs}_{ijk} + \beta_{16} \text{NoQuals}_{ijk} + \beta_{17} \text{PhysHealthProblem}_{ijk} +$
$\beta_{18} \text{SocialHousing}_{ijk} + \beta_{19} \text{SpouseNoJob}_{ijk} + \beta_{20} \text{SpouseGHQcase}_{ijk} + \beta_{21} \text{NoSpouse}_{ijk} +$

β_{22}Married/Cohabiting$_{ijk}$ + β_{23}Divorced/Widowed/Separated$_{ijk}$ + β_{24}Never Mar/Cohab$_{ijk}$ + β_{25}Gender$_{ij}$ + v_i + u_{ij} + e_{ijk}

Where:

$\mathbf{y_{ijk}}$ = Outcome (GHQ-12 score) for LAD i, individual j at occasion k.

$\boldsymbol{\beta_0}$ = Intercept

$\boldsymbol{\beta_1}$ – $\boldsymbol{\beta_{25}}$ = Regression coefficients (i.e. fixed effects)

$\mathbf{v_i}$ = Between-LAD residual (i.e. the level 3 random effect)

$\mathbf{u_{ij}}$ = Between-individual residual (i.e. the level 2 random effect)

$\mathbf{e_{ijk}}$ = Within-individual residual (i.e. the level 1 random effect)

5.3 Results

5.3.1 Two-level random effects models

The detailed results of the series of two-level random effects models are presented in Appendix 5.2. As expected, the coefficients for the labour market status categories in model 1 were very similar to comparable results from chapter 4, showing that the addition of wave 18 and exclusion of Scottish data has not altered the results significantly. The intra-class correlation coefficient (ICC) for the null model was 0.39, showing that 39 percent of the total variance in GHQ-12 scores is attributable to between individual factors. The only substantial reduction in the ICC occurred when the hypothesised confounding covariates were adjusted for in Model 1. Results from chapter 4 showed that this is largely due to adjustment for the lagged GHQ-12 score from the previous wave. The trend for overall R^2 is also in line with the results from chapter 4; a substantial increase in the proportion of total variability in GHQ-12 scores explained by the variables in the model only occurs when hypothesised confounders are adjusted for. For the labour market status category coefficients, a similar pattern to the random effects models presented in chapter 4 emerges. Figure 5.8 shows the main effects for labour market status, at the mean LAD Claimant Count Rate, controlling for hypothesised confounders. All of the labour market status categories have significantly higher average GHQ-12 score than the securely employed. Compared to the securely employed, the insecurely employed have, on average, a GHQ-12 score 1.27 units higher. For the unemployed, GHQ-12 scores are 2.23 units higher than the securely employed group’s scores, and the coefficient for the permanently sick group is 2.79.

The coefficient for LAD Claimant Count Rate is very small, non-significant and negative in the crude model and model 1**.** A negative coefficient for LAD claimant count rate suggests that in years with high claimant count rate, there are lower GHQ-12 scores, inferring that high LAD claimant count rate is protective against psychological distress after controlling for employment status. However, these coefficients are not statistically significant.

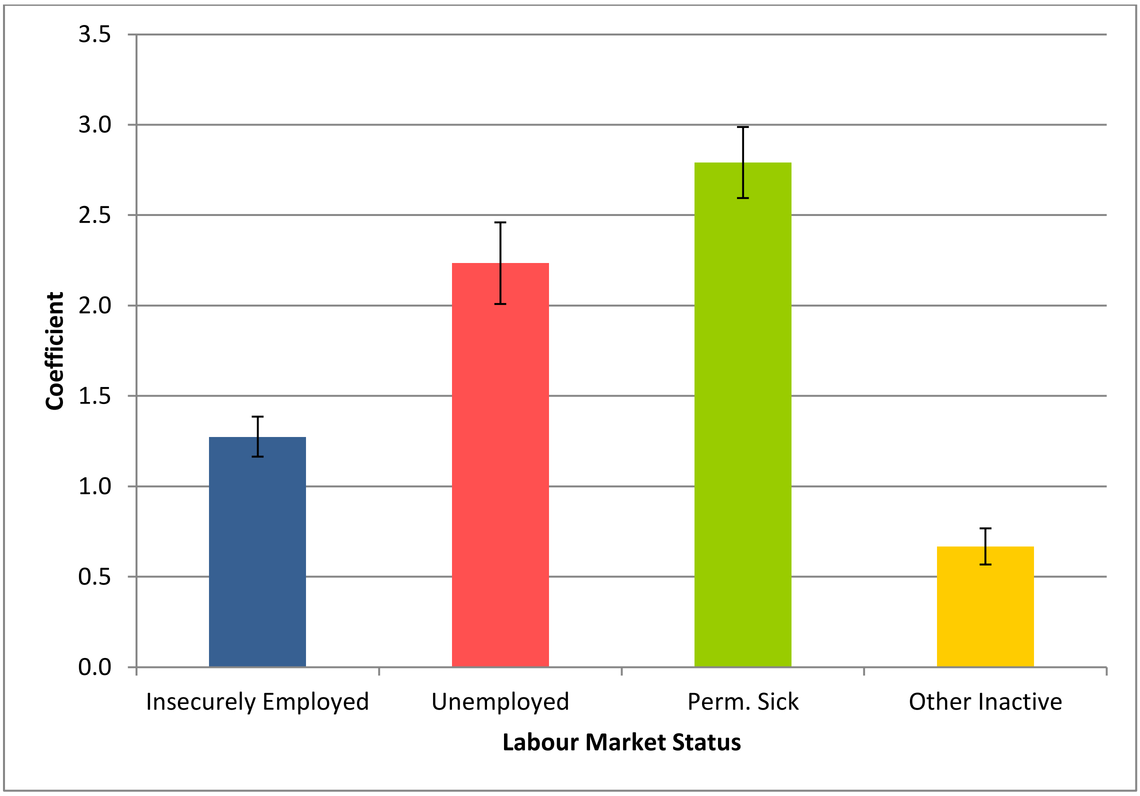

Figure 5.8 Random effects model showing the association between labour market status and GHQ-12 score, adjusted for confounders and LAD claimant count rate.

The addition of a term for the interaction between labour market status categories and LAD claimant count rate in model 2 allows for a deeper examination of the effects of this area-level variable on the relationship between labour market status and minor psychiatric morbidity. A Wald test showed that the interaction variable made a significant contribution to the model ($p<0.001$). Average GHQ-12 score by LAD claimant count rate was calculated for the fully adjusted model (M2) and the results are displayed in Figure 5.9. This shows that as LAD claimant count rate increases, the GHQ-12 scores of unemployed individuals decrease. For the unemployed, living in an area of low unemployment is associated with higher levels of psychological distress than living in an area of high unemployment, and that that this pattern remains after confounding factors have been adjusted for. To a lesser extent, this pattern is also shown for the insecurely employed, although the coefficient for the interaction between

LAD claimant count rate and insecure employment is not significantly different from that of the securely employed (Appendix 5.2). The opposite appears true for the other inactive, for whom living in an area of high claimant count rate appears associated with worse MPM outcomes than living in an area of low claimant count rate, although this interaction is also non-significant (Appendix 5.2). For the unemployed and permanently sick, living in an area of high unemployment is associated with better psychological wellbeing than living in an area of low unemployment.

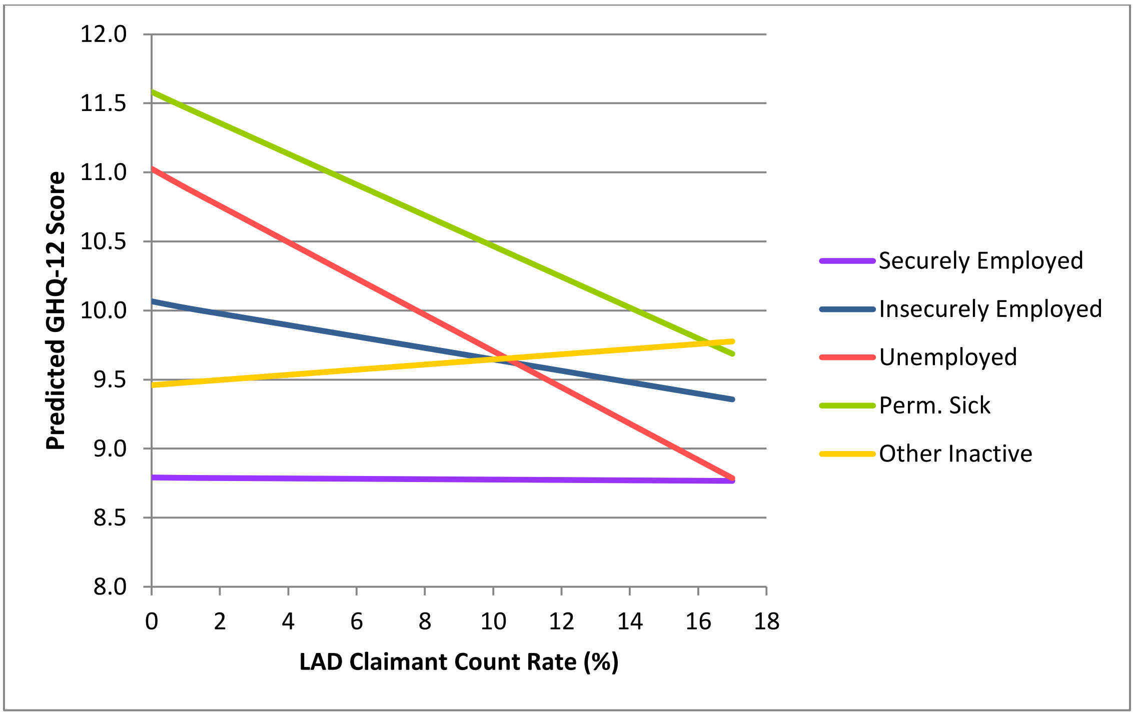

Figure 5.9 Average GHQ-12 score by LAD Claimant Count Rate. Adjusted for confounders.

However, it is important to note that sample size becomes very low when the sample is stratified by LAD claimant count rate. The number of LADs with claimant count rates in excess of 10 percent across the eighteen years of the study is low (37) and therefore, sample size in the higher end of the distribution is insufficient to allow consideration of a non-linear relationship.

5.3.2 Two-level cross-sectional multilevel models

The results for the four cross-sectional models are shown in Appendix 5.3, Appendix 5.4, Appendix 5.5 and Appendix 5.6. For all four cross-sectional models, the ICCs are very low, showing that only a small fraction of the total residual variance in GHQ-12 scores is attributable to LAD-level variation. However, the ICCs are higher in the models for later years. The ICC for the null model in 1992 was 0.002, compared to 0.010 in 1998, 0.014 in 2002 and

0.007 in 2008, suggesting perhaps that the effects of the LAD in which an individual lives are greater in some years than others. However, all of these figures are very small, suggesting that there is very little LAD-level variation in GHQ-12 scores overall. For each year's series of models, the -2*log likelihood figures decreases as more variables are added into the model, suggesting a better fit, as expected.

The coefficients for LAD claimant count rate across the four series of cross-sectional models are generally non-significant. Only two are statistically significant at the 5 percent level: a coefficient of 0.18 in the 2002 crude model and a coefficient of 0.23 in the 2008 model. These coefficients are positive, meaning that areas with higher claimant count rates have higher average GHQ-12 scores. This picture diverges from the one given by the two-level random effects models, in which LAD claimant count rates were non-significant but generally negative. Using cross-sectional models with individuals nested within the areas they inhabited at that time allows a more ecological perspective with a greater spatial focus, compared to the more temporal, individualistic perspective achieved by the random effects model

Comparison of the coefficients for labour market status categories in the crude models for all four years shows that unemployment and permanent sickness appear to become comparatively more predictive of psychological distress in the later waves, and that the extent to which insecure employment predicts higher GHQ-12 scores also fluctuates (Figure 5.10). The coefficient for the unemployed category increases through time from 1.81 in 1992 to 3.69 in 2008. Inspection of overlapping confidence intervals suggests that in 1992, 1998 and 2002, unemployment is no more predictive of higher GHQ-12 scores than insecure employment, whereas in 2008, unemployment is significantly worse for mental health. The effects of 'other' inactivity have been attenuated to the null in 1998, and reduced to small effect sizes in the other years (0.64 in 2008). It should be noted that splitting the sample into cross sections has reduced the sample size in each labour market status and for categories of covariates considerably. This led to wide confidence intervals and as such, limits the extent to which categories of labour market status can be compared to one another.

Support for the hypothesis that living in an area of low overall unemployment is associated with higher levels of psychological distress among the unemployed than living in an area of high overall unemployment is mixed in the cross-sectional models. A significant interaction with LAD claimant count rate exists for the unemployed in the models for 1992 (Appendix 5.3) and 2008 (Appendix 5.6), but not in 1998 (Appendix 5.4) or 2002 (Appendix 5.5). A significant interaction between permanent sickness and LAD claimant count rate was found only in the 2002 model (Appendix 5.5).

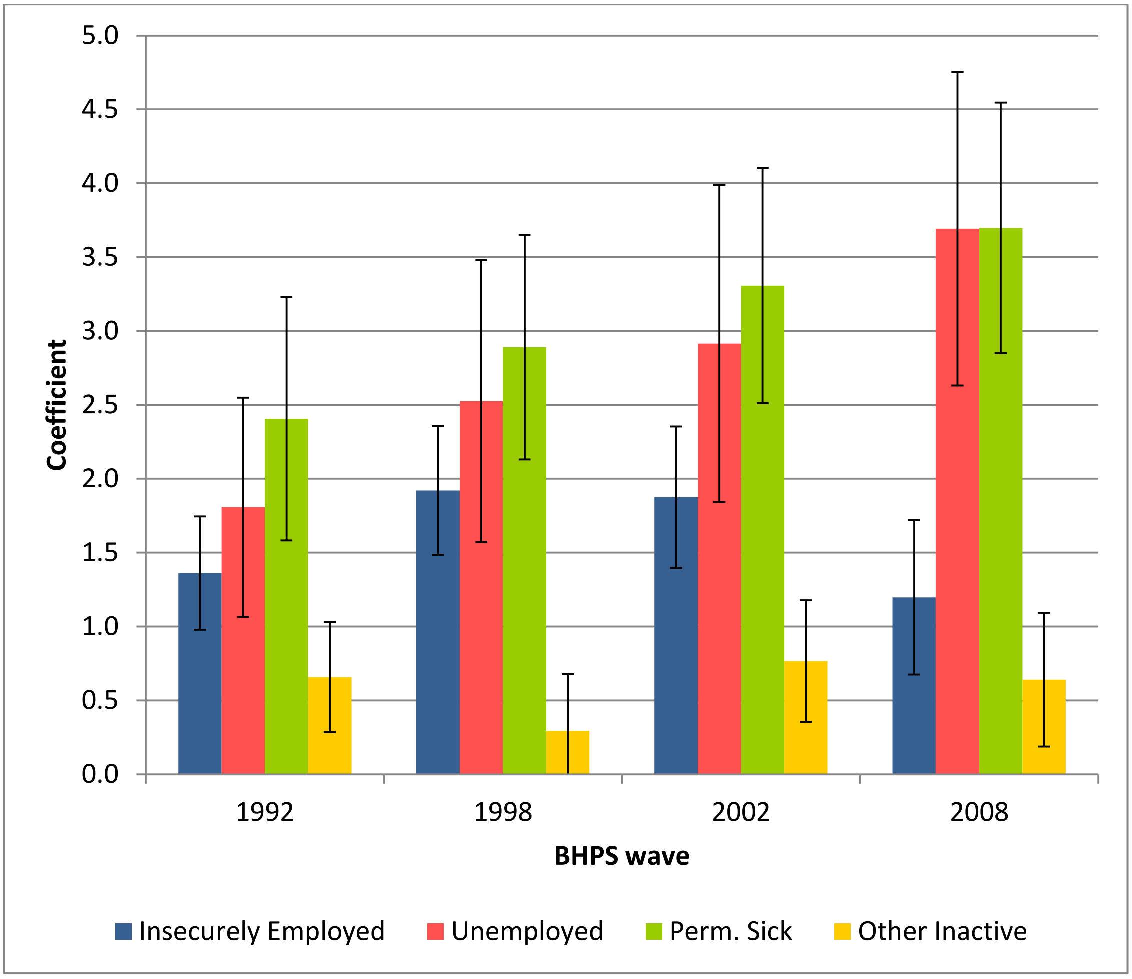

Figure 5.10 Cross-sectional Multilevel Models showing association between Labour Market Status and GHQ-12 Score, adjusted for LAD Claimant Count Rate and hypothesised confounding factors

5.3.3 Three-level multiple membership multilevel models

In the series of multiple membership models, the coefficients for the labour market status categories reflect the general pattern seen in this and previous chapters (Figure 5.11 and Appendix 5.7). In model 2, the insecurely employed group had GHQ-12 scores 1.24 units higher than the securely employed category. This coefficient was significantly lower than that of the unemployed category (2.31). This was consistent with the pattern seen in the random effects models in this chapter. The permanently sick had average GHQ-12 scores 3.07 units higher than the securely employed, compared to a coefficient of 0.45 for the other inactive category. The coefficient for LAD claimant count rate in the series of multiple membership models reflected that of the two-level random effects models. The coefficient in the crude model was small, negative and non-significant (-0.01, 95% CI: -0.02-0.01) and remained similar in models 1 and 2. In the two-level random effects model, significant interactions between LAD claimant count rate and unemployment and permanent sickness were found (section 5.3.1). In the three-level multiple membership model only the interaction between unemployment and LAD claimant count rate was found to be significantly different from that of the securely employed (Appendix 5.7). The multiple membership model therefore supports the hypothesis that living in an area of low overall unemployment is associated with higher levels of psychological distress among the unemployed than living in an area of high overall unemployment. However, a similar hypothesis for the permanently sick is not supported by this model.

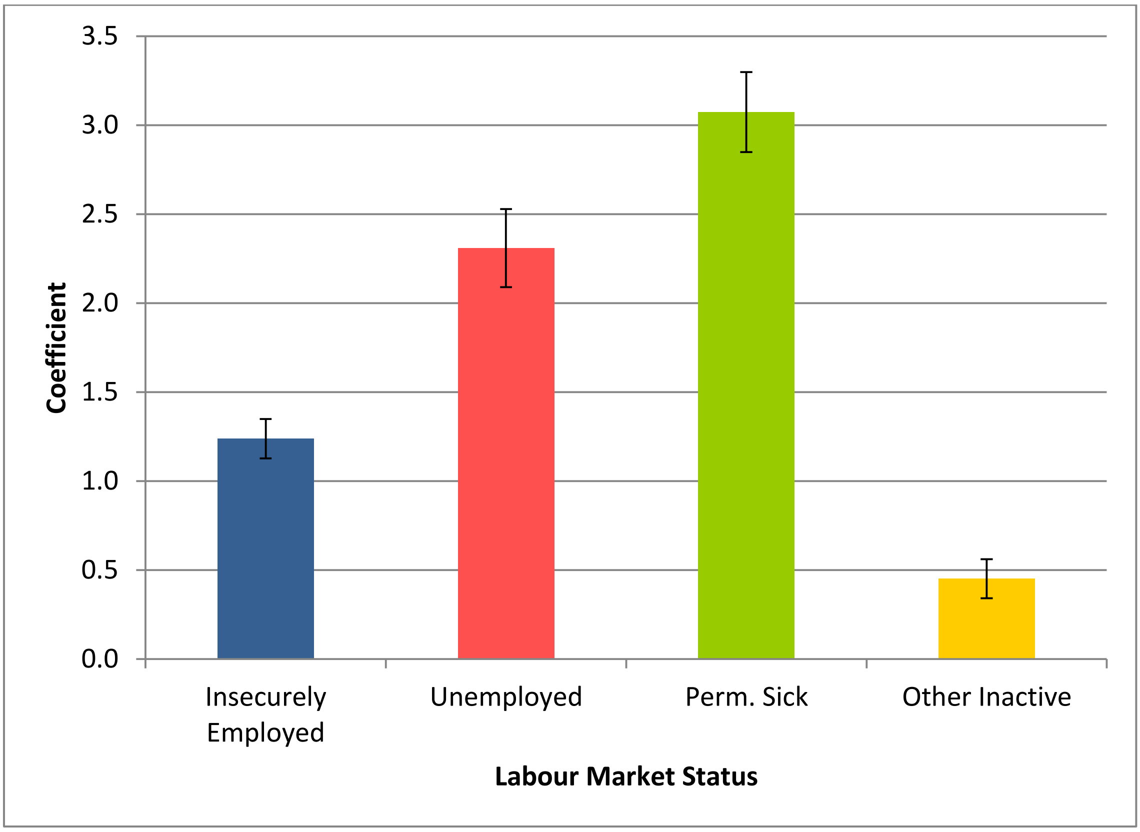

Figure 5.11 Three-level multiple membership linear model showing association between labour market status and GHQ-12.

As shown in Figure 5.12, the proportion of the unexplained variation in GHQ-12 scores attributable to within-individual (level 1) variation was 0.21 in the final model. The proportion of the unexplained variation in GHQ-12 scores attributable to between-individual differences within LADs was high (0.99) and remained so throughout the model series. The proportion of unexplained variance in GHQ-12 scores attributable to differences between LADs was very small, falling from 0.005 in the crude model to 0.001 in the final model.

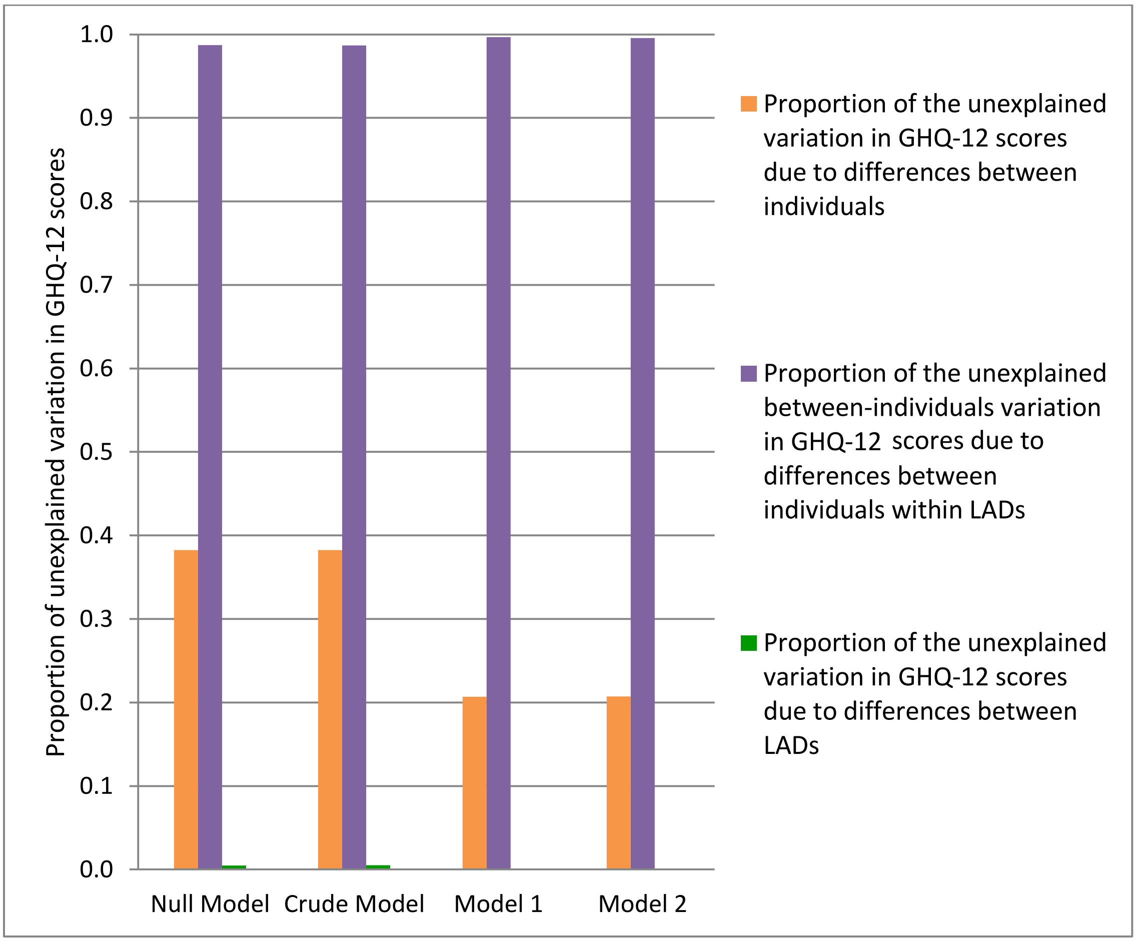

Figure 5.12 Intraclass correlation coefficients from three-level multiple membership linear multilevel models, showing proportion of unexplained variance in GHQ-12 scores at the different levels.

5.4 Discussion

The first objective of this chapter set out to address was the extent to which independent variation in GHQ-12 scores exists at the area level. It was hypothesised that there would be a small amount of independent variation in GHQ-12 scores at the area level, and that this would disappear once individual-level covariates such as age, gender etc. were adjusted for. Evidence gained from all three model types would suggest that there is essentially no variation at the area level. In the null three-level model, the proportion of variance in GHQ-12 scores attributable to differences between LADs was just 0.005 suggesting that even before the addition of any covariates at any level, the LAD(s) in which the individual lived were very poor predictors of GHQ-12 score. The figure is so close to zero that it is almost as though individuals were randomly assorted among areas, with regards to their GHQ-12 scores. When area level claimant count rate and individual level covariates are added, the intraclass correlation coefficient dropped even lower, to 0.001 in the final model. This failure to isolate any real 'place' effect is consistent with the literature. Smith and Easterlow (2005) note that an overreliance on traditional representations of space based on administrative boundaries limits the value of quantitative research in the field of health and place. Local Authority Districts are relatively large areas and mask huge variety in context. Whilst it is therefore possible to conclude from this research that the LAD of residence cannot explain variations in GHQ-12, it would be wrong to conclude that 'area', 'neighbourhood' or 'place' cannot affect and predict mental health outcomes at the individual level. The difficulty in defining 'place', and in doing so adequately for all individuals in a study (who in reality will have complex, multi-nodal, overlapping and temporally shifting understandings of 'neighbourhood') is a great challenge in quantitative health geography and spatial epidemiology, and one which could not be adequately addressed within the data and methodological constraints of this PhD thesis.

The second stated objective of this chapter was to investigate the extent to which the claimant count in an area was related to the GHQ-12 scores of individuals living in the area. It was hypothesised that area level claimant count rate would have a small independent association with individual GHQ-12 score, but this would disappear once individual-level characteristics were adjusted for. The evidence in support of this hypothesis is mixed between the different model types. Statistically significant positive crude coefficients for LAD claimant count rate in two of the cross-sectional models show that in these years (2002 and 2008), the mean GHQ score for individual residents was higher, that is, psychological wellbeing was lower on average. Individual propensity towards lower psychological wellbeing (high GHQ-12 scores) was then taken into account by allowing repeated measures within individuals in the two-level random effects models and the three-level multilevel models. When this is done, then areas with higher claimant count rates no longer have higher mean GHQ-12 scores. The regression coefficients for LAD claimant count rate in both of these longitudinal model series are non-significant. This leads to the conclusion that overall, an area's claimant count rate does not affect GHQ-12 scores, but that individuals who have a tendency towards higher GHQ-12 scores live in areas with higher claimant count rates.

The third objective was to further unpack the relationship between LAD claimant count rate and individual employment status categories and assess whether it is more distressing to be unemployed or economically inactive in an area of high claimant count rate, compared to an area with a low claimant count rate. It was hypothesised that the effect of area level claimant count rate on GHQ-12 score varies according to an individual's labour market status. It was expected that living in an area of low overall unemployment would be associated with higher levels of psychological distress among the unemployed than living in an area of high overall unemployment, and that this would also be true for the permanently sick group. The evidence broadly supports this hypothesis, with significant interactions between unemployment and LAD claimant count rate found in the two-level random effects model and the three-level multiple membership model. However, these were of mixed significance in the cross-sectional models. Graphical representation of the interaction from the random effects models (Figure 5.9) showed the trend one might expect to see, given the wider literature. Predicted GHQ-12 scores for the unemployed decreased from 11.03 to 8.79 as LAD claimant count rates increased from 0 to 17 percent. Conclusions about the interaction between LAD claimant count rate and other labour market status categories are more tentative. The results for the two-level random effects model suggested that the slopes for the permanently sick categories were significantly different to that of the securely employed, when adjusting for confounding factors. When holding sociodemographic, financial, spousal, physical health and other factors constant in the random effects model, the permanently sick in areas of high claimant count rate had better mental health than in areas of low claimant count rate. It is possible that this could be an isolation of the effects of 'hidden unemployment' (Beatty *et al.,* 2002), as the permanently sick appear more similar to the unemployed in the sense that their mental health suffers less in an area of high claimant count rate. Because claimant count rate measures only the proportion of registered unemployed people claiming unemployment-related benefits, it consistently underestimates unemployment when compared to the survey based ILO unemployment rate (http://www.detini.gov.uk/ unemployment_measures.pdf). Claimant count rate underestimates unemployment more within certain groups who are less likely to sign on to unemployment benefits, such as people with illnesses or disabilities who may be looking or hoping for employment, but do not claim unemployment benefits. Areas with a high claimant count rate are likely to also be areas with high levels of hidden unemployment uncaptured by claimant count rate and which may also not be captured by the BHPS labour market status questioning. A jobless individual with a health condition may classify themselves as 'permanently sick', but by token of their joblessness, may be at risk of the same psychosocial effects felt by the unemployed. These could then be ameliorated by high local joblessness rates, via the same mechanisms as are hypothesised in the literature on unemployment. However, this was not corroborated by the cross-sectional models or the three-level multiple membership model.

5.4.1 Causal Mechanisms

As outlined by Cummins *et al.* (2007), the overemphasis on merely quantifying 'place' effects on health without unpacking the causal mechanisms has been a major limitation of research in the field. Understanding the ways in which precise characteristics of environments affect certain health outcomes is not only important in terms of establishing causality, but is necessary if research is to lead to effective policy intervention. As described in the introduction to this chapter, Clark and colleagues in the field of economics suggest that unemployment is less distressing in areas where, by token of its prevalence, it has become a normalised social role and therefore the unemployed in such areas are not subject to the distressing effects of social disapproval and loss of status. Akerlof (1980) suggested that social comparison effects are important and that the primary mechanism is thought to be a reduction in the stigma and disapproval surrounding unemployment in areas where it is more prevalent and socially normed. In critiquing these hypotheses, it is useful to refer to Warr's definition of eight pathways through which joblessness can lead to psychological distress (Figure 5.13). Of these, only two appear to map directly on to the 'social norming' hypothesis: a general feeling of being a 'scrounger', and decline in social position and status. The other suggested pathways in Warr's schema pertain mainly to the unemployed individual in isolation, who is conceptualised has having lost time structure, traction, scope for decision making, and the hope of acquiring life-affirming new skills (Warr, 1985).

1. Restricted behaviours and environments: due to lack of money and no 'reason' to leave home.

2. Loss of traction: when having nothing to do means that small tasks fill an entire day, and an individual has no super-imposed way of structuring time.

3. Loss of scope for decision-making

4. Reduced opportunities for acquiring new skills, due to lack of money and a lack of motivation associated with being jobless.

5. Increased exposure to humiliating experiences, such as job rejections and generally feeling as though one is regarded as a 'failure' or a 'scrounger'.

6. Anxiety about the future

7. Reduced quality of interpersonal contacts: officials with whom a jobseeker has to interact in their job search come to replace the relationships they had with colleagues, which were likely to have a more equal power balance.

8. Decline in social position and status.

Figure 5.13 Pathways through which joblessness can lead to decreases psychological wellbeing (Warr, 1985)

Jackson and Warr suggested a causal mechanism whereby areas experiencing high rates of unemployment develop higher levels of community-level social support, providing psychological protection for unemployed men and ameliorating the potential effects of unemployment on GHQ-12 scores to a greater degree than would be the case in areas of low unemployment.

When seeking to explain results which show a protective effect of high area-level unemployment on the psychological wellbeing of the unemployed, it is crucial to guard against employing a populist discourse in which the unemployed residents of high-unemployment areas are essentialised and stereotyped as being 'happy' with worklessness and its associated psychosocial, material and physical health disadvantages. Whilst the weight of evidence suggests that the unemployed, permanently sick and insecurely employed may not suffer as high levels of psychological distress in areas of high claimant count rate compared to their counterparts in areas of low claimant count rate, it is crucial to emphasise that even in areas of very high unemployment, the unemployed, permanently sick and insecurely employed still have higher average GHQ-12 scores than the securely employed. The discussion here is about the extent to which the jobless and insecurely employed are psychologically worse off than the securely employed. In addition, Jackson and Warr emphasise that unemployment remains significantly associated with physical health problems and lower life expectancy in general (Jackson and Warr, 1987).

5.4.2 Limitations

As outlined in chapter 3, measurement bias limitations must be considered with regards to the derived insecure employment category and the subjective financial status covariates. The importance of not over-interpreting results pertaining to the permanently sick category is also worth repeating. Whilst physical health condition is controlled for, reverse causality cannot be ruled out in the case of the permanently sick, many of whom are out of work owing to mental health conditions. In addition to these wider considerations, the methodology and data used in this chapter introduces further limitations to the study.

Perhaps the most serious limitation is the issue, referred to in section 5.2.1, of using administrative geographical units to represent a theoretically meaningful notion of 'place'. Whilst this is always imperfect, the use of local authority districts in particular is problematic. LADs are relatively large areas, and therefore cannot be considered 'neighbourhoods'. In addition, LADs cannot be considered synonymous with local labour markets, since it is highly likely that individuals will live and work in contiguous LADs. Theoretically, one cannot state that there is no 'place' effect on a health outcome if one has used a meaningless geographical unit to define 'place'. The community level resilience to the ill effects of unemployment on mental health hypothesised by Jackson and Warr may operate at the level of a single housing estate, a few streets, or within locally meaningful boundaries defined physically, by railway cuttings or motorway flyovers; or more intangibly. However, in a comparison of health inequality outcomes using three area definition strategies in two London boroughs, Stafford *et al.* (2008) found no support for the hypothesis that health differences would be smallest across arbitrarily chosen administrative boundaries, and larger across boundaries defined using physical and social geographical features. Nevertheless, whilst outside the data availability and methodological scope of this PhD project, the application of smaller geographical areas might have been more informative. However, the work undertaken by Clark and colleagues in the field of economics used larger administrative areas and found there to be significant differences in the geography of unemployment and psychological wellbeing. As discussed in section 5.2.1, the choice of geographical unit in this chapter was dictated by the need for a compromise between accessing 18 years of comparable area level data and choosing areas theoretically relevant to the research question. Overall, the combination of longitudinal and spatial perspectives achieved by this work makes an important contribution to the literature, despite questions over use of local authority districts as theoretically relevant geographical units. A related limitation is the use of a unidimensional and problematic variable to characterise local authority districts. As described above, claimant count rate underestimates unemployment among economically inactive groups and the extent to which it adequately captures unmet need for employment varies geographically. It is important when drawing conclusions about this work, therefore, not to overstate the extent to which claimant count rate can characterise regional economic buoyancy, deprivation or any other socioeconomic dimension. Again, compromises were made in order to achieve the valuable temporal insights that longitudinal research can provide.

A further limitation is the limited utility of the cross-sectional models, owing to small sample sizes particularly in the unemployed and permanently sick categories, which resulted in wide confidence intervals around the parameter estimates.

5.4.3 Conclusion

This chapter has shown that whilst there is essentially no independent variation in GHQ-12 scores at the local authority district level, there is support for the hypothesis that living in an area with high claimant count rate confers a degree of protection against the negative psychological effects of joblessness or insecure employment, although GHQ-12 scores among these groups are still significantly and substantially higher than among their securely employed counterparts. The use of multilevel models to represent the realistically complex structure of the BHPS data and to take account of the nesting of occasions with individuals, and of individuals within (multiple) areas, and the use of lagged GHQ-12 scores, allow us to be confident that this methodology produces reliable estimates and that direction of causality can be inferred with reasonable confidence. This chapter not only corroborates the findings of the previous chapter with very similar effect sizes and significance levels, but adds an important new spatial dimension to our understanding of the relationship between labour market status and minor psychiatric morbidity.

This chapter has explored spatial dimensions of the relationship between labour market status and MPM. The following chapter will go on to investigate the temporal dimension; assessing the effects of age and unpacking causal processes.

5.5 Appendices

Appendix 5.1 Summary of area level indicators investigated for use in chapter 5: from Nomis and Places data sources

NOMIS DATA SOURCE	INDICATOR	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Annual population survey	APS	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	APS wkplace	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	local area labour force survey	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0
	LFS: quarterly four quarter averages	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0
	LFS: Quarterly old unreweighted	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
	LFS: annual	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
	model based estimates of unemp	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Annual survey of hours and earnings	ASHR Resident analysis	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
	ASHR Workplace analysis	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
Claimant Count	CC w/ rates and proportions	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	CC age & duration	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Claimant stocks & flows - ethn age duration	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	CC occupation	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	CC occupation age and duration	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Claimant Flows	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Claimant flows - age and duration	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Claimant flows - occupation	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Claimant on-flows - occ & age	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Claimant off-flows - occ, age and duration	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Claimant off-flows - reasons, age & duration	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
	Claimant off-flows reasons by occ	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Claimant off-flows reasons by occ, age duration	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	CC - age and duration	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
	CC occupation	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
	CC occ age duration	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
	CC denominators - current res/workforce series	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DWP benefits	Benefit claimants- wking age client group	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
	Benefit payments - IB/severe disablement	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
	Benefit payments - income support	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
	Benefit payments - JSA	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
	Benefit payments - carer's allowance	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
	Benefit claimants - DLA	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
	Benefit payments - pension credits	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
	Benefit claimants - state pension	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
	Benefit claimants 5% data - wking age client grp	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	Benefit claimants 5% data - children of wk age cl	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	Benefit claimants 5% data - wking age families	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	Benefit claimants 5% data - pensionable age	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0
	Benefit payments 5% data - attendance allowance	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Benefit payments 5% data - DLA	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
	Benefit payments 5% data - income support	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
	Benefit payments 5% data - IB/SDA	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
	Benefit payments 5% data - JSA	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
	Benefit payments 5% data - pension credit	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
	Benefit payments 5% data - state pension	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1

		1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Job centre plus vacancies	vacancies - summary analysis	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	vacancies notified by occ	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
	vacancies unfilled by duration and occ	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	vacancies outflow by duration and occ	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	vacancies notified by industry	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
	vacancies unfilled by duration and industry	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	vacancies outflow by duration and industry	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
Jobs density	Jobs density	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Population estimates	Mid year population estimates	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
VAT registrations and stocks	Vat reg/dereg by industry	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

PLACES DATA SOURCE	**INDICATOR**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
	Total employees (count)	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	Share of national English Employment	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
	% of employees working full time	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	Recorded crime for seven key offences per1000	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Employment Urban Competitiveness	Enterprise: VAT registrations per 10,000 adults	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0
	Self-employment rate	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0
	Employment rate of those with the lowest/no qualifications	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0
	Four quarter average employment rate - Labour Force Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
	Quarterly Claimant Count rate from the Working Age Client Group	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
EMPLOYEES BY SECTOR: % of employees (FTE) by key sector (SOCD 36B)	Percentage of total FTE working in medium-high- tech industries	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	Percentage of total FTE working in Narrow Definition of Knowledge Inten	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	Percentage of total FTE working in Wide Definitions of knowledge-intens	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	Percentage of total FTE working in The 'creative industries'	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	Percentage of total FTE working in High technology sectors	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
EMPLOYEES BY SECTOR: % of employees by sector (SOCD 35A)	% of Employees in Manufacturing	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Construction	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Distribution, hotels and restaurants	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Transport and communications	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Banking, finance and insurance	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Public administration,education & health	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
	% of Employees in Other services	0	0	0	1	0	1	0	0	0	0	0	1	1	1	1	1	0
Educational performance	Percentage of pupils achieving 5+ GCSEs grades A*-C	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0
	% pupils in LAmaintainedSch's passed 5+ GCSEs A*-C prev summer	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1

Appendix 5.2 Results from series of two level random effects models

Two-level Random Effects Model		**Null Model** Coef. (95% C.I)			**Crude Model CR** Coef. (95% C.I)			**Model 1** Coef. (95% C.I)			**Model 2** Coef. (95% C.I)		
Labour market status (securely employed omitted)	**Insecurely Employed**							**1.26**	1.16	1.37	**1.27**	1.16	1.38
	Unemployed							**2.11**	1.89	2.32	**2.23**	2.01	2.46
	Perm. Sick							**2.75**	2.56	2.95	**2.79**	2.59	2.99
	Other Inactive							**0.68**	0.58	0.78	**0.67**	0.57	0.77
	LAD Claim Rate				-0.01	-0.02	0.01	-0.01	-0.03	0.00	0.00	-0.02	0.01
Interaction between labour market status and LAD Claimant Count Rate	**Insec.Emp x ClaimRate**										-0.04	-0.08	0.00
	Unemp. x ClaimRate										**-0.13**	-0.19	-0.07
	Sick x ClaimRate										**-0.11**	-0.18	-0.04
	Inactive x ClaimRate										0.02	-0.02	0.05
	Constant	**11.08**	11.01	11.16	**11.08**	11.01	11.16	**8.78**	8.40	9.16	**8.79**	8.41	9.18
	n: wave	84665			84665			84665			84665		
	n: individual	10702			10702			10702			10702		
	sigma_u	3.43			3.427			0.731			0.731		
	sigma_e	4.31			4.310			4.235			4.235		
	rho	0.39			0.387			0.029			0.029		
	R-sq: within	<0.001			<0.001			0.021			0.021		
	between	<0.001			0.001			0.601			0.601		
	overall	<0.001			<0.001			0.255			0.255		

Appendix 5.3 Results from two-level cross-sectional multilevel model: 1992

1992	Null Model Coef. (95% C.I)			Crude Model CR Coef. (95% C.I)			Model 1 Coef. (95% C.I)			Model 2 Coef. (95% C.I)		
Insecurely Employed							**1.37**	0.98	1.75	**1.36**	0.98	1.75
Unemployed							**1.65**	0.93	2.38	**1.81**	1.06	2.55
Perm. Sick							**2.45**	1.64	3.26	**2.41**	1.58	3.23
Other Inactive							**0.66**	0.29	1.04	**0.66**	0.28	1.03
LAD Claim Rate				0.01	-0.06	0.07	-0.05	-0.10	0.01	0.00	-0.08	0.08
Insec.Emp xCCR										-0.14	-0.31	0.02
Unemp. xCCR										**-0.25**	-0.46	-0.03
Perm. Sick xCCR										-0.04	-0.18	0.11
Inactive xCCR										0.04	-0.28	0.36
Constant	**11.12**	10.97	11.27	**11.12**	10.97	11.27	**9.24**	8.82	9.67	**9.25**	8.82	9.67
Unexplained variance at Ind. level	**29.595**	28.448	30.742	**29.593**	28.446	30.740	**22.089**	21.234	22.944	**22.059**	21.204	22.914
Unexplained variance at LAD level	0.064	-0.134	0.262	0.066	-0.132	0.264	0.023	-0.116	0.162	0.022	-0.117	0.161
ICC	0.002			0.002			0.001			0.001		
-2*loglikelihood:	32745			32744			31201			31193		
n: Individual	5258			5258			5258			5258		
n: LAD	231			231			231			231		

Appendix 5.4 Results from two-level cross-sectional multilevel model: 1998

	1998	Null Model			Crude Model CR			Model 1			Model 2		
		Coef. (95% C.I)			Coef. (95% C.I)			Coef. (95% C.I)			Coef. (95% C.I)		
Labour market status (securely employed omitted)	Insecurely Employed							**1.91**	1.47	2.34	**1.92**	1.48	2.36
	Unemployed							**2.61**	1.68	3.54	**2.53**	1.57	3.48
	Perm. Sick							**2.63**	1.90	3.35	**2.89**	2.13	3.65
	Other Inactive							**0.30**	-0.08	0.68	**0.29**	-0.09	0.68
	LAD Claim Rate				0.05	-0.05	0.15	-0.01	-0.09	0.06	0.03	-0.06	0.12
Interaction between labour market status and LAD Claimant Count Rate	Insec.Emp xCCR										**-0.26**	-0.51	-0.02
	Unemp. xCCR										0.12	-0.30	0.54
	Perm. Sick xCCR										-0.02	-0.23	0.18
	Inactive xCCR										**-0.51**	-0.95	-0.07
	Constant	**11.12**	10.96	11.29	**11.13**	10.96	11.29	**9.33**	8.96	9.71	**9.33**	8.96	9.70
	Unexplained variance at Ind. level	29.36	28.23	30.49	29.36	28.23	30.49	21.62	20.81	22.44	21.58	20.77	22.40
	Unexplained variance at LAD level	0.31	0.03	0.58	0.29	0.02	0.57	0.00	0.00	0.00	0.00	0.00	0.00
	ICC	0.010			0.010			<0.001			<0.001		
	-2*loglikelihood:	33548			33547			31852			31842		
	n: Individual	5388			5388			5388			5388		
	n: LAD	321			321			321			321		

Appendix 5.5 Results from two-level cross-sectional multilevel model: 2002

2002		Null Model Coef. (95% C.I)			Crude Model CR Coef. (95% C.I)			Model 1 Coef. (95% C.I)			Model 2 Coef. (95% C.I)		
Labour market status (securely employed omitted)	Insecurely Employed							**1.87**	1.39	2.35	**1.88**	1.40	2.35
	Unemployed							**2.74**	1.70	3.78	**2.92**	1.84	3.99
	Perm Sick							**2.90**	2.16	3.63	**3.31**	2.51	4.10
	Other Inactive							**0.79**	0.38	1.21	**0.77**	0.35	1.18
	LAD Claim Rate				**0.18**	0.03	0.33	0.08	-0.05	0.20	0.06	-0.09	0.21
Interaction between labour market status and LAD Claimant Count Rate	Insec.Emp xCCR										0.02	-0.39	0.43
	Unemp. xCCR										-0.36	-1.02	0.31
	Perm. Sick xCCR										**0.38**	0.06	0.71
	Inactive xCCR										**-0.73**	-1.35	-0.11
	Constant	**11.10**	10.92	11.27	**11.11**	10.93	11.28	**9.39**	9.01	9.77	**9.40**	9.02	9.78
	Unexplained variance at Ind. level	29.261	28.081	30.441	29.277	28.097	30.457	21.534	20.668	22.400	21.483	20.619	22.347
	Unexplained variance at LAD level	0.412	0.089	0.735	0.348	0.040	0.656	0.150	-0.050	0.350	0.142	-0.054	0.338
	ICC	0.014			0.012			0.007			0.007		
	-2*loglikelihood:	30694			30689			29155			29142		
	n: Individual	4930			4930			4930			4930		
	n: LAD	322			322			322			322		

Appendix 5.6 Results from two-level cross-sectional multilevel model: 2008

2008		Null Model Coef. (95% C.I)			Crude Model CR Coef. (95% C.I)			Model 1 Coef. (95% C.I)			Model 2 Coef. (95% C.I)		
Labour market status (securely employed omitted)	Insec Employed							**1.20**	0.67	1.72	**1.20**	0.67	1.72
	Unemployed							**3.43**	2.39	4.47	**3.69**	2.63	4.76
	Perm. Sick							**3.88**	3.05	4.70	**3.70**	2.85	4.55
	Other Inactive							**0.65**	0.20	1.10	**0.64**	0.19	1.09
	LAD Claim Rate				**0.23**	0.05	0.40	0.09	-0.05	0.23	0.06	-0.11	0.23
Interaction between labour market status and LAD Claimant Count Rate	Insec.Emp xCCR										0.07	-0.45	0.59
	Unemp. xCCR										**-0.81**	-1.49	-0.13
	Perm. Sick xCCR										0.22	-0.18	0.63
	Inactive xCCR										0.69	-0.09	1.48
	Constant	**11.10**	10.92	11.28	**11.11**	10.94	11.28	**9.50**	9.11	9.89	**9.49**	9.11	9.88
	Unexplained variance at Ind. level	29.446	28.154	30.738	29.454	28.164	30.744	21.189	20.282	22.096	21.136	20.230	22.042
	Unexplained variance at LAD level	0.212	-0.106	0.530	0.153	-0.147	0.453	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
	ICC	0.007			0.005			<0.001			<0.001		
	-2*loglikelihood:	26060			26054			24655			24645		
	n: Individual	4185			4185			4185			4185		
	n: LAD	329			329			329			329		

Appendix 5.7 Results from multiple membership three-level multilevel model

Three-level Multiple Membership Model		**Null Model** Coef. (95% C.I)			**Crude Model CR** Coef. (95% C.I)			**Model 1** Coef. (95% C.I)			**Model 2** Coef. (95% C.I)		
Labour market status (securely employed omitted)	Insecurely Employed							**1.23**	1.12	1.34	**1.24**	1.13	1.35
	Unemployed							**2.21**	2.00	2.42	**2.31**	2.09	2.53
	Perm. Sick							**3.07**	2.85	3.29	**3.07**	2.85	3.30
	Other Inactive							**0.46**	0.35	0.57	**0.45**	0.34	0.56
	LAD Claim Rate				-0.01	-0.02	0.01	-0.01	-0.03	0.00	-0.01	-0.03	0.01
Interaction between labour market status and LAD Claimant Count Rate	Insec.Emp xCCR										-0.02	-0.06	0.01
	Unemp. xCCR										**-0.10**	-0.16	-0.04
	Perm. Sick xCCR										0.03	-0.01	0.06
	Other Inactive xCCR										-0.03	-0.11	0.04
	Constant	**11.07**	10.98	11.15	**11.07**	10.97	11.16	**9.32**	9.18	9.46	**9.33**	9.19	9.46
	Unexplained variance within indiv. **e0ijk**	**18.60**	18.41	18.79	**18.60**	18.41	18.79	**18.36**	18.17	18.55	**18.36**	18.16	18.55
	Unexplained variance between indiv within LADs **u0jk**	**11.37**	10.97	11.78	**11.37**	10.95	11.80	**4.77**	4.52	5.02	**4.77**	4.51	5.03
	Unexplained variance between LADs v**0k**	**0.15**	0.05	0.25	**0.15**	0.03	0.27	0.02	-0.02	0.05	0.02	-0.01	0.05
	Proportion of the variance due to between individuals	0.3825			0.3826			0.2068			0.2071		
	Proportion of the between-individual variance due to differences between individuals within LADs	0.9872			0.9867			0.9967			0.9954		
	Proportion of the variance due to differences between LADs	0.0049			0.0051			<0.0017			0.0010		
	DIC	495653			495654			492890			492873		
	L1 (wave) n	84665			84665			84665			84665		
	L2 (indiv.) n	10702			10702			10702			10702		
	L3 (LAD) n	347			347			347			347		

Chapter 6

Investigating the Temporal Relationship between Labour Market Status and Minor Psychiatric Morbidity

6 Investigating the temporal relationship between labour market status and Minor Psychiatric Morbidity

6.1 Introduction

This chapter aims to investigate the temporal relationship between labour market status and minor psychiatric morbidity, and in so doing, examine the evidence for causality and the processes underlying the relationship. For the purposes of this study, the temporal relationship is conceptualised as having two dimensions. The first dimension is the ways in which individuals remain within or switch between labour market status categories throughout their working lives, and how this is related to changes in their psychological wellbeing. Analyses in this chapter will build on the longitudinal modelling methods used in chapters 4 and 5 by assessing the ways in which specific labour market status transitions cause subsequent deviations in psychological wellbeing from each individual's norm. The statistical methods used in this chapter will allow us to make more confident assertions about the extent to which job loss, job insecurity and joblessness cause psychological distress, independently of other factors.

Disentangling the direction of causality in the relationship between labour market status and psychological wellbeing has been tackled by previous longitudinal research, but has focused overwhelmingly on registered unemployment and employment. It has generally been found that transitions from employment to unemployment are associated with a decline in psychological wellbeing, whereas transitions from unemployment to employment are associated with an improvement (Kinicki *et al.,* 2000; Wanberg, 1995; Winefield *et al.,* 1991). However, with regards to reemployment, some studies have suggested that selection effects may be in operation. Claussen *et al.* (1999) found that unemployed Norwegians who attained 'normal' scores on mental distress tests were more likely to be reemployed compared with their counterparts who scored poorly on the mental distress tests. These results were corroborated by Taris (2002) who found that greater psychological wellbeing was associated with reemployment probability among unemployed Dutch adults and suggested that poor mental health during a period of unemployment reduces the capacity of the unemployed to positively engage with their situation and actively seek work. However, Warr and Jackson (1985), Kessler *et al.* (1989) and Schaufeli and Van Yperen (1993) did not find any evidence for such a relationship.

Research by Thomas and colleagues (2005) is a rare example of work in this field which addresses the effects of transitions between employment and permanent sickness or other inactivity. Using BHPS data from 1991-1998, it was found that transitions from employment to unemployment or permanent sickness were associated with increased GHQ-12 scores, and that moving into employment from these roles was associated with improved psychological wellbeing (Thomas *et al.* 2005). A strength of this study is that the sample is stratified by gender in order to reveal the differences between men and women with regards to labour market engagement and the extent to which this affects psychological wellbeing. It was found that moving from employment to maternity leave or home-making was predictive of decreased psychological wellbeing for women, but not for men. However, key issues not addressed by Thomas *et al.* include the effects of insecure employment, and the extent to which the relationship between labour market status transitions and psychological wellbeing is moderated by age.

Ferrie *et al.* (1995) investigated the hypothesis that employees who anticipate job instability or job loss experience declines in their health prior to the event. Using data from the Whitehall II longitudinal study of British civil servants they found that self-reported health status deteriorated among those anticipating privatisation and its associated job cuts, compared with those who weren't facing job changes or losses. It is likely therefore that lowered mental health amongst employees who become unemployed in the future can be explained in terms of the distressing experience of anticipating job insecurity or loss, rather than as 'health selection', in which those with worse mental health are selected into unemployment in preference to their healthier colleagues.

The second dimension relates to the age of individuals, the stage of the lifecourse in which they experience labour market status transition or continuity and how this affects their psychological wellbeing. The literature is somewhat divided on the extent to which age moderates the relationship between labour market status and wellbeing, with conflicting findings and theoretical explanations. In their review, McKee-Ryan *et al.* (2005) outlined studies in which the relationship between age and the association between unemployment and psychological wellbeing was found to be non-significant (Baik *et al.,* 1989; Creed, 1999; Creed *et al.,* 2001; Hepworth, 1980; Ullah, 1990; Vuori *et al.*, 2002; Wanberg, 1997; Wiener *et al.,* 1999), negative (Kemp and Mercer, 1983; Reynolds and Gilbert, 1991; Wanberg *et al.,* 1999), and positive (P. R. Jackson and Warr, 1984; Macky, 1984). There is a dearth of literature on the extent to which age moderates the relationship between labour market inactivity and psychological wellbeing.

In order to understand the ways in which specific labour market transitions affect psychological wellbeing, and the extent to which this varies with age, it is first necessary to re-examine the theoretical underpinnings. As described in section 2.3.1, Jahoda's functionalist perspective remains the most frequently cited theory in the literature on the links between unemployment and health. Jahoda (1981, 1982) outlined five latent psychological functions considered crucial to maintaining good levels of psychological wellbeing (Figure 6.1), and theorised that these could only be provided by employment.

1. Time structure
2. Social contacts
3. Participation in collective purposes
4. Status and identity
5. Regular activity

Figure 6.1 Five latent psychological functions provided by employment (Jahoda 1981)

However, this perspective is criticised by Strandh (2000) on the basis that it sets up a false dichotomy between employment and unemployment, into which the myriad other forms of labour market engagement cannot fit. Jahoda's theories have their roots in her seminal research undertaken during the Great Depression of the 1930s. It is suggested that applying the same ideas to the era of the modern welfare state and post-Fordist labour market flexibility renders them inadequate. Furthermore, Strandh argues that Jahoda's approach conceptualises the individual as passive and psychologically dependent on the characteristics of social institutions beyond their control. In contrast, Fryer's agency theory casts the individual as an intrinsically motivated social actor, perpetually attempting to assert control over their situation and achieve their goals (Fryer and Payne, 1984, Fryer, 1986). Fryer theorises that when an individual's ability to exercise agency is restricted by conditions beyond their control, this results in lowered psychological wellbeing. Unemployment is an inherently insecure status which inhibits the individual's capacity to plan for the future and control the lifecourse. Fryer contends that when the individual is primarily concerned with living week-to-week, on benefits and looking for work, the conditions are fulfilled for low psychological wellbeing. Fryer's agency theory is employed by Strandh (2000) in order to construct hypotheses about the effects of transitions into and out of unemployment on psychological wellbeing. Strandh's paper makes an important contribution by looking not just at transitions between unemployment and employment, but at transitions between unemployment and permanent sickness, retirement and other inactivity such as parental leave and full time education in a nationally representative longitudinal sample of 3,500 unemployed men in Sweden. The approach taken is an assessment of the security and predictability of the labour market status compared to that of unemployment. For example, in the Swedish context, Strandh considers permanent sickness to be a less secure and predictable status than unemployment, with no mediating increase in income, and therefore predicts that a transition from unemployment to permanent sickness would be associated with a decline in mental wellbeing. This hypothesis was supported, however it is possible that the cultural context plays a large part in the extent to which permanent sickness is considered a less secure and more psychologically distressing status, compared to unemployment. These results may therefore not translate well to a UK setting.

Unusually in the literature, Strandh also makes the distinction between secure and insecure reemployment, hypothesising that the importance of predictability is such that reemployment in a temporary job would be significantly less predictive of improved mental wellbeing than reemployment in a job with a permanent contract. In line with agency theory, Strandh's results support this hypothesis, with those exiting unemployment to secure employment improving in GHQ-12 score more than those exiting to insecure employment. However, Strandh's work does not consider the potential mediating effect of age in the relationship between transitions from unemployment and mental wellbeing, and does not investigate the effects of transitions into unemployment or transitions between employment and permanent sickness or other inactivity.

Theoretically, both Jahoda's latent functions approach and Fryer's agency theory lead to the conclusion that the effect of transitions to or from joblessness on psychological wellbeing could vary depending on stage of the lifecourse. For example, whilst the maintenance of social contacts and participation in collective endeavour is likely to affect psychological wellbeing throughout the lifecourse, the extent to which these are provided solely by paid employment could vary by age. Jackson and Warr suggest, for instance, that school leavers and those in the early years of labour market engagement carry forward a social network of friends from school and therefore already have established leisure and social activities which may ameliorate the effects of unemployment (Jackson and Warr, 1984). In contrast, for those in mid-life, work is likely to form a more central part of their existence and therefore be more responsible for promoting the essential latent psychological functions described by Jahoda. Taking an agency approach, it is also possible to see reasons for why different age groups may be differentially affected by their labour market status. Security and predictability may be more important for the psychological wellbeing of those with dependent children or financial obligations such as mortgage payments and therefore may be a more important factor for those in mid-life. In addition stability is more socially normed among this age group, compared with new labour market entrants, for whom a period of instability in which the future remains unpredictable is considered fairly normal and therefore potentially less distressing. A number of studies have shown that middle aged unemployed men show greater psychological distress than those who are either younger or older (Daniel, 1974; Eisenberg and Lazarsfeld, 1938; Hepworth, 1980). It is argued by Hanisch (1999) that older individuals face greater challenges with regards to keeping their jobs and finding reemployment in the event of job loss. Older people face both real and perceived discrimination in the labour market and may fear that their skills and training are outdated and that they are ill-equipped to compete with younger counterparts with regards to avoiding redundancy or gaining reemployment (Hanisch, 1999). However, it is suggested by Jackson and Warr (1984) that those who are jobless but approaching retirement age may consider themselves as having informally 'retired early'. Retirement potentially offers an alternative and valid social role for those who find themselves out of work in later life, even if their 'retirement' is unofficial and involuntary. Jackson and Warr (1984) also suggest that the financial commitments and responsibilities in later working life are likely to be fewer than in mid-life.

Whilst there is a reasonable amount of existing research on the effects of transitions between employment and unemployment on psychological wellbeing, very little investigation of the effects of switching between jobless states, or between employment and permanent sickness has been undertaken. In order to construct any hypothesis about this relationship, it is first necessary to appreciate that the experience of economic inactivity due to permanent sickness is a varied one and likely to be dependent on the age, gender and socioeconomic position of the individual. Superficially, it seems intuitive that a transition from unemployment (where one is engaged in the labour market and actively seeking work) to permanent sickness (where one has a physical or mental health condition serious enough to preclude one from engaging in paid labour) would be predictive of a significant decline in psychological wellbeing. This is largely because the presence of a physical health problem is known to have a substantial negative effect on mental wellbeing (Kathol and Petty 1981; Langner and Michael 1963**;** Neff *et al.,* 1980), and clearly incapacity due to mental illness is also predictive of, and potentially capturing the same dimensions as the outcome. A transition from unemployment to permanent sickness between one year and the next, for example, is superficially indicative of the sudden onset of an incapacitating medical problem, or the development of a chronic health problem beyond a critical tipping point. Likewise, a transition from permanent sickness to unemployment may indicate recovery or remission, and as such is likely to be associated with a substantial increase in psychological wellbeing. However, it is also possible that a transition from unemployment to permanent sickness may be positive in some instances, especially if health problems are present during unemployment. The incapacity benefits paid to the permanently sick throughout much of the study period were more generous than Jobseekers Allowance, and did not carry the same condition of active job searching, with its potential for repeated disappointments and knock-backs in difficult labour market conditions. It is also possible that in some cultural contexts, permanent sickness is a more acceptable social role than unemployment and thus less susceptible to the elements of Jahoda's theory regarding social status. The extent to which this is true may depend on age. For the young, permanent sickness is less prevalent and therefore less socially normal than in old age, which may make it more distressing. However, the notion of being "on the scrap heap" (Ranzijn *et al.* 2006, p.467) in mid or later life is argued to be more conductive to psychological distress, particularly with regards to the 'lost generation' of male former manufacturing industry workers who have been marginalised by the deindustrialised economy (Ranzijn *et al.,* 2006) and have drifted from unemployment to permanent sickness with age. It is also important to recognise that the health profiles of the permanently sick groups are likely to differ with age.

6.1.1 Research Aim

Investigating the temporal dimensions of the relationship between labour market status and GHQ-12: causation, process and lifecourse.

6.1.2 Objectives

1. To distinguish between the effects of changing labour market status on GHQ-12 within individuals' lives over time; and the comparison of GHQ-12 outcomes between individuals in different labour market status categories.

2. To determine the extent to which labour market status affects GHQ-12 scores differently by age group, and to investigate how this varies within and between individuals.

3. To examine the temporal sequencing of changing labour market status and variation in GHQ-12 scores through the lives of individuals: what can we conclude about the direction of causality and is there support for a health selection hypothesis?

4. To determine whether the temporal sequencing of labour market status changes and variations in GHQ-12 scores varies by age group.

5. To disentangle the processes surrounding which specific labour market status transitions are more strongly predictive of GHQ-12 score decline or improvement.

6. To establish whether certain labour market transitions have different effects on different age groups

6.1.3 Hypotheses

1. Differences in the association between labour market status and GHQ-12 score will be seen when comparing across individuals and when looking at change within individuals over time.

2. When looking within individuals over time, there will be some significant differences between the age groups in terms of the extent to which different labour market statuses predict psychological distress.

(a) It is hypothesised that being permanently sick will be comparatively more distressing for the young, compared to those in mid-life or later working life. This is because permanent sickness is less common in this age group and therefore less socially normed.

(b) It is hypothesised that being unemployed will be comparatively more distressing for those in mid-life, who are likely to have the greatest burden of financial responsibilities and commitments, compared to the young and those in later working life. In addition, those in mid-life are likely to place a higher premium on stability and security compared to the young, and would therefore find the inherent unpredictability of unemployment more distressing.

(c) Insecure employment will be comparatively more distressing for those in mid-life, owing to its inherent instability and unpredictability.

(d) With regards to ‘other inactivity’, the oldest and youngest groups will be least affected owing to a higher prevalence of retirement and full-time education (respectively) among the other inactive at these ages.

3. Moving into insecure employment, unemployment or permanent sickness from employment will be significantly predictive of increased psychological distress, when controlling for confounders and the contemporaneous effects of the current labour market status on GHQ-12.

4. Those that are currently securely employed but become insecurely employed or unemployed one year into the future will have had significantly higher levels of psychological distress whilst employed, due to anticipation of job loss or job insecurity.

5. Controlling for current labour market status and confounders, making a transition from secure to insecure employment will be predictive of a decrease in psychological wellbeing. The inverse will also be observed. This will be the case for all age groups, but comparatively more so for those in mid-life.

6. Controlling for current labour market status and confounders, making a transition from secure or insecure employment to unemployment will be predictive of a decrease in psychological wellbeing.

7. Controlling for current labour market status and confounders, making a transition from secure or insecure employment to permanent sickness will be predictive of a decrease in psychological wellbeing. This will be true for all age groups but comparatively more so for those in mid-life.

8. Controlling for current labour market status and confounders, making a transition from unemployment to permanent sickness will be predictive of a decrease in psychological wellbeing for the youngest and middle age groups, but will not predict any significant change in wellbeing for the oldest group. Switching from permanent sickness to unemployment will be predictive of an increase in psychological wellbeing for all groups, as this would be likely to denote recovery from sickness.

9. Other Inactivity will act as a heterogeneous category in transition analyses. It is assumed that for the youngest group, the other inactive are largely those in full time education. As a predictable and secure status, it is predicted that this will provide similar psychological benefits to secure employment. For the mid-life group, it is assumed that much of the other inactivity will be female and fall into the category of home making. For the older category, it is assumed that retirees predominate amongst the other inactive. Therefore, other inactivity is generally conceptualised as a more predictable and secure labour market status than unemployment, permanent sickness or insecure employment.

6.2 Methods

6.2.1 Deriving variables

For the purposes of the age-group stratified analyses presented in this chapter, a categorical age variable was derived with three categories: early working life (16-29); mid-life (30-49); and later working life (50-65).

Lagged and advanced versions of the explanatory variable, labour market status were derived. The lagged labour market status variable describes the individual's labour market status in the wave preceding the current BHPS wave, and the advanced variable describes the individual's labour market status one wave ahead. The lagged and current labour market status variables were used to create 25 binary transition variables, for each combination of previous and current labour market categories.

6.2.2 Defining the sample

The study sample was defined as outlined in Figure 6.2, and the number of observations and individuals in the unstratified and age-group stratified samples are detailed in Table 6.1.

Table 6.1 Sample size for observations and individuals in unstratified and age-group stratified samples

Final Sample	Observations	Individuals
All age groups	88,885	10,494
Age 16-29	23,297	4,829
Age 30-49	43,549	6,088
Age 50-65	22,049	3,436

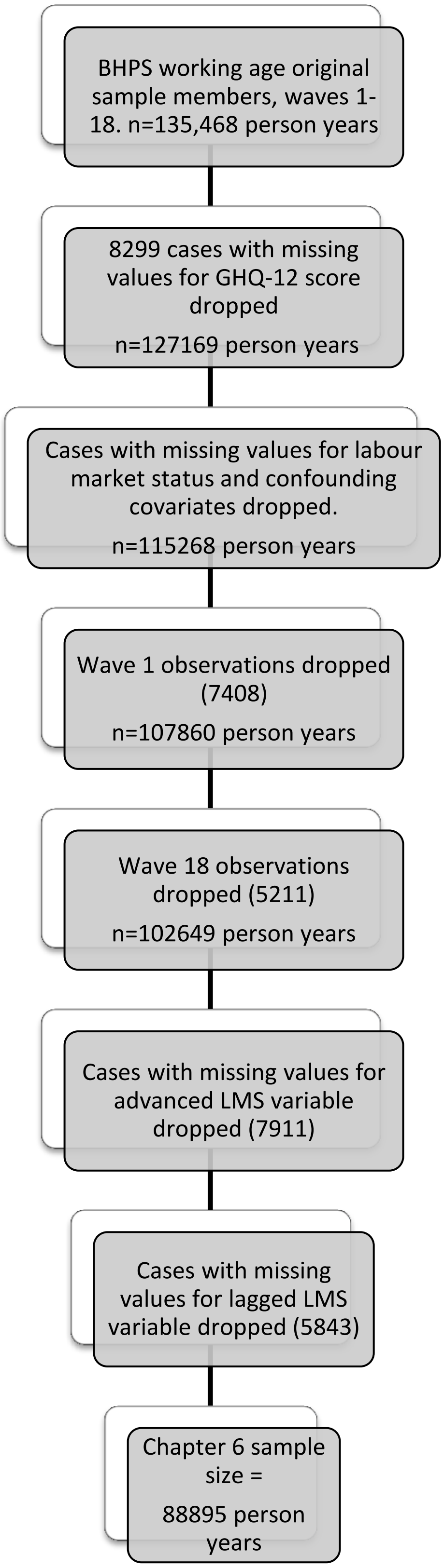

Figure 6.2 Flowchart to show sample size definition

6.2.3 Between, fixed and random effects models

In order to explore the temporal dimensions of the relationship between labour market status and GHQ-12 score in greater detail it is necessary to build on the modelling methods previously outlined. In chapter 4, random effects models were used to assess the relationship between the explanatory and outcome variables when adjusting for thematically linked groups of hypothesised confounding and mediating covariates. Random effects models work under the assumption that the change in the outcome predicted by a change in the explanatory variable will be the same, no matter whether this is observed between two separate individuals or between two observations on the same individual. In other words, random effects models use a weighted average of the within-individual and between-individual estimators. However, for the purposes of this chapter, it is important to differentiate between these fixed and between effects. A fixed effects model, using only the within estimator, allows us to answer the following question: *What is the expected change in Person 1's outcome value if the value of their explanatory variable increases by 1 unit between two time points?* In contrast, a between effects model asks*: What is the expected difference in the outcome values between Person 1 and Person 2 if they differ in the explanatory variable by a unit of 1?* As explained above, the random effects model assumes that there is no need to differentiate between these two dimensions. An important property of fixed effects models is that because they only estimate within-person effects, unobserved variables which differ between individuals but are constant over time are automatically controlled for. In contrast, between effects models automatically control for omitted variables which change over time, but are shared by all individuals. Between effects models are an inherently cross-sectional approach and longitudinal information is lost as the approach is equivalent to taking the within-individual mean for each variable and assuming that individuals do not change over time.

The Hausman test (Hausman, 1978) allows us to test the null hypothesis that coefficients estimated by random effects (i.e. an average of the coefficient estimated by between effects and the coefficient estimated by fixed effects) are equal to the coefficients estimated by fixed effects. When using panel data, fixed effects are always an appropriate approach and give consistent results (i.e. close to the true value). However, random effects models are more efficient, estimating effects with less error, and should therefore be used in preference to fixed effects if this can be justified. The Hausman test compares the more efficient random effects model with the inefficient but more consistent fixed effects model. If the random effects model is also found to give results consistent with the fixed effects model, the Hausman test will report a p-value greater than 0.05 and the use of the random effects model can be justified. If the test finds that the coefficients are significantly different between the random and fixed effects models, then it is not appropriate to use random effects and the less efficient fixed effects model should be used instead.

6.2.4 Modelling strategy

As this chapter builds on the detailed analysis of the role of confounding and mediating covariates in the relationship between labour market status and psychological wellbeing in Chapter 4, it was not deemed necessary to repeat the nested series of models. All of the models presented in this chapter are adjusted for the range of individual-level confounders which were found in chapters 4 and 5 to have a significant effect on the relationship between labour market status and GHQ-12 score, with the exception of lagged GHQ-12 score and gender (Table 6.2). The inclusion of lagged GHQ-12 score was deemed inappropriate for the methods used in this chapter and gender is a time invariant variable in this sample, so was excluded from fixed effects analysis. In addition the continuous age and age-squared variables were excluded from the age-group stratified analyses.

Table 6.2 Properties of hypothesised confounding covariates used in the analysis

Variable	Properties
Age *(not included in age group stratified models)*	Continuous, mean centred
Age-squared *(not included in age group stratified models)*	Continuous, mean centred
Educational attainment	5 categories
1+ Unemployed spells in past year	Binary
1+ Physical health problem	Binary
Social housing tenure	Binary
Spousal joblessness	3 categories
Spousal GHQ-12 caseness	3 categories
Marital status	3 categories
Gender *(time invariant therefore not used in fixed effects models)*	Binary

As discussed above, the use of fixed effects models allows one to be more confident about having addressed residual confounding to some extent, as the method adjusts for 'case effects' by looking only at what causes a deviation from each individual's own mean outcome value.

The relationship between the fixed effects, random effects and between effects models is shown below:

The equation for the random effects model is:

$$y_{ij} = \alpha + \sum x_{ij} \beta_{RE} + u_i + \varepsilon_{ij}$$

And for the between effects model it is:

$$\overline{y}_i = \alpha + \sum \overline{x}_i \beta_{BE} + u_i + \overline{\varepsilon}_i$$

Which with a differencing transformation gives the fixed effects model as:

$$(y_{ij} - \overline{y}_i) = \sum (x_{ij} - \overline{x}_i) \beta_{FE} + (\varepsilon_{ij} - \overline{\varepsilon}_i)$$

Where, for individual i on occasion j:

y_{ij} is the outcome of interest (GHQ-12 score)

α is a constant

x_{ij} are the time-variant independent variables

β is the linear regression coefficient associated with x_{ij}

u_i is the individual-specific residual which differs between individuals but is constant within individuals over time.

ε_{ij} is the occasion-specific residual, describing how occasions within individuals differ from the individual average.

$\overline{y}_i, \overline{x}_i, \overline{\varepsilon}_i$ are the means of the outcome variable, independent variables and occasion-specific residual, averaged for all individuals over time.

Both residuals conform to the usual assumptions: having a mean of zero and being uncorrelated with themselves, uncorrelated with each other and homoscedastic.

6.2.4.1 Comparison of unstratified fixed and random and between effects models, with age stratification

The first analytical step in this chapter was to compare the results from random, fixed and between effects models and to perform a Hausman test to assess whether fixed effects models are necessary. The Hausman test indicated that fixed effects models were necessary, so this method was adopted for the further analyses in this chapter.

In these models, the x_{ij} terms were: insecure employment; unemployment; permanent sickness; other inactivity; age ; age^2; one or more unemployment spells in the past year; achieving A-levels or equivalent as the highest level of educational attainment; achieving GCSEs or equivalent as the highest level of education; attaining no formal educational qualifications; suffering one or more physical health problem; living in social housing; spousal GHQ-12 caseness; spousal joblessness; having no spouse; being married or cohabiting; being divorced; widowed or separated; having never married or cohabited; and gender (although the latter was not included in the fixed effects models as it is time-invariant in the BHPS).

In order to assess whether the relationship between labour market status and psychological wellbeing is affected by age, the fixed effects model described above was run with an interaction term between age group and labour market status added. A Wald test was performed to establish whether the interaction variable was significant overall, and the significance levels of the coefficients for each interaction term were used to assess the extent to which certain age groups were more affected by specific labour market status categories. After a significant interaction had been confirmed, stratified random, fixed and between effects models were then run for each of the three age groups separately.

6.2.4.2 Preliminary investigation of causality: comparing lagged and advanced explanatory variables, with age stratification

The lagged and advanced labour market status variables generated were used as covariates in fixed effects models as a preliminary investigation of the direction of causality in the relationship between labour market status and GHQ-12 score. Firstly, a model containing lagged labour market status as the key explanatory variable was run, controlling for current labour market status and the standard set of time variant confounders. Lagged labour market status was derived as described in section 6.2.1 and was added to the model described in section 6.2.4.1 as an additional x_{ij} term. Interpretation of the coefficients for lagged and current labour market status in conjunction with one another reveals the ways in which the chronological sequencing of labour market statuses produces changes in GHQ-12 scores. Addition of current and lagged labour market coefficients allows, for example, comparison between the effects of remaining unemployed in two consecutive waves and the effects of losing a job between one wave and the next. This method therefore allows causality to be inferred. Secondly, the model was run with advanced labour market status as the key explanatory variable, also controlling for current labour market status and confounding covariates. Advanced labour market status was derived as described in section 6.2.1 and was added to a version of the model described in section 6.2.4.1 as an additional x_{ij} term. Positive coefficients for advanced labour market status categories in this model would indicate that becoming insecurely employed, unemployed, permanently sick or other inactive in the future is associated with pre-existing higher GHQ-12 scores when securely employed in the current wave. This model can therefore show if poorer psychological wellbeing predates a change in labour market status. This exploratory modelling using advanced labour market status as a covariate was employed as a preliminary investigation and whilst it cannot be used to infer causality, it can give a useful indication of the need for further exploration of the relative contributions of health selection and social causation.

In order to make a preliminary assessment of whether the direction of causality is the same for each age group, two further fixed effects models were run: one which included in interaction between lagged labour market status and age group; and one which included an interaction between advanced labour market status and age group. Wald tests were performed for each of these models, in order to assess the extent to which age group differences exist. The models were then run with age stratification, for clearer presentation and interpretation of the results.

6.2.4.3 Exploring labour market transitions

Investigation of the nature of the causal relationship between labour market status and psychological wellbeing was then further developed by looking at the extent to which specific labour market status transitions predicted changes in GHQ-12 scores, in order to further elucidate the nature of the relationship. Firstly, all 25 possible combinations of labour market status transitions (including stable transitions) were identified (Table 6.3). A binary variable was then derived for each possible transition and the prevalence of the occurrence of each transition across the sample was calculated and presented as descriptive analysis.

Table 6.3 All possible labour market status transitions between two consecutive waves

LMS at t / LMS at t-1	**Secure Employment**	**Insecure Employment**	**Unemployment**	**Permanent Sickness**	**Other Inactivity**
Secure Employment	*Sec to Sec*	Sec to Insec	Sec to Unemp	Sec to Perm Sick	Sec to O. Inactive
Insecure Employment	Insec to Sec	*Insec to Insec*	Insec to Unemp	Insec to Perm Sick	Insec to O. Inactive
Unemployment	Unemp to Sec	Unemp to Insec	*Unemp to Unemp*	Unemp to Perm Sick	Unemp to O. Inactive
Permanent Sickness	Perm Sick to Sec	Perm Sick to Insec	Perm Sick to Unemp	*Perm Sick to Perm Sick*	Perm Sick to O. Inactive
Other Inactivity	O. Inactive to Sec	O. Inactive to Insec	O. Inactive to Unemp	O. Inactive to Perm Sick	*O Inactive to O Inactive*

The first stage in the modelling strategy was to run 20 separate fixed effects models to establish the association between each of the non-stable transition binary variables and the GHQ-12 score outcome, controlling for current labour market status and confounders. These were also repeated to include an interaction between the transition variable and age group. The transition variables which were found to be significantly associated with GHQ-12 score, independently of current labour market status and confounders, were then selected for unstratified multivariate analysis. These selected transition variables were then all added into a final fixed effects model together, also controlling for current labour market status and confounders. When interpreted in conjunction with the coefficients for current labour market status, the coefficients for each of the transition variables show whether making the transition is associated with higher or lower current GHQ-12 score, over and above the contemporaneous effects of current labour market status on psychological wellbeing. In this way, analysis of specific labour market status transitions allows fuller understanding of the complex processes and mechanisms at work.

In order to assess the extent to which these processes vary by age group, a simplified version of the final model was run with age stratification. In addition, a series of fixed effects models were run, containing current labour market status, a binary transition variable, and an interaction between age group and the transition indicator of interest. Wald tests were performed to assess the significance of the interaction variable in each of these models. The results from the stratified transition models were then were interpreted in conjunction with the Wald tests performed on the interaction variables to assess whether differences by age group were significant.

6.3 Results

6.3.1 Descriptive analysis

Figure 6.3 shows the number of observations taken at each age in the sample. It should be noted that many of these are repeated observations on the same individual as they age throughout the study. The number of observations at each age group decreases slightly between the ages of 17 and 21, probably due to early drop-out, before rising to a peak around the age of 35. Declining numbers of observations can then be seen as age at interview rises to 65.

Figure 6.3 Number of observations taken at each age in the sample

For each possible GHQ-12 score, Figure 6.4 shows the proportion of observations from each of the age groups. There are a greater proportion of younger and 30-49 year old people with low GHQ-12 scores, and the older age group are underrepresented here. At high GHQ-12 scores, the proportion of young people drops below 20 percent, and high GHQ-12 scores are disproportionately recorded for people in the middle and older age groups.

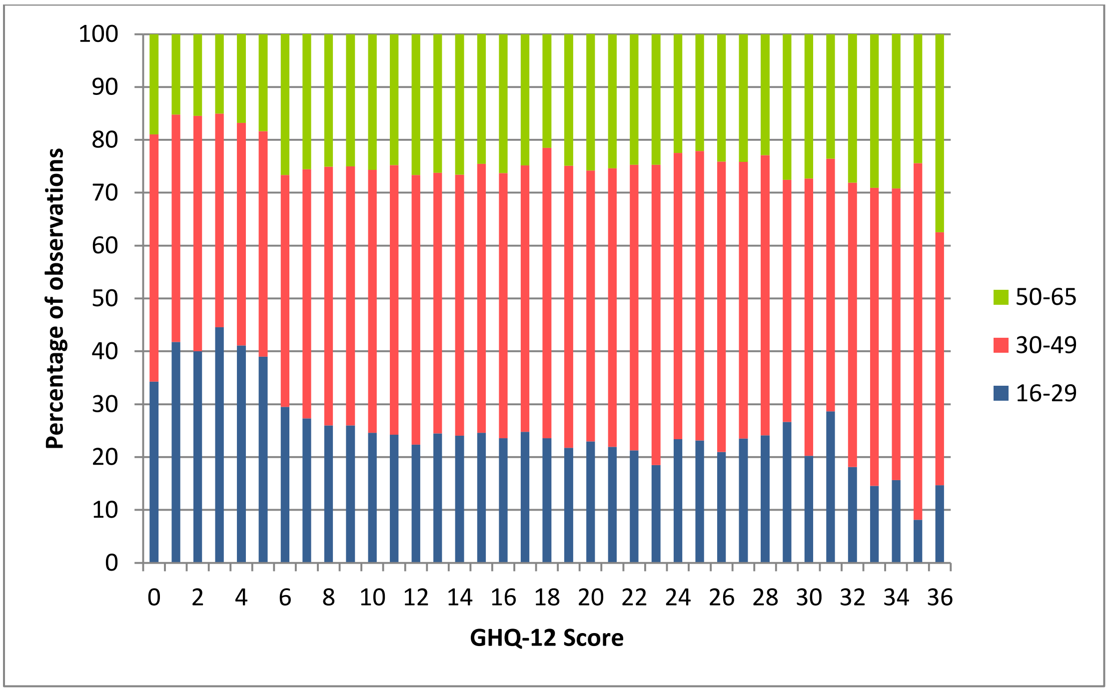

Figure 6.4 Prevalence of each GHQ-12 score by age group (person-years of data)

Figure 6.5 shows the proportion of all observations for each age group in the different labour market status categories. Secure employment was by far the most prevalent status, accounting for 68 percent of observations in the youngest age group, 72 percent of observations in the 30-49 category, and 55 percent of observations in the oldest group. Insecure employment has a similar prevalence across all age groups, ranging from 8 percent of observations from the youngest age group to 12 percent in mid-life and 9 percent in the 50-65 age brackets. Unemployment appears to be most prevalent among the 16-29 year olds, with a rate of 5.7 percent across all BHPS observations. This compares with just 2.8 percent and 3 percent among the mid-life and older categories respectively. As one might expect, the prevalence of permanent sickness increases through the age groups. Other inactivity was the second most prevalent status, especially amongst the older group, in which it accounted for 24 percent of observations. The differing prevalence of other inactivity between the age groups can be explained by the heterogeneity of this category. The 24 percent of observations at older ages are largely attributable to early retirement and female retirement at 60 years. The 17 percent of ‘other inactive’ observations in the youngest age group is due to the high proportions of individuals in full time education in this age bracket, from sixth form college to university. The 10 percent of ‘other inactive’ observations in the 30-49 bracket are women looking after the home and family during this part of their lifecourse.

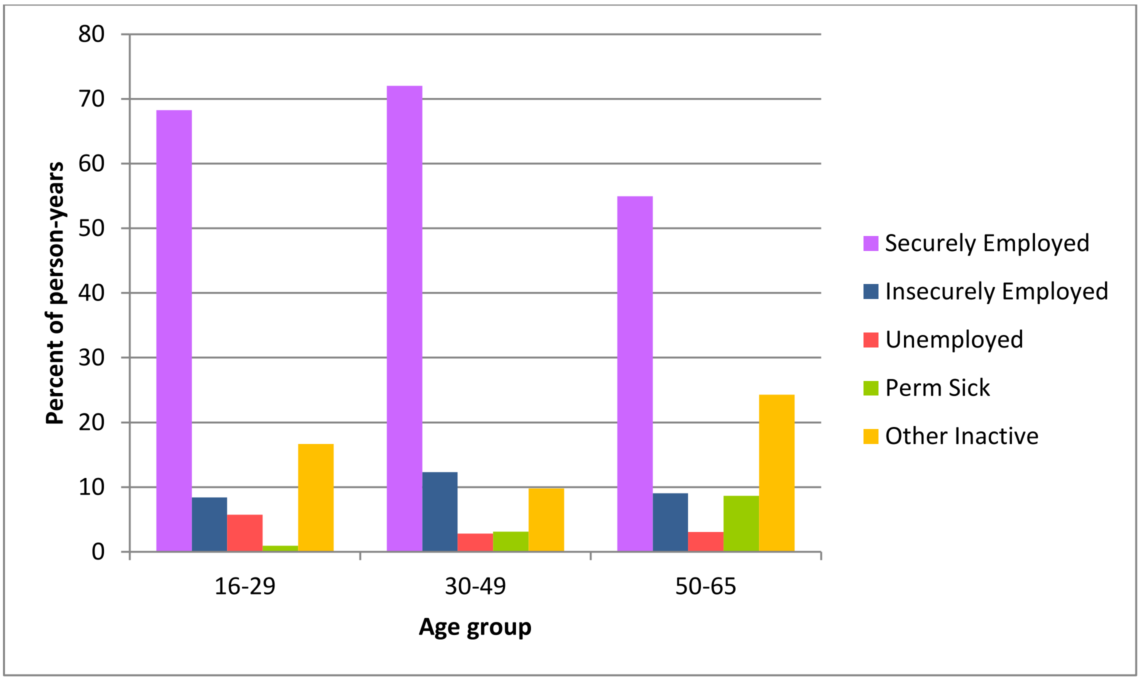

Figure 6.5 Proportion of all observations for each age group in the different labour market status categories

Figure 6.6 provides a slightly different perspective. It shows the age structure of each labour market status category. This brings into clearer focus how observations at younger ages account for approximately half of all unemployment observations, and how observations at older ages account for 69 percent of 'permanently sick' observations.

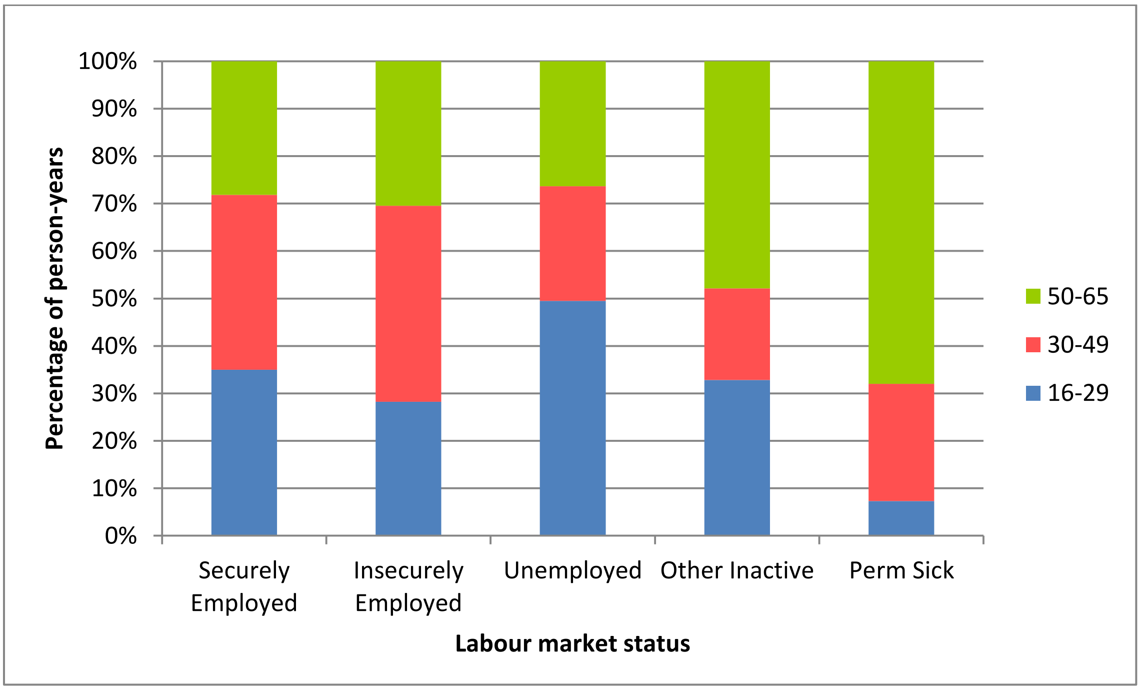

Figure 6.6 Age structure of each labour market status category (person-years of data)

6.3.2 Between, fixed and random effects

6.3.2.1 Comparison of unstratified between, fixed and random effects models

The results from the fixed, random and between effects models can be compared using Figure 6.7 (with full details in Appendix 6.1). The results from the between effects model differ to those of the fixed and random effects models. For each of the labour market status categories besides unemployment, the coefficient is greater for the between effects model. This means that there were greater differences in GHQ-12 between individuals of different labour market statuses than there were within individuals who switch between labour market statuses during their time in the study. When controlling for hypothesised confounders in the between effects model, insecurely employed individuals had GHQ-12 scores 2.5 units higher than those who were securely employed. The unemployed had GHQ-12 units 1.5 times higher, the permanently sick 4.8 units higher, and the other inactive have GHQ-12 scores 1.4 units higher than securely employed individuals. It is clear from this model that, despite adjustment for confounders, those individuals who were jobless or insecurely employed were considerably more likely to have higher levels of psychological distress.

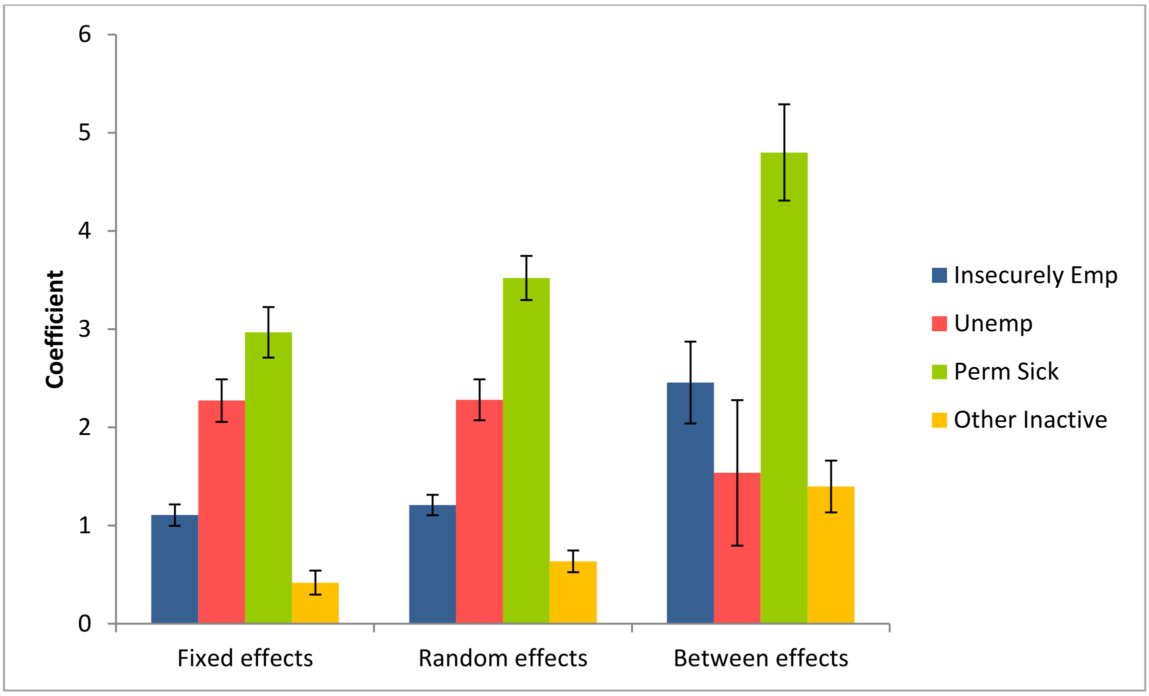

Figure 6.7 Results from unstratified fixed, random and between effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates

The fixed effects model shows that when individuals were insecurely employed or jobless, they had higher GHQ-12 scores than the same individuals did when they were securely employed. Compared to when they were securely employed, an individual experiencing a spell of insecure employment had a GHQ-12 score elevated by 1.1 units. An unemployed spell was associated with a GHQ-12 increase of 2.3 units. Experiencing permanent sickness was associated with a 3 unit increase in GHQ-12, whilst a spell of other inactivity predicted a 0.4 unit increase in GHQ-12 score, compared to when the individual was securely employed. The direction of the switch between secure employment and a different labour market status category cannot be inferred from this fixed effects model. The coefficient just shows the expected change in an individual's GHQ-12 value if s/he switched from being, for example, unemployed to being securely employed, or vice versa. The random effects model shows a weighted average of the between and within estimators. In this instance, the random effects model more closely resembles the fixed effects model than the between effects model. The Hausman test was performed in order to formally test this and therefore to establish whether the more efficient random effects model is justifiable, or whether the more consistent fixed effects model is necessary. The results of the test (χ^2=404.3, p<0.001) show that there is a significant difference between the coefficients estimated for the random effects and fixed effects model, and therefore that use of the fixed effects model is preferable.

No chronological sequencing is specified, so causality cannot be confidently inferred. In order to make conclusions about the direction of causation, lagged and advanced measures of labour market status are explored in section 6.3.3.1 to see if there is any suggestion of reverse causation (i.e. of health selection).

6.3.2.2 Comparison of age-stratified between, fixed and random effects models

A fixed effects model containing an interaction between labour market status and age group, also controlling for confounders, showed that there was a significant interaction between these two variables (Wald test, p<0.001), but that only the coefficients for interactions between: unemployment and age 30-49; other inactive and age 50-65; permanent sickness and ages 30-49; and permanent sickness and age 50-65 were significant at the 5 percent level (Appendix 6.2). Results from three sets of age group stratified models are shown in Appendix 6.3 and in Figure 6.8, Figure 6.9 and Figure 6.10. For the age stratified fixed effects models, it seems that compared to being in a secure job, a spell of insecure employment led to a similar GHQ-12 increase across all age groups (all three coefficients are around 1). Being in a state of unemployment was predictive of a slightly greater GHQ-12 score increase among those aged 30-49 (2.5 units) than either the younger (2.1 units) or older (1.9 units) categories. The coefficient for the interaction term for unemployment and the 30-49 age group was statistically significant (p=0.014), allowing us to be confident that those in midlife do experience greater declines in psychological wellbeing when unemployed compared to when securely employed, than those of other ages. A spell of permanent sickness was associated with a greater GHQ-12 increase compared to secure employment for the youngest group (4.6 units), followed by the 30-49 category (2.9 units) and then the oldest group (1.8 units). Again, the significant coefficients for the interactions between permanent sickness and all age groups allow us to be confident that genuine differences exist between the age groups with regards to permanent sickness and GHQ-12 score. The differing coefficients for other inactivity may reflect the differing make-up of this category across the three age groups. When looking within individuals over time, being in an 'other inactive' state compared to secure employment was predictive of a slightly elevated GHQ-12 score (0.4 units) among the youngest group, many of whom were likely to be students or home-makers. Amongst the 30-49 age group, being 'other inactive' was predictive of the most elevated GHQ-12 score compared to secure employment (0.8 units). The 'other inactive' in this group were likely to be predominantly those looking after the home and family. This age group contained the highest proportion of secure or insecure employment (72 and 12 percent, respectively).

It is clear that, like the unstratified models, there are differences between the fixed, random and between effects estimates. Confidence intervals around the coefficients for the between effects age-stratified model are very wide, reflecting low sample size for some labour market status categories in some age groups (particularly for the unemployed in the 50-65 category, the coefficient for which is non-significant). It is also the case that, like the unstratified models, coefficients are generally greater in the between effects model than the fixed effects model.

As described above, it appears that within individuals across all age groups, a phase of insecure unemployment was similarly predictive of a higher GHQ-12 score. However when looking solely between individuals, it appears that the insecurely employed among the 50-65 year old category were more different from the securely employed individuals of their age than insecurely employed 16-29 year olds were from their securely employed peers. This suggests that older individuals who were insecurely employed had higher GHQ-12 scores on average, and that people were more selected into insecure employment as they aged. The between effects model also suggests selection for the unemployed in the 30-49 age group. Figure 6.10 shows that individuals in this age group were the least likely to be unemployed, and yet the between effects estimates for unemployment were the highest, and statistically significant. Discrepancy between the model types is also apparent with regards to the coefficients for the permanently sick.

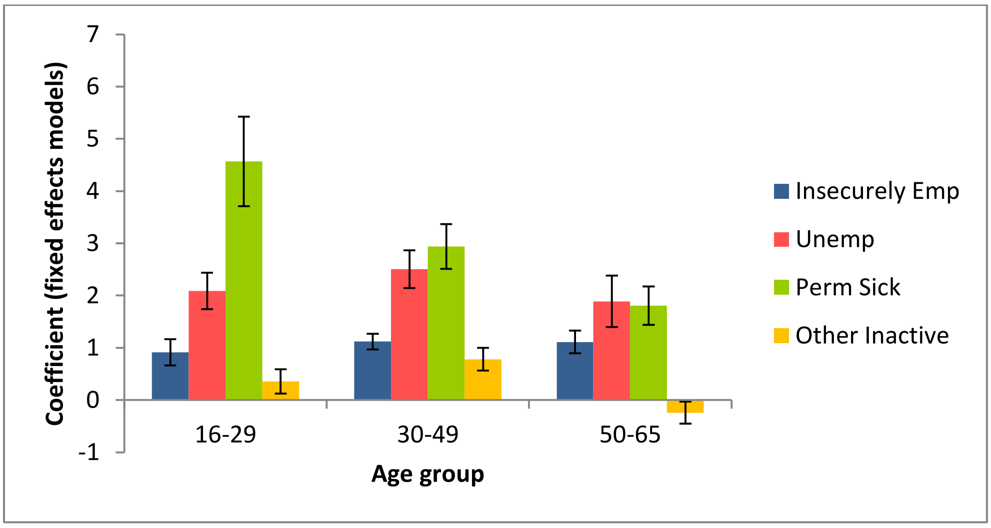

Figure 6.8 Results from age group stratified fixed effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates (see Table 6.2)

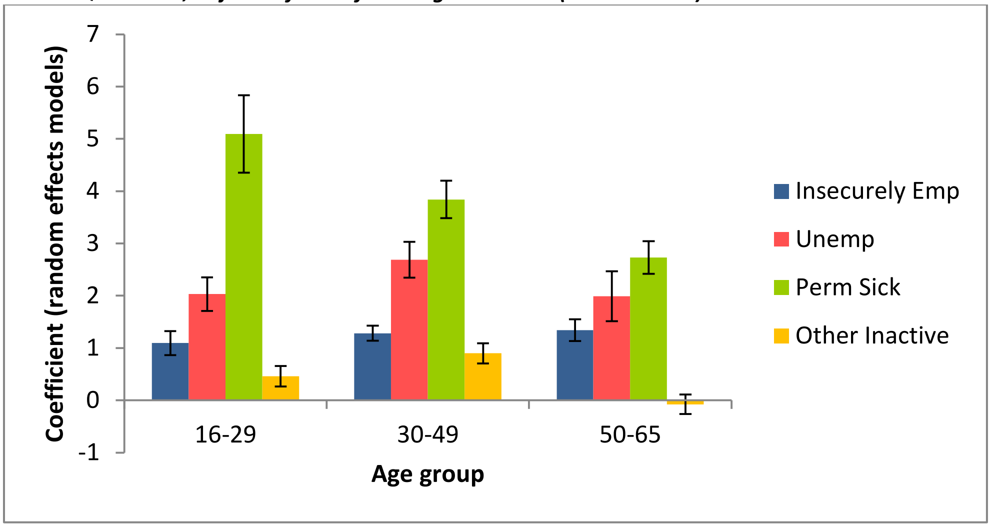

Figure 6.9 Results from age group stratified random effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates (see Table 6.2)

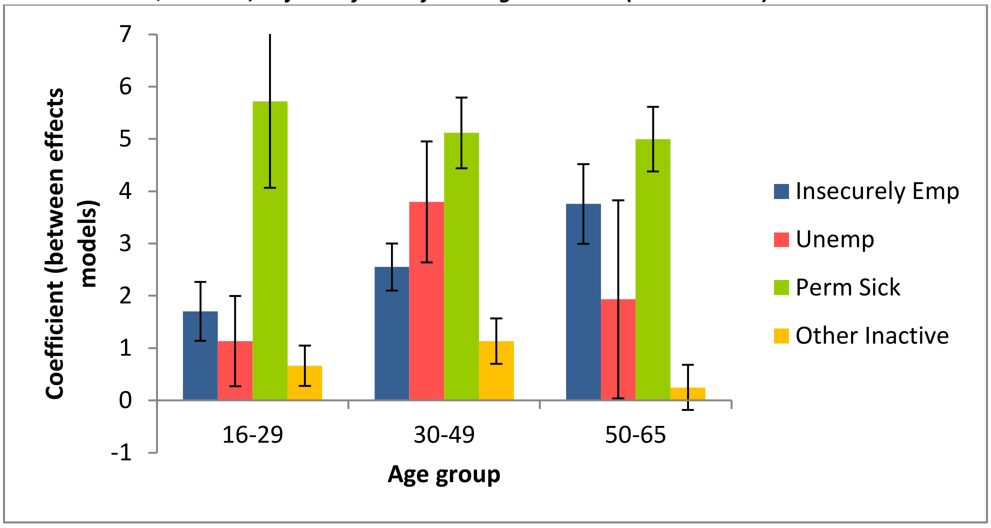

Figure 6.10 Results from age group stratified between effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates (see Table 6.2)

When using just the within individuals estimator, it appears that a spell of permanent sickness was associated with a greater GHQ-12 increase compared to secure employment for the youngest group, followed by the 30-49 category and then the oldest group. This pattern is also shown by the random effects model, and is to be expected, given that the prevalence of permanent sickness in the 16-29 age group was low (0.9 percent of person-years compared to 3.1 percent for the 30-49 age group and 8.6 percent for the 50-65 year olds) and therefore would be less socially normed. It is also likely that the nature of health conditions for which younger people are signed onto permanent sickness benefits is different to that of older people. Whilst this relationship between age, permanent sickness and psychological distress was not as pronounced when looking at between-individual effects, the coefficient for the youngest age group was relatively similar to the fixed effects model (5.7 versus 4.5). This suggests that being permanently sick affected GHQ-12 in this age group and would be consistent with the evidence that mental ill-health is a major cause of permanent sickness in the 16-29 age group. In the older age groups, between effects estimates were relatively larger than the fixed and random effects estimates. This suggests selection processes could be involved and that those with a physical health condition and co-morbid psychological distress were more likely to leave the labour market.

6.3.3 Exploring causality

6.3.3.1 Fixed effects models with lagged and advanced labour market status

Comparison of fixed and between effects models has given some indication that health selection may be in operation. In order to investigate this further, lagged and advanced versions of labour market status were modelled. Table 6.4 and Figure 6.11 show the results for three fixed effects models: Model 1 with current labour market status as the explanatory variable (measured at the same time as the outcome variable, GHQ-12 score); Model 2 with a lagged labour market status from the previous wave as the explanatory variable, in addition to current labour market status; and Model 3 with the labour market status from one wave ahead as the explanatory variable, also controlling for current labour market status. The full set of hypothesised confounding variables were adjusted for in each model.

Table 6.4 Results from three fixed effects models containing (a) current LMS, (b) current and lagged LMS, and (c) current and advanced LMS, adjusted for confounders

UNSTRATIFIED	M1: Current LMS			M2: Lagged LMS			M3: Advanced LMS		
FIXED EFECTS	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp				0.03	-0.08	0.14	**0.24**	0.13	0.35
Unemp				**-0.55**	-0.75	-0.36	**0.49**	0.30	0.69
Perm Sick				**-0.86**	-1.14	-0.58	**1.53**	1.26	1.80
Other Inactive				**-0.43**	-0.56	-0.30	**0.25**	0.11	0.38
Current Insec Emp	**1.11**	1.00	1.22	**1.10**	0.99	1.21	**1.08**	0.97	1.19
Current Unemp	**2.27**	2.06	2.49	**2.28**	2.06	2.50	**2.15**	1.93	2.37
Current P. Sick	**2.97**	2.71	3.22	**3.34**	3.06	3.62	**2.44**	2.16	2.71
Current OI	**0.42**	0.30	0.54	**0.62**	0.49	0.76	**0.30**	0.17	0.44
n: wave	88895			88895			88895		
n: individial	10494			10494			10494		
R-sq: within	0.03			0.0309			0.0317		
between	0.11			0.1057			0.1153		
overall	0.07			0.0718			0.0785		
sigma_u	3.89			3.90			3.87		
sigma_e	4.22			4.22			4.22		
rho	0.46			0.46			0.46		

M1 shows the familiar pattern, in which a spell of insecure employment, unemployment, permanent sickness and other inactivity was predictive of elevated GHQ-12 score, compared to when the individual was securely employed. When coefficients for lagged and current labour market status are interpreted in conjunction with one another, M2 also shows that if an individual was currently securely employed but was unemployed in the previous year, an improvement in psychological wellbeing is predicted, when controlling for hypothesised confounders. This model also shows that being currently unemployed but also unemployed in the previous year was not as harmful to psychological wellbeing as being currently unemployed but previously employed. This suggests a causal association between job loss and psychological distress. This is also true for those who were 'other' inactive in the previous year, and to a greater extent, for individuals who were permanently sick in the previous year. This model demonstrates the benefits to psychological wellbeing of getting into employment and/or recovering from sickness. When current labour market status and confounders are taken into account, being insecurely employed in the previous wave was not significantly predictive of any elevated GHQ-12 score compared to secure employment.

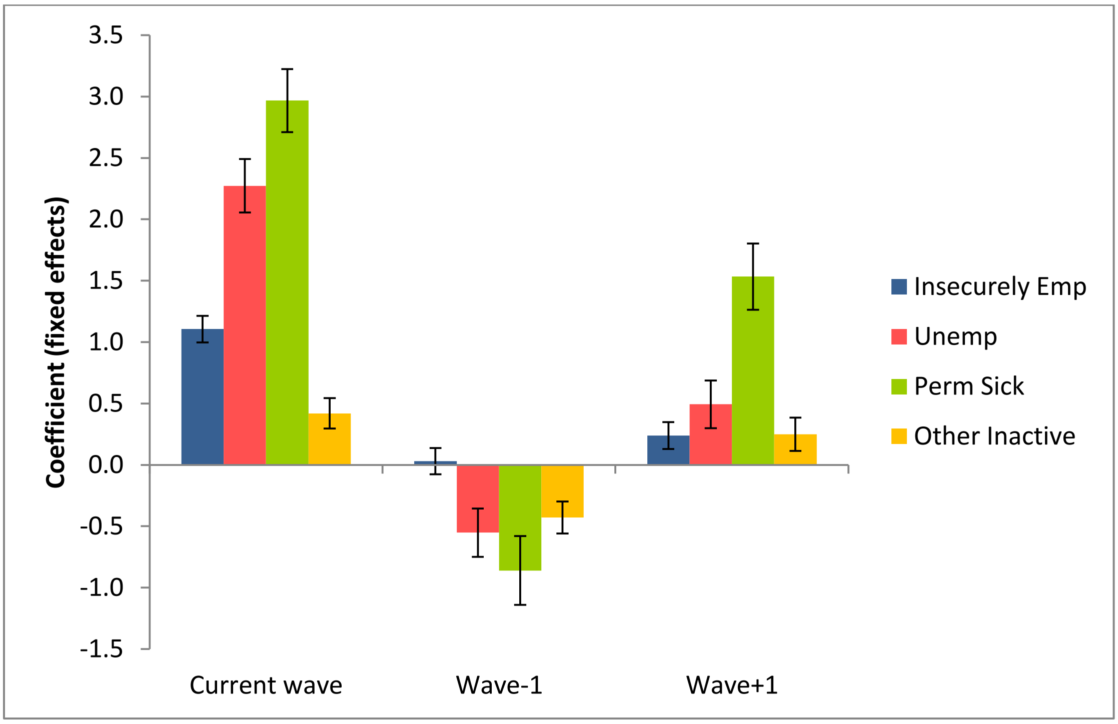

Figure 6.11 Results from three fixed effects models containing (a) current LMS, (b) current and lagged LMS, and (c) current and advanced LMS, adjusted for confounders (see Table 6.2)

M3 shows that if an individual was currently employed, but became insecurely employed, unemployed, permanently sick or other inactive one year into the future, then they had a higher GHQ-12 score whilst originally employed. This is by only 0.24 or 0.25 units for those secure employees who became insecurely employed or other inactive in the following year (respectively), but the coefficients were greater for future unemployment and permanent sickness. Those who became unemployed one year into the future had GHQ-12 scores 0.5 units higher when they were initially securely employed, compared to if they had remained securely employed into the future. Securely employed individuals who became permanently sick in the future are predicted to have GHQ-12 scores 1.5 units higher while securely employed, than if they had remained securely employed throughout both waves. Similarly, the model shows that current unemployment predicts psychological distress, and unemployment in the following year predicts even poorer current GHQ-12 score. This suggests that those who would remain unemployed into the future already had a poorer GHQ-12 score to begin with. The results for M3 could show that individuals pre-empt future labour market status change, which would affect their psychological wellbeing levels before the event. It could also provide support for a health selection hypothesis, in which those who become jobless or insecurely employed are individuals who had higher levels of psychological distress in the first place, and were therefore selected into joblessness or insecurity.

6.3.3.2 Age-stratified fixed effects models with lagged and advanced labour market status

The interaction between age group and lagged GHQ-12 score was significant overall (Wald test, p=0.027 Appendix 6.4). The age stratified versions of M2 are presented in Figure 6.12, Figure 6.13 and Table 6.5. They show no real differentiation between the 16-24 and 30-49 age groups, and are reflective of the pattern seen in the unstratified model, except with higher magnitude coefficients. Lagged labour market status coefficients in the model for the oldest age group however, were all non-significant with the exception of lagged other inactivity (-0.3). For those in the 50-65 age group, current insecure employment, unemployment or permanent sickness were significantly predictive of higher GHQ-12 scores, but previous labour market status was not significantly associated with current GHQ-12 score when adjusting for current labour market status. A different picture emerges with regards to other inactivity for this age group. Current other inactivity was not significantly associated with current GHQ-12 score, whereas lagged other inactivity was. The interaction between age group and advanced GHQ-12 score was also found to be significant overall (Wald test, p<0.001 (Appendix 6.5). Age stratification of M3, showing the association between future labour market status and current GHQ-12, adjusted for current labour market status, showed that only future permanent sickness was significantly predictive of higher present GHQ-12 scores for the youngest age group. This is perhaps reflective of the high burden of mental illnesses amongst the permanently sick in this age group, and suggests low levels of psychological wellbeing in advance of transition to a permanent sickness status. The pattern for the 30-49 age group mirrored the unstratified pattern, in which future insecure employment, unemployment, permanent sickness and other inactivity were all significantly predictive of elevated current GHQ-12 scores. In the older age group, only future permanent sickness and insecure employment significantly predicted higher current GHQ-12 scores.

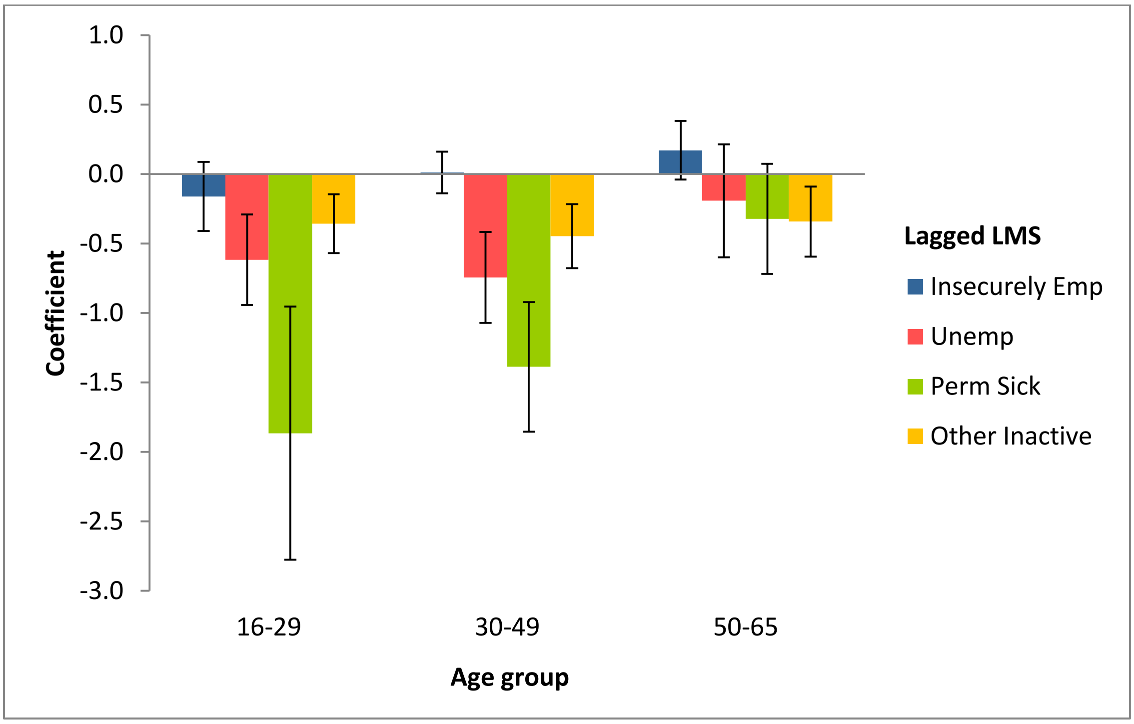

Figure 6.12 Lagged LMS coefficients from age group stratified fixed effects models containing current and lagged LMS, adjusted for confounders (see Table 6.2)

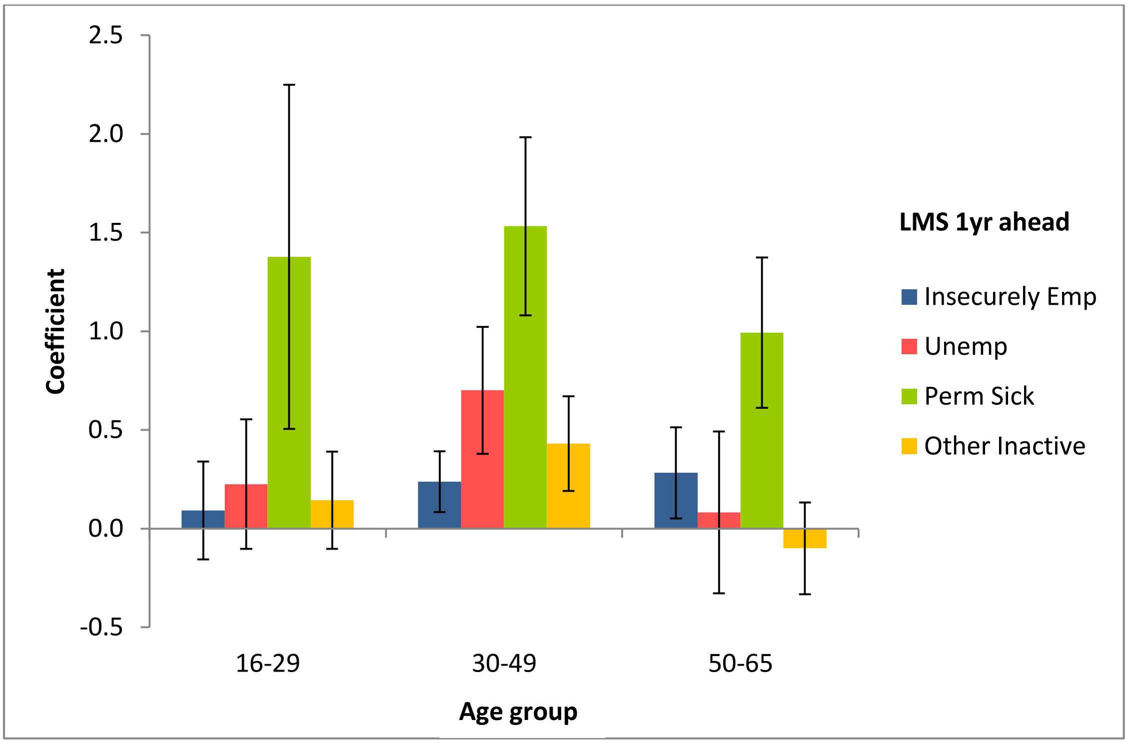

Figure 6.13 Advanced LMS coefficients from age group stratified fixed effects models containing current and advanced LMS, adjusted for confounders (see Table 6.2)

Table 6.5 Results from age group stratified fixed effects models containing (a) current LMS, (b) current and lagged LMS, and (c) current and advanced LMS, adjusted for confounders (see Table 6.2)

FIXED EFECTS	M1a Current LMS			M2a Lagged LMS			M3a Advanced LMS		
Age 16-29	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp				-0.16	-0.41	0.09	0.09	-0.16	0.34
Unemp				**-0.62**	-0.94	-0.29	0.23	-0.10	0.55
Perm Sick				**-1.87**	-2.78	-0.95	**1.38**	0.51	2.25
Other Inactive				**-0.36**	-0.57	-0.15	0.14	-0.10	0.39
Current Insec Emp	**0.91**	0.67	1.16	**0.91**	0.66	1.16	**0.92**	0.67	1.17
Current Unemp	**2.09**	1.74	2.44	**2.07**	1.72	2.42	**2.06**	1.71	2.41
Current PS	**4.57**	3.71	5.42	**4.94**	4.07	5.81	**4.36**	3.49	5.22
Current OI	**0.36**	0.13	0.59	**0.45**	0.21	0.68	**0.33**	0.09	0.56
R-sq: within	0.02			0.02			0.02		
between	0.05			0.04			0.05		
overall	0.04			0.04			0.04		
sigma_u	4.08			4.09			4.07		
sigma_e	4.32			4.32			4.33		
rho	0.47			0.47			0.47		
Age 30-49	**M1b**			**M2b**			**M3b**		
Insecurely Emp	**1.12**	0.97	1.27	0.01	-0.14	0.16	**0.24**	0.08	0.39
Unemp	**2.50**	2.14	2.87	**-0.74**	-1.07	-0.42	**0.70**	0.38	1.02
Perm Sick	**2.94**	2.51	3.37	**-1.39**	-1.85	-0.92	**1.53**	1.08	1.98
Other Inactive	**0.78**	0.56	1.00	**-0.45**	-0.68	-0.22	**0.43**	0.19	0.67
Current Insec Emp				**1.12**	0.97	1.27	**1.10**	0.95	1.25
Current Unemp				**2.47**	2.11	2.83	**2.34**	1.98	2.71
Current PS				**3.51**	3.04	3.97	**2.39**	1.98	2.71
Current OI				**1.01**	0.77	1.24	**0.60**	0.36	0.83
R-sq: within	0.03			0.03			0.03		
between	0.13			0.13			0.14		
overall	0.08			0.07			0.08		
sigma_u	4.00			4.03			3.98		
sigma_e	4.26			4.26			4.26		
rho	0.47			0.47			4.66		
Age 50-65	**M1c**			**M2c**			**M3c**		
Insecurely Emp	**1.11**	0.89	1.33	0.17	-0.04	0.38	**0.28**	0.05	0.51
Unemp	**1.89**	1.39	2.38	-0.19	-0.60	0.22	0.08	-0.33	0.49
Permanently Sick	**1.81**	1.44	2.17	-0.32	-0.72	0.07	**0.99**	0.61	1.37
Other Inactive	**-0.24**	-0.45	-0.03	**-0.34**	-0.59	-0.09	-0.10	-0.33	0.13
Current Insec Emp				**1.09**	0.87	1.31	**1.09**	0.87	1.30
Current Unemp				**1.89**	1.40	2.39	**1.88**	1.38	2.38
Current PS				**1.99**	1.59	2.38	**1.65**	1.26	2.03
Current OI				-0.05	-0.30	0.19	-0.18	-0.42	0.06
R-sq: within	0.03			0.28			0.03		
between	0.07			0.07			0.08		
overall	0.06			0.56			0.66		
sigma_u	4.34			4.34			4.31		
sigma_e	3.76			3.76			3.76		
rho	0.57			0.57			0.57		

6.3.4 Exploring labour market status transitions

Table 6.6 shows the prevalence, in person-years, of each possible labour market status transition. By far the most common was when an individual remained in secure employment between two consecutive waves. This accounted for 57 percent of all observations. Remaining in 'other' inactivity for two consecutive waves was the second most common, accounting for 11 percent of the data. Overall, 77 percent of the 'transitions' made between successive waves, were actually individuals staying in the same labour market status.

Table 6.6 Prevalence of each possible LMS transition (person-years)

Transition			Freq.	Percent
Sec Emp	to	Sec Emp	50,615	56.94
O.Inactive	to	O.Inactive	10,042	11.30
Insec Emp	to	Sec Emp	5,101	5.74
Sec Emp	to	Insec Emp	5,004	5.63
Insec Emp	to	Insec Emp	3,799	4.27
Perm Sick	to	Perm Sick	2,616	2.94
O.Inactive	to	Sec Emp	2,442	2.75
Sec Emp	to	O.Inactive	2,186	2.46
Unemp	to	Unemp	1,310	1.47
Unemp	to	Sec Emp	1,115	1.25
Sec Emp	to	Unemp	922	1.04
Unemp	to	O.Inactive	563	0.63
O.Inactive	to	Unemp	529	0.60
Perm Sick	to	O.Inactive	396	0.45
O.Inactive	to	Perm Sick	345	0.39
Insec Emp	to	Unemp	342	0.38
Insec Emp	to	O.Inactive	307	0.35
Unemp	to	Insec Emp	259	0.29
O.Inactive	to	Insec Emp	234	0.26
Unemp	to	Perm Sick	228	0.26
Sec Emp	to	Perm Sick	223	0.25
Perm Sick	to	Unemp	132	0.15
Perm Sick	to	Sec Emp	92	0.10
Insec Emp	to	Perm Sick	72	0.08
Perm Sick	to	Insec Emp	21	0.02
		Total	**88,895**	**100**

But how does making one of these transitions in employment status affect psychological wellbeing, over and above the effects of current labour market status and hypothesised confounders? Appendix 6.6 shows the results for a set of 25 separate fixed effects models which tested the association between the binary transition variable and GHQ-12 score, controlling for current labour market status and confounding covariates. The results are summarised in Table 6.7 and Table 6.8**.**

Table 6.7 Summary of results from series of 25 separate fixed effects models* which tested the association between the binary transition variable and GHQ-12 score, controlling for current labour market status and confounding covariates. Significant associations listed in order of effect size, from highest to lowest magnitude.

Transitions significantly predictive of higher GHQ-12 scores	Insecure Employment	to	Permanent Sickness
	Secure Employment	to	Permanent Sickness
	Insecure Employment	to	Unemployment
	Unemployment	to	Permanent sickness
	Secure Employment	to	Unemployment
Transitions significantly predictive of lower GHQ-12 scores (protective)	Permanent Sickness	to	Insecure employment
	Permanent Sickness	to	Secure employment
	Unemployment	to	Insecure Employment
	Other Inactivity	to	Permanent sickness
	Unemployment	to	Secure employment
	Other Inactivity	to	Secure employment
Transitions not significantly associated with GHQ-12 score	Other Inactivity	to	Unemployment
	Insecure Employment	to	Secure Employment
	Secure Employment	to	Insecure Employment
	Unemployment	to	Other Inactivity
	Other Inactivity	to	Insecure Employment
	Insecure Employment	to	Other Inactivity
	Secure Employment	to	Other Inactivity
	Permanent Sickness	to	Unemployment

** Stable states t-1 to t are not shown*

Whereas transitioning from other inactivity into secure employment had a positive effect on psychological wellbeing, moving from employment into other inactivity did not have a significant association with GHQ-12 score. With this exception, the securely and insecurely employed categories seem undifferentiated with regards to transition into or out of employment.

Table 6.8 Summary of results from series of 25 separate fixed effects models which tested the association between the binary transition variable and GHQ-12 score, controlling for current labour market status and confounding covariates.

LMS at t / LMS at t-1	**Secure Employment**	**Insecure Employment**	**Unemployment**	**Permanent Sickness**	**Other Inactivity**
Secure Employment	*Sec Emp to Sec Emp*	Sec Emp to Insec Emp	Sec Emp to Unemp	Sec Emp to Perm Sick	Sec Emp to O. Inactive
Insecure Employment	Insec Emp to Sec Emp	*Insec Emp to Insec Emp*	Insec to Unemp	Insec to Perm Sick	Insec to O. Inactive
Unemployment	Unemp to Sec Emp	Unemp to Insec Emp	*Unemp to Unemp*	Unemp to Perm Sick	Unemp to O. Inactive
Permanent Sickness	Perm Sick to Sec Emp	Perm Sick to Insec Emp	Perm Sick to Unemp	*Perm Sick to Perm Sick*	Perm Sick to O. Inactive
Other Inactivity	O. Inactive to Sec Emp	O. Inactive to Insec Emp	O. Inactive to Unemp	O. Inactive to Perm Sick	*O. Inactive to O. Inactive*

Red: transition significantly predictive of higher GHQ-12 scores	**Green: transition significantly predictive of lower GHQ-12 scores**	**White: transition not significantly associated with GHQ-12 score**	**Grey: stable state/no transition**

Figure 6.14 shows the results from a fixed effects model containing all of the transition variables shown to be significantly associated with GHQ-12 score, controlling for current labour market status and confounding covariates. In this model, the coefficients for the permanently sick to other inactive and other inactivity to unemployment transitions became non-significant, but all other transition variables remained significantly associated with GHQ-12 score, controlling for current labour market status and confounders.The coefficients for the current labour market status categories were 1.11, 1.49, 2.33 and 0.05 for insecure employment, unemployment, permanent sickness and other inactivity respectively. When interpreting the results of the models therefore, it should be noted that irrespective of the transition, a current insecurely employed or jobless labour market status was predictive of higher GHQ-12 score within individuals, compared to a spell of secure employment.

Overall, the model shows that moving from active labour market engagement, whether employed or seeking work, into permanent sickness was associated with a significantly increased level of psychological distress. This was over and above the negative effect of current permanent sickness on its own.

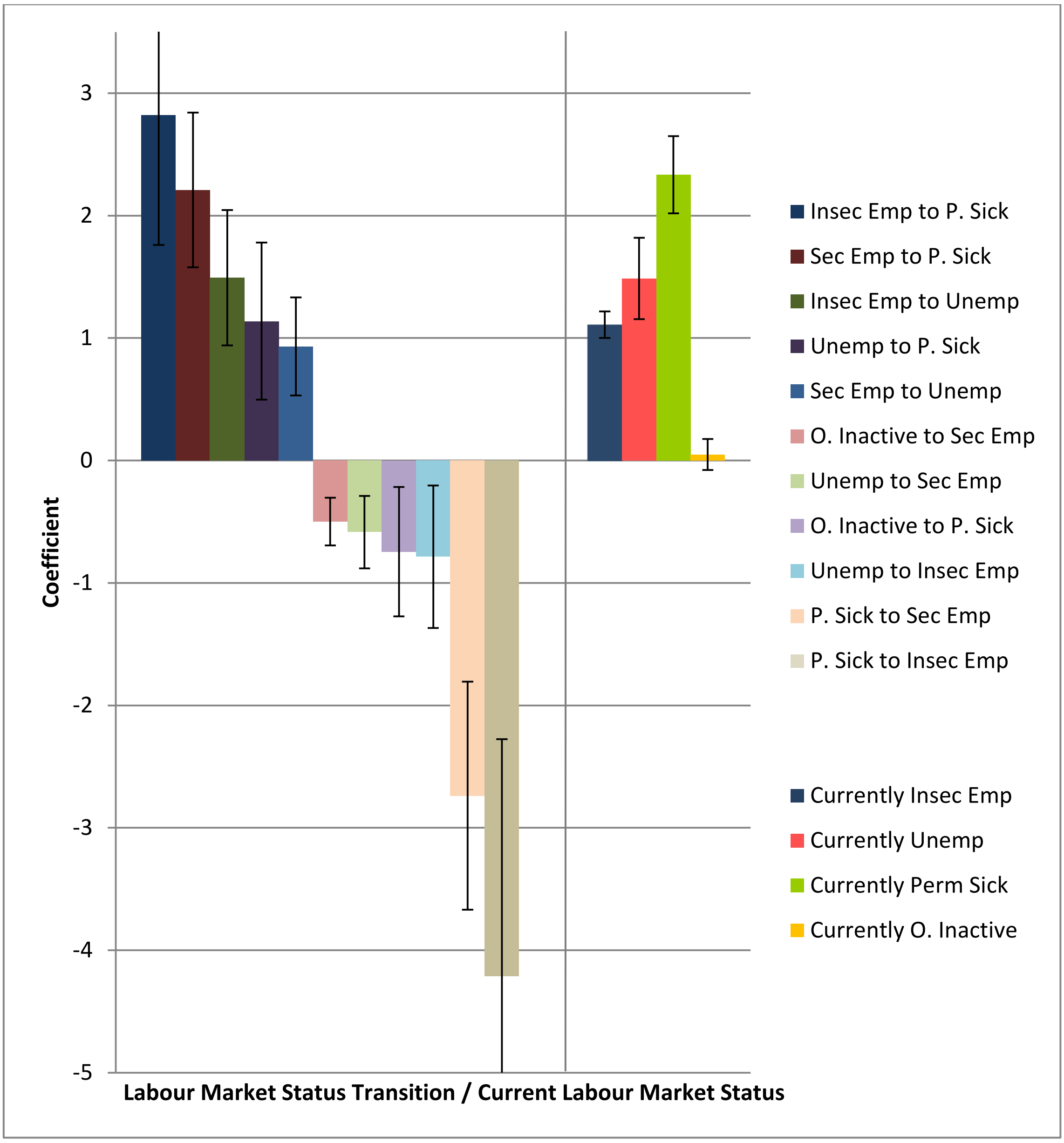

Figure 6.14 Results from a fixed effects model containing all of the transition variables shown to be significantly associated with GHQ-12 score, controlling for current labour market status and confounding covariates

The model also shows that moving back into employment from permanent sickness was significantly associated with improved psychological wellbeing, but that there was no significant association between transitioning from permanent sickness to unemployment and GHQ-12 score. With regards to unemployment, the model shows that losing either a secure or insecure job and moving into unemployment was associated with increased levels of psychological distress, in addition to the contemporaneous negative effects of current unemployment. Moving into insecure or secure employment from unemployment was significantly associated with improved psychological wellbeing, but the benefits to mental health of finding a job did not appear to be as great as the negative effects of losing a job (Figure 6.15).

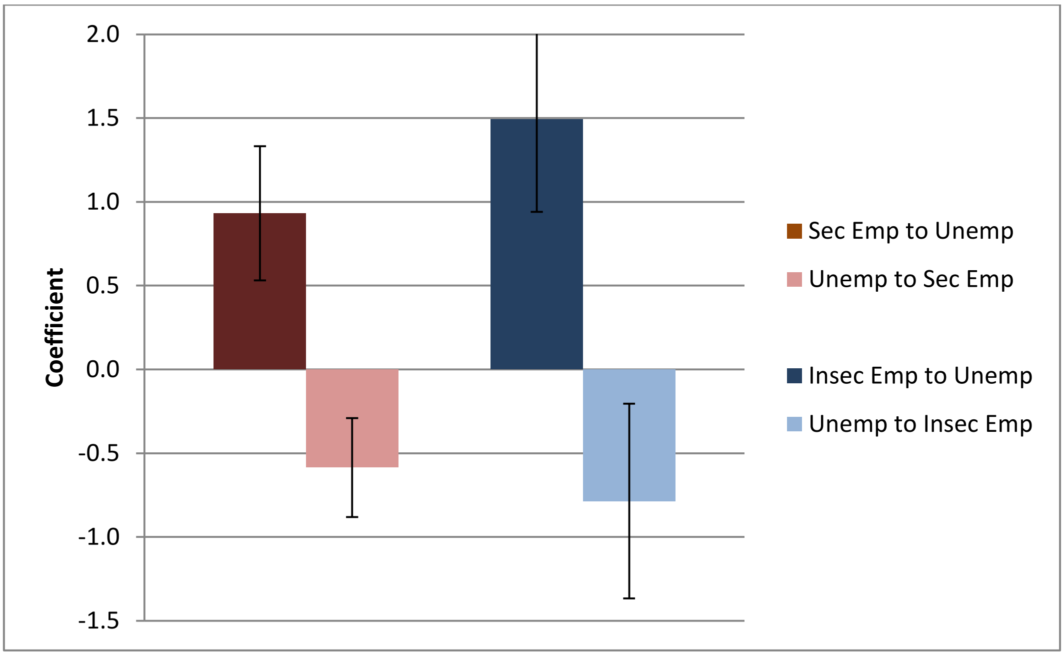

Figure 6.15 Coefficients for employment to unemployment transition variables, from fixed effects model containing all of the transition variables shown to be significantly associated with GHQ-12 score, controlling for current labour market status and confounding covariates

6.3.4.1 Exploring labour market status transitions: stratification by age group

Owing to reduced sample size for binary labour market transition variables when stratifying by age group, categories were collapsed or dropped, based on the results of the unstratified analyses. As no differentiation was found between secure and insecure employment with respect to labour market transitions, the categories were collapsed into a single 'employed' category for the purposes of the age-stratified transition analysis. The person-years prevalence figures for the labour market status transition categories are shown in Table 6.9.

Figure 6.16 and Appendix 6.7 show that when controlling for the effects of current labour market status and confounders, moving from employment to sickness was predictive of the greatest increase in GHQ-12 scores across all three age groups, but that this was more exaggerated for the young. A significant interaction between age group and the employment to permanent sickness transition (Wald test, p<0.001, Appendix 6.8) means we can be confident that age differences shown in the age stratified models are genuine for this variable. Moving from employment to unemployment was significantly predictive of elevated GHQ-12 score amongst all three age groups, but the coefficient was smallest for the youngest group.

Table 6.9 Prevalence of each LMS transition category used in age-stratified analysis, by age group (person-years)

Transition		Age group			
		16-29	**30-49**	**50-65**	**Total**
Unemp to Emp	Freq	658	540	176	1,374
	% person-years	*2.82*	*1.24*	*0.8*	*1.55*
Emp to Unemp	Freq	492	527	245	1,264
	% person-years	*2.11*	*1.21*	*1.11*	*1.42*
Emp to Perm Sick	Freq	33	135	127	295
	% person-years	*0.14*	*0.31*	*0.58*	*0.33*
Perm Sick to Emp	Freq	15	66	32	113
	% person-years	*0.06*	*0.15*	*0.15*	*0.13*
Sec Emp to Insec Emp	Freq	1,116	2,844	1,044	5,004
	% person-years	*4.79*	*6.53*	*4.73*	*5.63*
Insec Emp to Sec Emp	Freq	1,146	2,887	1,068	5,101
	% person-years	*4.92*	*6.63*	*4.84*	*5.74*
Other transitions	Freq	19,837	36,550	19,357	75,744
	% person-years	*85.15*	*83.93*	*87.79*	*85.21*
Total	Freq	23,297	43,549	22,049	88,895
	% person-years	*100*	*100*	*100*	*100*

Moving from unemployment to employment was significantly predictive of improved psychological wellbeing in the youngest and mid-life groups, but was not significantly associated with GHQ-12 score for the oldest group, when controlling for current labour market status and confounders. Wald tests showed that the differences observed between age groups for transitions between employment and unemployment were not statistically significant (see Appendix 6.9 and Appendix 6.10). For all groups, moving from permanent sickness to employment was predictive of significant and substantial increases in psychological wellbeing. However, a Wald test on the interaction between age group and this transition variable showed that no statistically significant difference exists between the age groups (p=0.06) with regards to how it predicts change in GHQ-12 score after controlling for current labour market status and confounders (Appendix 6.11).

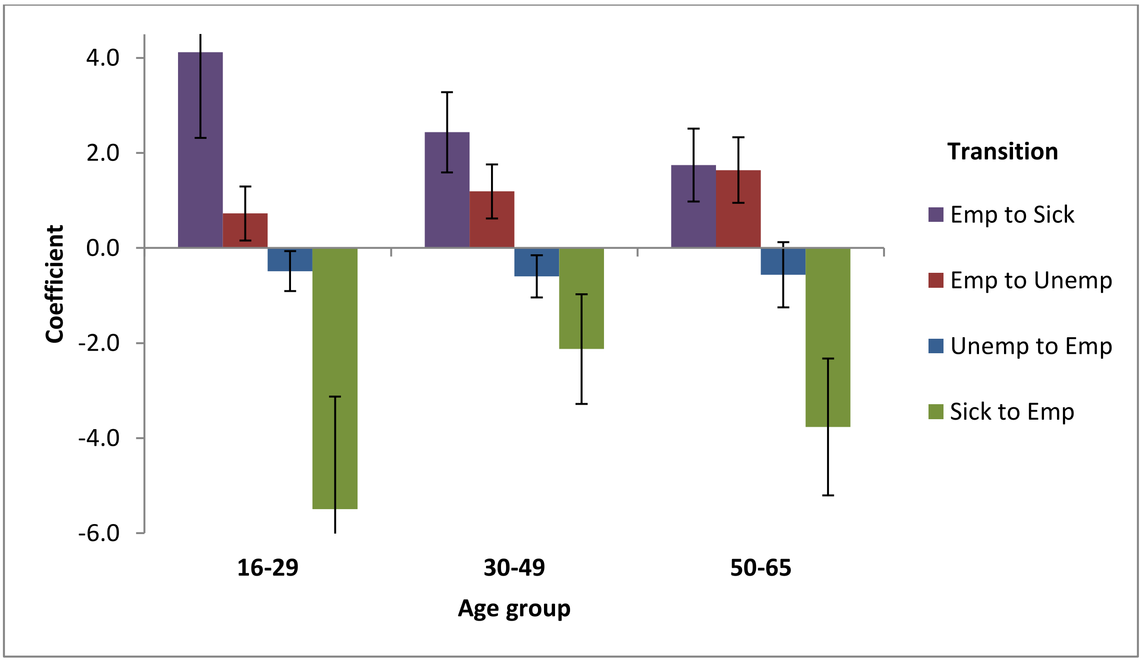

Figure 6.16 Results from three age group stratified fixed effects model containing selected transition variables, controlling for current labour market status and confounding covariates (see Table 6.2).

6.4 Discussion

The aim of this chapter was to investigate the temporal dimensions of the relationship between labour market status and GHQ-12. More specifically, the research presented in this chapter aimed to further our understanding of the causal nature of the relationship and the extent to which labour market status and labour market status transitions affect the psychological wellbeing of individuals differently, depending on their stage in the lifecourse.

In support of the results presented in previous chapters, it has been shown that when controlling for confounders, a spell of insecure employment, unemployment, permanent sickness or other inactivity was predictive of a significant increase in GHQ-12 score, compared to that individual's mean GHQ-12 score during their time in secure employment. In essence, having a secure job was optimal for all, with the exception of those aged 50-65 who were economically inactive and therefore likely to have taken early retirement. It was found that exposure to insecure employment, unemployment and permanent sickness was associated with an increase in GHQ-12 scores in all age groups in the age stratified models, but that permanent sickness had a comparatively worse effect on the young, compared to secure employment. Only 1 percent of labour market status observations on individuals aged between 16 and 29 were recorded as 'permanently sick' and the fact that this status is so uncommon among this age group suggests that it is not normed as an 'acceptable' social role in this stage of the lifecourse. It is also likely that the composition of the permanently sick group in early working life was different to that in mid or later working life with regards to the health profile of the category. Mental health problems may account for a higher proportion of reasons for permanent sickness amongst the younger age group, compared to older people (Table 6.10). At older ages, permanent sickness was far more common, accounting for 8.6 percent of labour market status observations on individuals between the ages of 50 and 65. In this stage of life, the sick role may act as a valid alternative social role, owing to its relative commonness. The differing meaning of permanent sickness by age can also be observed in the results for the transition analyses (section 6.3.5) in which there appears to be a greater impact of permanent sickness for the youngest group than for the mid-life or older groups.

Table 6.10 Causes of incapacity, August 1999. Source: DWP Information Directorate: Work and Pensions Longitudinal Study

Causes of incapacity, based on the WHO International Classification of Diseases, August 1999.	% of total caseload for age group 16-24	25-49	50-64
Other	23	21	23
Mental and Behavioural Disorders	50	41	19
Injury, Poisoning and certain other consequences of external causes	13	8	5
Diseases of the Musculoskeletal system and Connective Tissue	8	19	30
Diseases of the Nervous System	4	6	4
Diseases of the Circulatory or Respiratory System	2	5	20
Total	100	100	100

Similarly, it was found that average GHQ-12 scores whilst unemployed were higher than average GHQ-12 scores when securely employed across all age groups, with limited evidence to support the hypothesis that unemployment had a comparatively greater effect on those in mid-life. This was also shown to be true for insecure employment, and can be explained with reference to Fryer's agency theory, in which it is suggested that the extent to which unemployment affects psychological health is dependent on the extent to which threats to the security, stability and predictability affect wellbeing. When an individual has a greater need for security and stability, this is when unemployment may have the most distressing effect. Whist this is not referred to in the recent literature, it also stands to reason that job insecurity is likely to have the most negative effect on those who have financial commitments and responsibilities towards dependants.

The results presented in section 6.3.3 allowed us to investigate the ways in which the direction of causality might operate in the relationship between labour market status and psychological wellbeing. For the youngest and mid-life groups, the labour market status the individual experienced in the previous year was found to have a significant impact on their psychological wellbeing in the following year, adjusted for the effects of their contemporaneous labour market status and confounders. Furthermore, it is clear that switching from secure employment to unemployment or permanent sickness had a worse effect on psychological wellbeing than remaining in the same disadvantaged labour market status for two consecutive years. Job loss or transition into permanent sickness from employment constitutes a shock to psychological wellbeing before adaptation to the new status can occur (Warr, 1987). These results are corroborated by the transition analyses which show that transitions from employment to unemployment or permanent sickness were significantly predictive of increased GHQ-12 score, independently of the contemporaneous effects of current labour market status on psychological wellbeing.

Interestingly though, transition analyses showed that the positive effects of moving into work from unemployment were not as large as the negative effects of job loss. This was also true for the transition from permanent sickness into work, which did not affect GHQ-12 scores as greatly as leaving work for permanent sickness. A possible explanation for this finding is that among those entering employment from permanent sickness, there may be some individuals who have not recovered from their illness or disability, but have returned to work anyway. Perhaps the conditions for receipt of incapacity benefits were changed, or medically deemed to no longer be met. Alternatively, the individual could have foregone incapacity benefits and returned to work out of a necessity to earn a higher income, perhaps due to increased demands from dependants or other changing financial circumstances. In such instances, the return to work may have a negative effect on psychological wellbeing for some individuals, reducing the net positive effect of returning to work from a period of permanent sickness. In light of the recent changes to the conditions for sickness benefits and the introduction of the Fitness to Work assessments it is likely that future waves of the BHPS will show a greater weakening of the positive psychological effects of returning to work from permanent sickness, as greater numbers of individuals are compelled to enter the labour market whilst suffering from pre-existing health conditions no longer considered 'incapacitating' under the new system. In contrast, among individuals experiencing a transition from employment to permanent sickness, there could be some hidden job loss which would exaggerate the negative effects of a transition into permanent sickness. For example, an individual could be made redundant, but instead of claiming unemployment benefits and actively seeking reemployment, the individual could seek assessment for incapacity benefits, based on a pre-existing health condition which s/he may have coped with previously but fears will be a barrier to reemployment in the open labour market. Alternatively, the distress caused by anticipation and experience of redundancy could have resulted in an worsening of a pre-existing health condition, or been instrumental in the development of a mental illness, causing the individual to become 'permanently sick' instead of 'unemployed'. In sum, either through the development or worsening of a medical condition or through job loss and subsequent assessment for incapacity benefits instead of unemployment benefits, a transition from employment to permanent sickness is likely to be a near-universal negative experience, predictive of a substantial and significant increase in GHQ-12 scores.

Results presented in section 6.3.3 also show some evidence that selection into unemployment based on pre-existing psychological distress may have been in operation for some individuals. For the youngest age group, this was only the case for those who moved into permanent sickness. This group are shown to have been suffering higher than average GHQ-12 scores whilst employed, a year prior to becoming permanently sick. This is likely to be due to the high proportion of mental illness amongst young individuals in the permanently sick category (Table 6.10) who may have been suffering from minor psychiatric morbidity prior to diagnosis, which would have been detected by the GHQ-12 screening tool. It is also highly likely that those who went on to be permanently sick for reasons related to their physical health would also have been suffering higher than average GHQ-12 scores in the wave prior to this, owing to the gradual worsening of a chronic health problem. This explains why coefficients for future permanent sickness were positive and significant for all age groups in Table 6.5. The results also suggest that in mid-life, those who became unemployed or insecurely employed one year into the future had worse GHQ-12 scores compared to their individual average whilst still at work. It is suggested that this is due to the stressful effects of anticipating and pre-empting job insecurity or job loss. Compulsory redundancies are likely to have been anticipated by a permanent workforce in advance, either through knowledge of poor commercial performance by their employer, perception of general poor performance of the economy during times of recession or as a result of policy changes or spending cuts in the context of the public sector. Those on fixed term contracts were likely to have experienced higher levels of distress as the end of their contract approached, and this is especially true in times of national economic downturn. Therefore, it is suggested that those who became unemployed or insecurely employed one year into the future were very likely to either already have known the specifics about future redundancies or the end of a contract, or had perceived uncertainty and the likelihood of redundancies in the future.

The transition analysis shows that controlling for the contemporaneous negative effects of being permanently sick, having moved into permanent sickness from other inactivity in the previous wave was associated with an increase in psychological wellbeing. This result is at odds with the others, which generally show that a transition into permanent sickness from any other labour market status predicted an increase in psychological distress. This result is therefore counterintuitive, especially since other inactivity is the labour market status category which was consistently least strongly predictive of psychological distress, compared to secure employment, and for the older group, it was marginally protective against psychological distress, compared to secure employment. It would not be expected, therefore for the transition from what is usually found to be a more advantaged labour market status to the least advantaged would be predictive of greater distress. 396 observations across 296 separate individuals fell into the other inactive to permanent sickness transition category, making this a rare transition in the general context of the data (accounting for just 0.04 percent of all transitions made). Among this group, 66 percent were female and the mean age was 50 (with a standard deviation of 11.8). Ninety-six percent suffered from one or more physical health problems. In 92 percent of the observations reporting a transition from permanent sickness to other inactivity, the individual had reported suffering from one or more physical problem in the wave prior to becoming permanently sick, i.e. whilst they were inactive. Therefore, it is likely that this result is due to the psychosocial benefits of taking the sick role (Parsons, 1951) and the potential material benefits of moving onto incapacity benefits. A third of those who reported a transition from other inactivity to permanent sickness resided in social housing, compared to just 14 percent in the sample overall. It is therefore likely that the additional income gained when being defined as permanently sick, compared to inactive is likely to have made a positive difference to the lives of those in a disadvantaged socioeconomic position.

The initial fixed effects model presented in section 6.3.2.1, showed that a period of insecure employment was associated with a GHQ-12 score 1.1 units higher than it would have been when the individual was securely employed. Insecure employment had a significantly higher coefficient in the random effects and between effects models too, and has been shown to be significantly more predictive of psychological distress than secure employment throughout chapters 4 and 5. However, there appears to be no differentiation between secure and insecure employment with regards to transitions, when controlling for the effects of current labour market status. This was the case for all age groups in the lagged models in section 6.3.3 and transition models. However, there is evidence that for the middle and older age groups, those who became insecurely employed one wave into the future already had higher GHQ-12 scores than their average in the present wave, whilst still securely employed.

6.4.1 Limitations

This research, like most in the literature, uses age group as a proxy for stage of the lifecourse. This is an important factor, since much of the theoretical basis for the hypotheses and interpretation of the age stratified results depend on the assumption that those in certain age groups are likely to share characteristics with regards to how they cope with unemployment, permanent sickness or insecure employment. It is assumed that, on the whole those aged 16-29 will have lower psychological requirements for security and stability, owing to fewer financial and other commitments. Likewise, it is assumed that those in mid-life are more likely to have dependent children and mortgages. This is an oversimplification, because obviously many people have ‘settled’ lifestyles in their twenties and would be equally as affected by the unpredictability of unemployment as a comparable individual in their thirties or forties. The analyses in this chapter could be refined by using variables such as the presence of dependent children, and mortgage borrowing. However, the models presented in this chapter do include covariates for marital status and spousal joblessness.

The issue of gender is explored in chapter 4 and it is shown that gender is an important factor in determining the effects of labour market status on psychological wellbeing because men's and women's experiences of both the labour market and of psychological morbidity vary greatly. For the fixed effects models in this chapter, estimation of gender effects was not possible, since coefficients for time-invariant covariates cannot be estimated using fixed effects models. However, the effects of gender were still taken into account, as with all other time-invariant unobservables. It was not considered possible to stratify by gender, since this in addition to age group stratification would have rendered the sample size too small, especially for the transition analyses. An alternative approach would be to interact gender with labour market status using fixed effects models, although a larger sample would also be required for this. Further investigation of the role of mediators such as income and social support is required in order to further elucidate the causal processes and explain the effects reported.

6.4.2 Strengths

The strengths of this analysis are that it exploits the longitudinal nature of the data to look at what predicts a change in psychological wellbeing, controlling for unobserved time-varying covariates as well as specific variables hypothesised to confound the relationship between labour market status and GHQ-12 score. These covariates included the presence of physical health problems, meaning that the psychological effects of suffering from one or more physical health conditions are held constant. Social housing tenure was also adjusted for, which arguably acts as a proxy for certain elements of socioeconomic position as well as being conceptualised as a confounder.

6.4.3 Conclusions

This chapter set out to assess the temporal dimensions of the relationship between labour market status and psychological distress. It has been shown that exposure to insecure employment, unemployment and permanent sickness was associated with an increase in GHQ-12 scores in all age groups, but that permanent sickness had a comparatively worse effect on the young. Similarly, it was found that average GHQ-12 scores whilst unemployed were higher than average GHQ-12 scores when securely employed across all age groups, with limited evidence to support the hypothesis that unemployment had a comparatively greater effect on those in mid-life. Significant lagged labour market status coefficients and significant advanced labour market status coefficients show that both causality and selection probably operate. The further analyses undertaken using labour market transition variables add weight to the causal interpretation.

6.5 Appendices

Appendix 6.1 Results from unstratified fixed, random and between effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates

UNSTRATIFIED, CURRENT LMS	Fixed Effects			Random Effects			Between Effects		
Adj. confounders	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp	**1.11**	1.00	1.22	**1.21**	1.11	1.31	**2.46**	2.04	2.87
Unemp	**2.27**	2.06	2.49	**2.28**	2.07	2.49	**1.54**	0.79	2.28
Other Inactive	**0.42**	0.30	0.54	**0.64**	0.53	0.75	**1.40**	1.13	1.66
Perm Sick	**2.97**	2.71	3.22	**3.52**	3.30	3.75	**4.80**	4.31	5.29
n: wave	88895			88895			88895		
n: individial	10494			10494			10494		
R-sq: within	0.03			0.03			0.02		
between	0.11			0.13			0.14		
overall	0.07			0.08			0.08		
sigma_u	3.89			3.14			-		
sigma_e	4.22			4.22			-		
rho	0.46			0.36			-		

Appendix 6.2 Fixed effects model including interaction between labour market status and age group, adjusted for confounding covariates

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**0.97**	<0.001	0.75	1.20
	Unemp	**2.02**	<0.001	1.71	2.33
	Perm Sickness	**4.83**	<0.001	4.09	5.58
	Oth. Inactivity	**0.41**	<0.001	0.21	0.61
Age group (16-29 omitted)	Age 30-49	**0.37**	<0.001	0.23	0.50
	Age 50-65	0.16	0.094	-0.03	0.36
Interaction between labour market status and age group	Insec Emp x 30-49	0.20	0.135	-0.06	0.46
	Insec Emp x 50-65	0.10	0.560	-0.23	0.42
	Unemp x 30-49	**0.51**	0.014	0.10	0.91
	Unemp x 50-65	0.23	0.368	-0.27	0.73
	Perm Sick x 30-49	**-1.54**	<0.001	-2.34	-0.74
	Perm Sick x 50-65	**-2.62**	<0.001	-3.43	-1.80
	OI x 30-49	0.14	0.279	-0.12	0.41
	OI x 50-65	**-0.59**	<0.001	-0.87	-0.30
Wald test on interaction variable		F=10.26	p<0.001		

Appendix 6.3 Results from age group stratified fixed, random and between effects models for the association between labour market status and GHQ-12 score, adjusted for confounding covariates

CURRENT LMS	Fixed Effects			Random Effects			Between Effects		
Age 16-29	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp	**0.91**	0.67	1.16	**1.09**	0.87	1.32	**1.70**	1.14	2.27
Unemp	**2.09**	1.74	2.44	**2.03**	1.71	2.35	**1.13**	0.27	2.00
Perm Sick	**4.57**	3.71	5.42	**5.09**	4.35	5.83	**5.72**	4.06	7.38
Other Inactive	**0.36**	0.13	0.59	**0.46**	0.26	0.65	**0.66**	0.28	1.05
n: wave	23297			23297			23297		
n: individial	4829			4829			4829		
R-sq: within	0.02			0.02			0.02		
between	0.05			0.12			0.12		
overall	0.04			0.08			0.07		
sigma_u	4.08			2.84			-		
sigma_e	4.32			4.33			-		
rho	0.47			0.30			-		
Age 30-49	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp	**1.12**	0.97	1.27	**1.28**	1.14	1.42	**2.55**	2.10	3.00
Unemp	**2.50**	2.14	2.87	**2.69**	2.34	3.03	**3.80**	2.64	4.95
Perm Sick	**2.94**	2.51	3.37	**3.84**	3.48	4.20	**5.12**	4.44	5.79
Other Inactive	**0.78**	0.56	1.00	**0.90**	0.70	1.09	**1.14**	0.70	1.57
n: wave	43549			43549			43549		
n: individial	6088			6088			6088		
R-sq: within	0.03			0.03			0.03		
between	0.13			0.16			0.17		
overall	0.08			0.09			0.09		
sigma_u	4.00			3.16			-		
sigma_e	4.26			4.26			-		
rho	0.47			0.35			-		
Age 50-65	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Insecurely Emp	**1.11**	0.89	1.33	**1.34**	1.13	1.55	**3.76**	3.00	4.52
Unemp	**1.89**	1.39	2.38	**1.99**	1.51	2.47	**1.93**	0.04	3.83
Perm Sick	**1.81**	1.44	2.17	**2.73**	2.42	3.04	**4.99**	4.38	5.61
Other Inactive	**-0.24**	-0.45	-0.03	-0.08	-0.26	0.11	0.25	-0.18	0.68
n: wave	22049			22049			22049		
n: individial	3436			3436			3436		
R-sq: within	0.03			0.03			0.02		
between	0.07			0.16			0.18		
overall	0.06			0.11			0.11		
sigma_u	4.34			3.38			-		
sigma_e	3.76			3.76			-		
rho	0.57			0.47			-		

Appendix 6.4 Fixed effects model including interaction between lagged labour market status and age group, adjusted for confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.10**	<0.001	0.99	1.21
	Unemp	**2.26**	<0.001	2.04	2.48
	Perm Sickness	**3.36**	<0.001	3.09	3.64
	Oth. Inactivity	**0.56**	<0.001	0.43	0.70
Lagged Labour Market Status (sec emp omitted)	Insecure Emp	-0.12	0.307	-0.34	0.11
	Unemp	**-0.66**	<0.001	-0.95	-0.37
	Perm Sickness	**-1.08**	0.008	-1.88	-0.29
	Oth. Inactivity	**-0.39**	<0.001	-0.58	-0.20
Age group (16-29 omitted)	Age 30-49	**0.38**	<0.001	0.24	0.52
	Age 50-65	0.07	0.504	-0.13	0.26
Interaction between lagged labour market status and age group	Insec Emp x 30-49	0.19	0.160	-0.07	0.45
	Insec Emp x 50-65	0.21	0.197	-0.11	0.52
	Unemp x 30-49	0.03	0.891	-0.36	0.42
	Unemp x 50-65	0.29	0.243	-0.20	0.78
	Perm Sick x 30-49	0.31	0.481	-0.54	1.16
	Perm Sick x 50-65	0.08	0.861	-0.78	0.94
	OI x 30-49	-0.08	0.555	-0.33	0.17
	OI x 50-65	**-0.43**	0.003	-0.71	-0.15
Wald test on interaction variable		F=2.17	p=0.027		

Appendix 6.5 Fixed effects model including interaction between advanced labour market status and age group, adjusted for confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.08**	<0.001	0.97	1.19
	Unemp	**2.14**	<0.001	1.92	2.36
	Perm Sickness	**2.50**	<0.001	2.22	2.78
	Oth. Inactivity	**0.25**	<0.001	0.12	0.39
Advanced Labour Market Status (sec emp omitted)	Insecure Emp	0.14	0.211	-0.08	0.37
	Unemp	0.29	0.061	-0.01	0.59
	Perm Sickness	**2.20**	<0.001	1.46	2.93
	Oth. Inactivity	**0.30**	0.006	0.08	0.51
Age group (16-29 omitted)	Age 30-49	**0.37**	<0.001	0.24	0.51
	Age 50-65	0.14	0.169	-0.06	0.33
Interaction between advanced labour market status and age group	Insec Emp x 30-49	0.13	0.353	-0.14	0.39
	Insec Emp x 50-65	0.14	0.416	-0.19	0.47
	Unemp x 30-49	**0.45**	0.035	0.03	0.86
	Unemp x 50-65	0.01	0.963	-0.51	0.53
	Perm Sick x 30-49	-0.33	0.413	-1.11	0.45
	Perm Sick x 50-65	**-1.21**	0.003	-2.01	-0.41
	OI x 30-49	0.08	0.583	-0.19	0.34
	OI x 50-65	**-0.59**	<0.001	-0.88	-0.30
Wald test on interaction variable		F=6.01	p<0.001		

Appendix 6.6 Results for a set of 25 separate fixed effects models which tested the association between the binary transition variable and GHQ-12 score, controlling for current labour market status and confounding covariates

	adj. Current LMS + Confounders		
Transition	Coef	95% CI	
Sec to Insec	0.05	-0.14	0.24
Insec Emp	1.09	0.92	1.14
Unemp	2.27	2.05	2.49
Other Inactive	0.42	0.30	0.54
Perm Sick	2.97	2.71	3.22
Sec to Unemp	**0.73**	0.37	1.09
Insec Emp	1.10	0.99	1.21
Unemp	2.01	1.75	2.26
Other Inactive	0.40	0.28	0.53
Perm Sick	2.93	2.67	3.19
Sec to OI	-0.16	-0.38	0.05
Insec Emp	1.11	1.00	1.22
Unemp	2.28	2.06	2.50
Other Inactive	0.46	0.33	0.60
Perm Sick	2.98	2.73	3.24
Sec to P.Sick	**2.13**	1.51	2.75
Insec Emp	1.11	1.00	1.21
Unemp	2.26	2.04	2.48
Other Inactive	0.41	0.28	0.53
Perm Sick	2.71	2.44	3.00
Insec to Sec	0.03	-0.11	0.16
Insec Emp	1.11	1.00	1.22
Unemp	2.28	2.06	2.49
Other Inactive	0.42	0.30	0.55
Perm Sick	2.97	2.71	3.23
Insec to Unemp	**1.20**	0.69	1.72
Insec Emp	1.11	1.01	1.22
Unemp	2.11	1.88	2.34
Other Inactive	0.41	0.29	0.54
Perm Sick	3.00	2.70	3.21
Insec to OI	-0.50	-1.01	0.01
Insec Emp	1.10	0.99	1.21
Unemp	2.27	2.06	2.49
Other Inactive	0.44	0.31	0.56
Perm Sick	2.97	2.72	3.23
Insec to P.Sick	**2.61**	1.56	3.67
Insec Emp	1.11	1.00	1.22
Unemp	2.27	2.05	2.49
Other Inactive	0.41	2.89	0.54
Perm Sick	2.86	2.60	3.12
Unemp to Sec	**-0.47**	-0.76	-0.18
Insec Emp	1.09	0.99	1.20
Unemp	2.16	1.93	2.38
Other Inactive	0.41	0.28	0.53
Perm Sick	2.95	2.69	3.21
Unemp to Insec	**-0.66**	-1.24	-0.08
Insec Emp	1.12	1.02	1.23
Unemp	2.24	2.02	2.46
Other Inactive	0.42	0.30	0.54
Perm Sick	2.97	2.71	3.22

	adj. Current LMS + Confounders		
Transition	Coef	95% CI	
Unemp to OI	0.02	-0.38	0.41
Insec Emp	1.11	1.00	1.22
Unemp	2.27	2.06	2.49
Other Inactive	0.42	0.29	0.54
Perm Sick	2.97	2.71	3.22
Unemp to P.Sick	**1.07**	0.44	1.70
Insec Emp	1.11	1.00	1.22
Unemp	2.30	2.08	2.52
Other Inactive	0.41	0.29	0.54
Perm Sick	2.84	2.58	3.11
OI to Sec	**-0.43**	-0.62	-0.23
Insec Emp	1.09	0.98	1.20
Unemp	2.23	2.01	2.45
Other Inactive	0.35	0.22	0.47
Perm Sick	2.92	2.68	3.18
OI to Insec	-0.14	-0.74	0.45
Insec Emp	1.11	1.00	1.22
Unemp	2.27	2.05	2.49
Other Inactive	0.42	2.94	0.54
Perm Sick	2.97	2.71	3.22
OI to Unemp	**-0.96**	-1.39	-0.52
Insec Emp	1.11	1.00	1.22
Unemp	2.44	2.21	2.67
Other Inactive	0.40	0.27	0.52
Perm Sick	2.97	2.72	3.23
OI to P.Sick	**-1.22**	-1.74	-0.70
Insec Emp	1.11	1.00	2.22
Unemp	2.28	2.06	2.50
Other Inactive	0.41	0.28	0.53
Perm Sick	3.17	2.90	3.44
P.Sick to Sec	**-2.73**	-3.66	-1.79
Insec Emp	1.10	0.99	1.21
Unemp	2.25	2.03	2.47
Other Inactive	0.41	0.28	0.53
Perm Sick	2.90	2.64	3.16
P.Sick to Insec	**-4.22**	-6.16	-2.29
Insec Emp	1.12	1.01	1.22
Unemp	2.27	2.05	2.48
Other Inactive	0.17	0.29	0.54
Perm Sick	2.95	2.70	3.21
P.Sick to Unemp	0.05	-0.76	0.86
Insec Emp	1.11	1.00	1.22
Unemp	2.27	2.05	2.50
Other Inactive	0.42	0.30	0.54
Perm Sick	2.97	2.71	3.22
P.Sick to OI	**0.57**	0.09	1.06
Insec Emp	1.11	1.00	1.22
Unemp	2.80	2.06	2.50
Other Inactive	0.40	0.28	0.53
Perm Sick	3.05	2.78	3.31

Appendix 6.7 Results from 6 separate age group stratified fixed effects models showing the association between transition variable and GHQ-12 score, adjusted for current labour market status and confounders

Transition	Fixed effects, adjusted for Current LMS and Confounders								
	Age 16-29			**Age 30-49**			**Age 50-65**		
	Coef	95% CI		Coef	95% CI		Coef	95% CI	
Unemp to Emp	**-0.49**	-0.91	-0.07	**-0.60**	-1.04	-0.15	-0.56	-1.25	0.12
Insec Emp	0.92	0.67	1.17	**1.12**	0.97	1.27	**1.11**	0.89	1.33
Unemp	**1.93**	1.55	2.30	**2.31**	1.92	2.70	**1.72**	1.18	2.25
Other Inactive	**0.33**	0.10	0.57	**0.77**	0.55	0.98	-0.25	-0.46	-0.04
Perm Sick	**4.51**	3.65	5.37	**2.91**	2.48	3.34	**1.79**	1.43	2.16
Emp to Unemp	**0.73**	0.16	1.30	**1.19**	0.62	1.76	**1.64**	0.95	2.33
Insec Emp	**0.91**	0.66	1.16	**1.12**	0.97	1.27	**1.11**	0.90	1.33
Unemp	**1.74**	1.30	2.18	**1.84**	1.36	2.32	**1.04**	0.43	1.65
Other Inactive	**0.34**	0.11	0.57	**0.74**	0.52	0.96	-0.29	-0.50	-0.07
Perm Sick	**4.49**	3.63	5.35	**2.84**	2.41	3.27	**1.73**	1.36	2.10
Emp to Sick	**4.12**	2.31	5.93	**2.44**	1.59	3.28	**1.75**	0.98	2.51
Insec Emp	**0.92**	0.67	1.17	**1.12**	0.97	1.27	**1.11**	0.90	1.33
Unemp	**2.07**	1.72	2.42	**2.48**	2.12	2.84	**1.85**	1.36	2.34
Other Inactive	**0.34**	0.11	0.57	**0.76**	0.54	0.98	**-0.27**	-0.49	-0.06
Perm Sick	**3.75**	2.82	4.67	**2.47**	2.01	2.93	**1.54**	1.16	1.93
Sick to Emp	**-5.50**	-7.87	-3.12	**-2.12**	-3.28	-0.97	**-3.77**	-5.20	-2.33
Insec Emp	**0.92**	0.68	1.17	**1.12**	0.97	1.27	**1.10**	0.89	1.32
Unemp	**2.07**	1.72	2.41	**2.47**	2.11	2.83	**1.83**	1.34	2.32
Other Inactive	**0.35**	0.12	0.58	**0.77**	0.55	0.98	**-0.27**	-0.49	-0.06
Perm Sick	**4.41**	3.55	5.26	**2.84**	2.41	3.27	**1.70**	1.33	2.07
Sec to Insec	0.28	-0.17	0.74	-0.03	-0.29	0.23	-0.10	-0.47	0.28
Insec Emp	**0.73**	0.35	1.12	**1.14**	0.92	1.36	**1.17**	0.85	1.48
Unemp	**2.07**	1.72	2.42	**2.51**	2.14	2.87	**1.89**	1.40	2.39
Other Inactive	**0.35**	0.12	0.58	**0.78**	0.56	1.00	**-0.24**	-0.45	-0.03
Perm Sick	**4.56**	3.71	5.42	**2.94**	2.51	3.37	**1.81**	1.44	2.18
Insec to Sec	0.02	-0.29	0.32	-0.07	-0.26	0.11	0.16	-0.11	0.43
Insec Emp	**0.92**	0.66	1.18	**1.10**	0.94	1.26	**1.15**	0.92	1.38
Unemp	**2.09**	1.74	2.44	**2.49**	2.13	2.86	**1.91**	1.41	2.40
Other Inactive	**0.36**	0.13	0.59	**0.77**	0.55	0.99	**-0.22**	-0.44	-0.01
Perm Sick	**4.57**	3.71	5.42	**2.93**	2.50	3.36	**1.83**	1.46	2.20

Appendix 6.8 Results from fixed effects model showing association between Employment to Permanent Sickness transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.11**	<0.001	1.01	1.22
	Unemp	**2.24**	<0.001	2.02	2.46
	Perm Sickness	**2.56**	<0.001	2.29	2.83
	Oth. Inactivity	**0.27**	<0.001	0.15	0.39
Age group (16-29 omitted)	Age 30-49	**0.41**	<0.001	0.29	0.54
	Age 50-65	0.05	0.572	-0.13	0.23
Transition	Emp to PS	**5.65**	<0.001	4.07	7.22
Interaction	30-49 x Emp to PS	**-3.21**	<0.001	-4.94	-1.47
	50-65 x Emp to PS	**-4.12**	<0.001	-5.87	-2.37
Wald test on interaction variable		**F=10.63**	**p<0.001**		

Appendix 6.9 Results from fixed effects model showing association between Unemployment to Employment transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.11**	<0.001	1.01	1.22
	Unemp	**2.08**	<0.001	1.85	2.32
	Perm Sickness	**2.93**	<0.001	2.67	3.19
	Oth. Inactivity	**0.27**	<0.001	0.15	0.39
Age group (16-29 omitted)	Age 30-49	**0.40**	<0.001	0.28	0.53
	Age 50-65	0.02	0.790	-0.16	0.21
Transition	Unemp to Emp	**-0.52**	0.007	-0.91	-0.14
Interaction	30-49 x Unemp to Emp	-0.11	0.681	-0.64	0.42
	50-65 x Unemp to Emp	0.04	0.916	-0.72	0.80
Wald test on interaction variable		F=0.12	p=0.889		

Appendix 6.10 Results from fixed effects model showing association between Employment to Unemployment transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.11**	<0.001	1.01	1.22
	Unemp	**1.64**	<0.001	1.37	1.92
	Perm Sickness	**2.89**	<0.001	2.63	3.14
	Oth. Inactivity	**0.26**	<0.001	0.14	0.38
Age group (16-29 omitted)	Age 30-49	**0.39**	<0.001	0.26	0.52
	Age 50-65	0.02	0.838	-0.16	0.20
Transition	Emp to Unemp	**0.86**	<0.001	0.39	1.34
Interaction	30-49 x Emp to Unemp	**0.61**	0.036	0.04	1.18
	50-65 x Emp to Unemp	0.49	0.174	-0.22	1.19
Wald test on interaction variable		F=2.33	p=0.097		

Appendix 6.11 Results from fixed effects model showing association between Permanent Sickness to Employment transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.11**	<0.001	1.00	1.22
	Unemp	**2.22**	<0.001	2.01	2.44
	Perm Sickness	**2.88**	<0.001	2.62	3.13
	Oth. Inactivity	**0.27**	<0.001	0.15	0.40
Age group (16-29 omitted)	Age 30-49	**0.40**	<0.001	0.27	0.53
	Age 50-65	0.03	0.741	-0.15	0.21
Transition	PS to Emp	**-5.35**	<0.001	-7.59	-3.12
Interaction	30-49 x PS to Emp	**3.01**	0.018	0.51	5.50
	50-65 x PS to Emp	2.24	0.106	-0.48	4.95
Wald test on interaction variable		F=2.81	p=0.060		

Appendix 6.12 Results from fixed effects model showing association between Secure to Insecure Employment transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.09**	<0.001	0.93	1.24
	Unemp	**2.25**	<0.001	2.04	2.47
	Perm Sickness	**2.96**	<0.001	2.70	3.21
	Oth. Inactivity	**0.29**	<0.001	0.17	0.41
Age group (16-29 omitted)	Age 30-49	**0.40**	<0.001	0.27	0.53
	Age 50-65	0.02	0.832	-0.16	0.20
Transition	Sec to Insec	-0.01	0.960	-0.32	0.30
Interaction	30-49 x Sec to Insec	0.04	0.800	-0.28	0.37
	50-65 x Sec to Insec	0.13	0.513	-0.26	0.52
Wald test on interaction variable		F=0.23	p=0.796		

Appendix 6.13 Results from fixed effects model showing association between Insecure to Secure Employment transition and GHQ-12 score, adjusted for current labour market status, age group, an interaction between age group and the transition variable, and confounders

Fixed effects model, adjusted for confounding covariates*					
		Coefficient	**p-value**	**95% Conf. Interval**	
Labour Market Status (sec emp omitted)	Insecure Emp	**1.12**	<0.001	1.01	1.23
	Unemp	**2.26**	<0.001	2.04	2.48
	Perm Sickness	**2.96**	<0.001	2.71	3.22
	Oth. Inactivity	**0.29**	<0.001	0.17	0.42
Age group (16-29 omitted)	Age 30-49	**0.41**	<0.001	0.29	0.54
	Age 50-65	0.02	0.823	-0.16	0.20
Transition	Insec to Sec	0.10	0.481	-0.18	0.37
Interaction	30-49 x Insec to Sec	-0.16	0.333	-0.48	0.16
	50-65 x Insec to Sec	0.12	0.555	-0.27	0.51
Wald test on interaction variable		F=1.53	p=0.216		

Chapter 7

Discussion and Conclusions

7 Discussion and Conclusions

7.1 Research questions

This PhD project set out to address the following research questions:

i. To what extent does being insecurely employed, unemployed, permanently sick or economically inactive predict MPM (compared to being securely employed), controlling for the effects of potential confounding factors, and exploring the factors which might mediate the relationship? (Chapter 4).

ii. To what extent does area level claimant count rate affect minor psychiatric morbidity, independently of individual-level exposure to joblessness and insecure employment? (Chapter 5.)

iii. What is the nature of the temporal dimension of the relationship between labour market status and GHQ-12? Causation, process and lifecourse. (Chapter 6).

7.2 Summary of findings

The results presented across this thesis consistently show that being jobless or insecurely employed was significantly worse for mental health than being securely employed. Chapter 4 shows that this applied to both men and women, held true despite adjustment for a wide range of hypothesised confounding factors and could only be explained in part by financial status and household income differences. Chapter 5 corroborated these findings with very similar effect sizes and significance levels, and added an important new spatial dimension to our understanding of the relationship between labour market status and minor psychiatric morbidity. Whilst there was essentially no independent variation in GHQ-12 scores at the local authority district level, there was support for the hypothesis that living in an area with high claimant count rate conferred a degree of protection against the negative psychological effects of joblessness or insecure employment, although GHQ-12 scores among these groups were still significantly and substantially higher than among their securely employed counterparts.

In support of the results presented in previous chapters, results from chapter 6 showed that in essence, having a secure job was optimal for all, with the exception of those aged 50-65 who were economically inactive and therefore likely to have taken early retirement. It was found that exposure to insecure employment, unemployment and permanent sickness was associated with an increase in GHQ-12 scores in all age groups in the age stratified models, but that permanent sickness had a comparatively worse effect on the young, compared to secure employment. Similarly, it was found that average GHQ-12 scores whilst unemployed were higher than average GHQ-12 scores when securely employed across all age groups, with limited evidence to support the hypothesis that unemployment had a comparatively greater effect on those in mid-life. This was also shown to be true for insecure employment. Significant lagged labour market status coefficients and significant advanced labour market status coefficients in fixed effects models show that both causality and selection were probably in operation, but the further analyses undertaken using labour market transition variables added weight to the causal interpretation. Moving from employment into unemployment or permanent sickness was significantly associated with higher levels of psychological distress whilst unemployed, even when accounting for the contemporaneous effects of unemployment or permanent sickness on MPM, and a range of confounding factors. Conversely, moving from unemployment into employment was significantly associated with lower levels of psychological distress. A key strength of this research is the exploration of both transitions into joblessness and transitions into employment. These are not found to be equal and opposite, revealing a more complex relationship between MPM and labour market status transitions than a more superficial analysis could show.

7.3 Labour market status and Minor Psychiatric Morbidity: a causal association?

To what extent can we suggest that the relationship between labour market status and psychological distress is causal? It is valuable to revisit Bradford-Hill's criteria for causation (Bradford-Hill, 1965) and to consider whether these have been met. The first criterion is the **temporal sequencing** of cause and effect. Exploiting the power of longitudinal data, this thesis has employed various complementary approaches to assess temporal sequencing. Firstly, the inclusion of lagged GHQ-12 score as a covariate in the random effects models presented in chapter 4 effectively controlled for an individual's tendency towards generally higher or lower than average GHQ-12 scores over time. Secondly, the use of fixed effects models in chapter 6 allowed analysis of the within-individual change over time in GHQ-12 score compared to his/her average. Thirdly, the inclusion of lagged and advanced versions of the exposure as covariates in the fixed effects models presented in section 6.3.3.1 allowed preliminary investigation of the ways in which the chronological sequencing of labour market statuses produced changes in GHQ-12 scores, and whether poorer psychological wellbeing predated a change in labour market status. These approaches allowed tentative suggestions to be made about causation, but the use of transition variables in section 6.3.4 provides the most persuasive evidence for a causal relationship by allowing us to state that, after taking account of the contemporaneous effects of unemployment on MPM, and the impact of a range of confounding factors, experiencing a transition from employment to unemployment between the previous and current waves is significantly predictive of poorer psychological wellbeing. This modelling strategy therefore allows isolation of the effects of the labour market status transition itself.

The second of Bradford-Hill's criteria for causation is **strength of association**. The results of the nested linear and logit random effects models presented in chapter 4 show that labour market status remained a significant predictor of MPM, after controlling for the effects of a range of potential confounding factors, and adjusting for the effects of a number of supposed mediators. Unadjusted, the insecurely employed were twice as likely to be an MPM case than the securely employed, and had GHQ-12 scores 1.3 units higher. This reduced to an odds ratio of 1.7 and coefficient of 1.0 when all hypothesised confounders and mediators were adjusted for, both with high levels of statistical significance ($p<0.001$). A similar pattern was seen for the unemployed, who were 2.6 times more likely to be an MPM case prior to adjustment, and had GHQ-12 scores 2 units higher than the securely employed. After full adjustment, the unemployed remained 1.7 times more likely to be MPM cases, and had GHQ-12 scores 1.2 units higher than the securely employed. The permanently sick also remained significantly more likely to have higher GHQ-12 scores or be a MPM case than the securely employed. After full adjustment, this group were 3 times more likely to suffer psychological distress than the securely employed. As expected, the association was least strong for the other inactive group, especially after hypothesised confounders and mediators were adjusted for. Nonetheless, being a member of this group was still predictive of elevated GHQ-12 score or likelihood of caseness overall, although this was not true for the 50-65 age group or for females overall.

The majority of the odds ratios and regression coefficients reported here are from chapter 4's exploration of the mechanisms underlying the relationship between labour market status and MPM. Another of Bradford-Hill's criteria for causation is **consistency** of results across different study populations and methodologies. Whilst this PhD thesis has not compared the relationship between labour market status and MPM across different study populations, various complementary modelling approaches have been used throughout the thesis, and all have produced similar results with regards to the associations between the labour market status categories and psychological distress. In addition, similar effects can be seen for both continuous GHQ-12 score and MPM prevalence outcome measures used in chapter 4, showing that the relationship is not just controlled by the centre of the distribution, and that it applies to both the clinically relevant cut-off point and to the general population.

One can also make a tentative argument for the fulfilment of another of Bradford-Hill's criteria: the **dose-response relationship**, although this depends on whether one subscribes to the view that insecure employment, unemployment and perm sickness form an ordered set of categories with regards to their prediction of MPM.

A **plausible mechanism of action** is a key part of Bradford-Hill's schema and the theories of Jahoda, Warr, Fryer, Ferrie, Beatty and others referred to throughout this thesis provide insights into the complex material and psychosocial processes which underlie the relationship between labour market status and psychological wellbeing. The field is well theorised, and as described in chapter 2, gaps in the literature are more apparent with regards to the adequate quantification of the causal relationship and the ways in which contextual factors may moderate this.

7.4 Labour market status and Minor Psychiatric Morbidity in context

The findings presented in this PhD thesis have major implications for population mental health against the backdrop of ongoing global economic instability and the current austerity agenda. Whilst the analysis undertaken in chapter 4 failed to find any direct relationship between annual percentage GDP growth and GHQ-12 score, or any evidence that this acts as a confounder or mediator in the relationship between labour market status and psychological distress, it remains true that high levels of worklessness and perceived job insecurity are a fundamental part of the economic landscape during economic downturn, and that therefore, the psychological distress caused by these phenomena will be more widespread. It is likely that the way in which macroeconomic conditions were operationalised resulted in an underestimation of the effects they may have on MPM and on the relationship between labour market status and MPM. As discussed in section 4.4.1, percentage annual GDP growth is a crude measure of economic performance, and it may have been better to use national unemployment rates to characterise the state of the economy. Chapter 4 showed that subjective assessment of financial situation attenuated the association between labour market status and MPM to some degree. During times of economic strife, it is likely that a greater proportion of people will perceive their financial situation to be poor, and to be worse than it was in previous years. In the current climate of ongoing global economic instability, it seems likely that individuals may hold little hope of their financial situation improving in the months to come. These variables were found to be strongly predictive of high psychological distress, and associated with labour market status, and therefore could contribute further to a greater burden of psychological distress at the population level, and particularly among the jobless and insecurely employed. A significant interaction was found between Local Authority District level claimant count rate and individual level labour market status. This supported previous research by suggesting that unemployed individuals who live in an area of high unemployment experience less psychological distress than their counterparts who live in areas of low unemployment (although the unemployed were found to experience higher levels of psychological distress than the securely employed no matter where they lived). It appears therefore that the wider economic context in which an individual lives does affect their experience of unemployment, despite there being no significant variation in GHQ-12 scores at the area level.

7.5 Policy Implications

The results presented in this thesis support the notion that a secure job promotes psychological wellbeing, primarily via psychosocial processes. Even after adjusting for factors such as physical health status, educational attainment, social housing tenure, income, substance abuse, marital status and spousal joblessness, this was found to be true for both genders and for all age groups, with the exception of those in later life who were economically inactive but not permanently sick. It is clear therefore that reducing the number of people out of work will have a positive effect on population mental health. Interventions aimed at getting people into work commonly focus on the supply side, assuming that if individuals are given help with job searching and CV preparation, they are more likely to find a position. In the current economic climate, a greater focus must be placed on demand side interventions to stimulate and facilitate the creation of secure jobs. Whilst the data used in this PhD project was collected during a prolonged period of unprecedented economic prosperity, job insecurity was found to be both prevalent and distressing. It stands to reason that the number of people feeling insecure at work has risen sharply since 2008, as rationalisation takes place in the private sector and austerity measures threaten jobs in the public sector. When the Western economies emerge from the present crisis of capitalism, it is imperative that an emphasis be placed on restoring norms of job security to the labour market. These have been eroded and redistributed since the economic restructuring of the 1970s and 1980s, with a deleterious effect on population psychological wellbeing.

This thesis also shows that local social norms are a powerful force. Unemployed individuals in areas of high local unemployment experienced a smaller gulf in wellbeing between themselves and their securely employed neighbours than their counterparts in low-unemployment locales did. Despite this, it must be reemphasised that the unemployment was predictive of greater psychological distress than secure employment in all areas. If the power of local social norms could be harnessed to promote labour market engagement, psychological wellbeing levels would presumably rise as more individuals found work. However, it is important to note that availability of jobs in areas of high unemployment is commonly low. This is why an emphasis on demand-side interventions to boost vacancy numbers is crucial.

7.6 Evaluation

7.6.1 Limitations

A number of gaps in our current understanding of the relationship between labour market status and MPM were raised in chapter 2, and the research presented in this thesis has attempted to address some of those. Important findings, such as those relating to the relationship between insecure employment and MPM, the effects of living in a high-unemployment area and the processes underlying causality, have been introduced in this thesis. However, many questions go unanswered and will form the basis of future research. Firstly, no attention has been paid to the type of job undertaken by the individuals in the study. As Warr (1983) noted, not all work promotes mental health, and jobs which combine low autonomy with high demands, for example, can be psychologically damaging. Equally, working patterns and working hours can affect the extent to which a job is conducive to psychological wellbeing. A further omission from much research in the field, and from this PhD thesis is the issue of underemployment – the extent to which the employed members of the sample are working part-time hours but desire a full-time job. Individuals on a part-time wage could be equally as exposed to material disadvantage as the unemployed or those on sickness benefits. The research presented in this thesis has also failed to consider whether sample members have more than one job. Whilst care has been taken to divide the employed into secure and insecure categories, beyond this distinction they are conceptualised as fairly homogenous. This obviously does not reflect reality.

Perhaps the most obvious omission from this PhD research is the duration of labour market statuses beyond two consecutive waves. The damaging nature of long-term unemployment and inactivity and the extent to which adaptation ameliorates high levels of psychological damage has been addressed in other studies, and was judged to fall outside the scope of this project. Steps were taken to tackle the issue of status duration, such as the inclusion of an indicator of whether the respondent had experienced any spells of unemployment or inactivity in the months between BHPS interviews. However, it is recognised that this is an unsophisticated solution. Family structure was not included in the models but would have allowed a more nuanced investigation of the ways in which labour market engagement affects psychological health. Marital status was included, and offers a good proxy for social support, but no specific conclusions can be drawn about, for example, single parent families from this research, as this information was not included. Additionally, including information on family type would have allowed more precise conclusions to be made with regards to the relationship between labour market status and MPM at different stages in the lifecourse.

A key gap identified in the literature was a general failure to consider men and women separately with regards to the relationship between labour market status and MPM, owing to their differing patterns of labour market participation and different mental health profiles. However, owing to sample size constraints, this was only achieved in chapter 4. This analysis showed that important differences do indeed exist between the genders, and that secure employment is a more protective labour market status for men than it is for women. Ideally, with a larger sample size it would have been interesting to stratify the analysis in chapter 6 by gender, in order to assess the extent to which the relationship between labour market status and MPM varies between men and women differently over the lifecourse. It would also have been ideal if the transition analyses could have been performed separately by gender, but sample size considerations made this unwise.

The issues surrounding the use of self-assessed satisfaction with job security as a measure of job insecurity are raised in section 4.4.1 but warrant reiteration. It is possible that having low satisfaction with job security and a high GHQ-12 score are associated not because one causes the other, but because both observations are capturing the same underlying dimensions of minor psychiatric morbidity. An individual experiencing psychological distress may be liable to interpret any situation more pessimistically than average, or feel a greater need for job security in the face of other life challenges. An interesting avenue for further research might be to compare the results for subjectively assessed insecure employment with results from a more objective measure of insecure employment. This would allow us to see the extent to which the two are correlated, and to see whether the results for the relationship between subjectively assessed insecure employment and MPM can be replicated using objectively measured insecure employment. Whilst insecure employment was significantly predictive of MPM compared to secure employment throughout the random effects analyses in chapters 4 and 5 and in the fixed, between and random effects models in section 6.3.2, no differentiation was found between secure and insecure employment in the transition analyses (section 6.3.4).

This adds weight to the concerns that reverse causality could be in operation for this group of people.

7.6.2 Strengths

The strengths of this PhD project lie in the application of sophisticated longitudinal analysis methods to the research questions, allowing us to situate the relationship between labour market status and MPM in its spatial and temporal context. Analysis undertaken in this PhD project exploits the longitudinal nature of the data to look at what predicts a change in psychological wellbeing, controlling for unobserved time-invariant covariates as well as specific variables hypothesised to confound the relationship between labour market status and GHQ-12 score. A further major strength of this research is the differentiation between secure and insecure employment, a distinction often overlooked in the literature but one which is of great importance in the post-Fordist labour market. In addition, economic inactivity has been considered alongside registered unemployment. This research also allows separate conclusions to be drawn for each gender. Many previous studies in the field concentrate only on men, so investigation into the effects of labour market status on the psychological wellbeing of women is much needed.

7.7 Further research

The new Understanding Society survey, which provides data on 100,000 individuals across 40,000 households will be an invaluable resource for further research on the relationship between labour market status and health. The research presented in this PhD thesis could be extended to assess the impacts of the current macroeconomic conditions on the relationship between labour market status and psychological wellbeing, to investigate whether this is modified by higher levels of unemployment than were seen during the BHPS study period, especially at the local area level. The increased sample sizes available in Understanding Society would also allow area-level variation in GHQ-12 scores to be assessed using more smaller geographical units, allowing an investigation of the spatial level at which local unemployment rates affect MPM. Understanding Society data could also be used to boost sample size in order for stratification to be performed by both age group and gender. This would illuminate the processes underlying the relationship between labour market status and MPM yet further. A possible way to further test the theory that unemployment is comparatively less distressing in places where it is more common would be to identify an opportunity to assess a natural experiment. It could be hypothesised that the overall psychological wellbeing levels of a population would increase if a large employer located in the area and provided a large number of jobs, boosting the local employment rate. However, would the psychological wellbeing of those few who remained unemployed decline, as unemployment no longer constituted a local social norm? It would be crucial to account for possible selection effects in order to isolate the consequences of social comparison processes.

7.8 Final reflections

In 2010, inspired by the work of economists such as Layard (2005), ‘Happiness’ became a dominant political discourse. An ONS consultation on ‘Measuring National Wellbeing’ (Beaumont, 2011) was launched, aiming to uncover the dimensions of happiness (Figure 7.1) in order to develop an index by which future national success will be measured, as an accompaniment to the traditional yardstick: GDP growth.

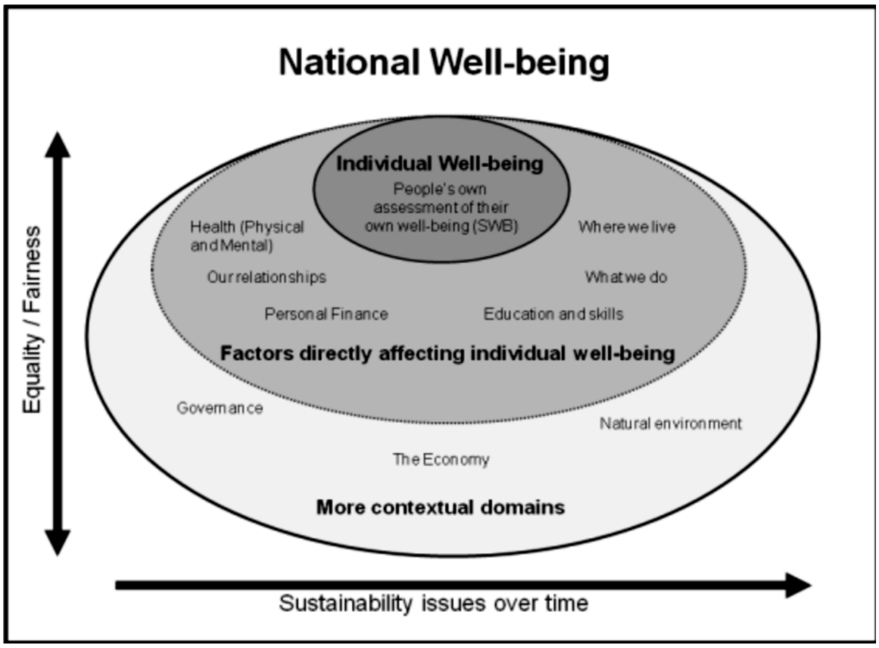

Figure 7.1 National wellbeing framework. Source: Office for National Statistics licensed under the Open Government Licence v.1.0.

The work presented in this PhD thesis contributes towards the renewed interest in psychological wellbeing and important findings on the nature of its relationship with labour market status, exploiting the power of longitudinal data to reveal the causal nature of the association. This research has shown the extent to which having a secure job benefits psychological wellbeing: across gender and age group, and through space and time. Against the current backdrop of high unemployment, spiralling job insecurity and wholesale changes to the incapacity benefits system, it is crucial to consider their ramifications for population mental health.

References

8 References

Akerlof G. A theory of social custom, of which unemployment may be one consequence, Quarterly Journal of Economics 1980;94(4):749–775.

Artazcoz L, Benach J, Borrell C. Social inequalities in the impact of flexible employment on different domains of psychological health. Journal of Epidemiology and Community Health 2005;59(9):761-767.

Atkinson T, Liem R, Liem JH. The Social Costs of Unemployment: Implications for Social Support. Journal of Health and Social Behaviour 1986;27(4):317-331

Baik K, Hosseini M, Priesmeyer HR. Correlates of psychological distress in involuntary job loss. Psychological Reports 1989;65:1227–1233

Balmer N, Pleasence P, Buck A, Walker HC. Worried Sick: The Experience of Debt Problems and their Relationship with Health, Illness and Disability. Social Policy and Society 2006;5(1):39-51.

Banks MH, Jackson PR. Unemployment and risk of minor psychiatric disorder in young people: cross-sectional and longitudinal evidence. Psychological Medicine 1982;12:789-798.

Bartley M. Unemployment and health: selection or causation - a false antithesis? Sociology of Health and Illness 1988;10:41-67.

Bartley M, Fagin L. Hospital admissions before and after shipyard closure. British Journal of Psychiatry 1990;156:421-424.

Bartley M, Ferrie J, Montgomery SM. Health and Labour market disadvantage: unemployment, non-employment and job insecurity. In: Marmot M, Wilkinson R, editors. Social Determinants of Health. 2nd ed. Oxford: Oxford University Press;2005.

Bartley M, Fitzpatrick R, Firth D, Marmot M. Social distribution of cardiovascular disease risk factors: change among men in England 1984-1993. Journal of Epidemiology and Community Health 2000;54:806-814.

Bartley M, Owen C. Relation between socioeconomic status, employment and health during a time of economic change 1973-1993. British Medical Journal 1996;313:445-448.

Beale N. Job loss and family morbidity: a study of a factory closure. Journal of the Royal College of General Practitioners 1985;35(280):510-514.

Bean C. Measuring Recession and Recovery: An Economic Perspective. Speech by Charles Bean, Deputy Governor for Monetary Policy, Bank of England. RSS Statistics User Forum Conference, 27th October 2010. Downloaded on 12/09/11 from: http://www.bankofengland.co.uk/ publications/speeches/2010/speech457.pdf

Beatty C, Fothergill S, Macmillan R. A theory of employment, unemployment and sickness. Regional Studies 2000;34(7):617-630.

Beaumont J. Measuring National Well-being - Discussion paper on domains and measures. Office for National Statistics, 31 October 2011. Downloaded 04/11/11 from: http://www.ons.gov.uk/ons/dcp171766_240726.pdf

Beck AT, Ward CH, Mendelson M, Mock J, Erbaugh J. An Inventory for Measuring Depression. Archives of General Psychiatry 1961;4:561-571

Ben-Shlomo Y. Real epidemiologists don't do ecological studies? International Journal of Epidemiology 2005;34(6):1181-1182.

Best NG, Spiegelhalter DJ, Thomas A, Brayne CEG. Bayesian analysis of realistically complex models. Journal of the Royal Statistical Society 1996;159:232-342

Birtchnell J, Masters N, Deahl M. Depression and the physical environment: a study of young married women on a London housing estate. British Journal of Psychiatry 1988;153:56-64.

Blanchflower DG, Oswald AJ. Well-Being Over Time in Britain and the USA. Journal of Public Economics 2004;88(7-8):1359-1386.

Blanchflower DG, Oswald AJ. Is well-being U-shaped over the life cycle? Social Science & Medicine 2008;66(8):1733-1749

Blaxter M. Health and Lifestyle. London: Tavistock/Routledge, 1990.

Bolton W, Oatley A. A longitudinal study of social support and depression in unemployed men. Psychological Medicine 1987;17:453-460

Booker CL, Sacker A. Psychological well-being and reactions to multiple unemployment events: adaptation or sensitisation? Journal of Epidemiology and Community Health, Published Online First: 20 June 2011. *doi:10.1136/jech.2010.126755*

Bortner RW, Hultsch DF. Patterns of subjective deprivation in adulthood. Developmental Psychology 1974;10(4):534-545.

Bradburn NM. The Structure of Psychological Well-Being. Chicago: Aldine, 1969

Bradford-Hill A. The Environment and Disease: Association or Causation? Proceedings of the Royal Society of Medicine 1965;58:295-300

Brenner HM. Economic changes and heart disease mortality. American Journal of Public Health 1971;61(3):606-611.

Brenner HM. Mental Illness and the Economy. Cambridge, Massachusetts: Harvard University Press, 1973.

Brenner HM. Relation of economic change to Swedish health and social wellbeing, 1950–1980. Social Science & Medicine 1987;25(2):183-195.

Brenner HM, Mooney A. Unemployment and health in the context of economic change. Social Science & Medicine 1983;17(16):1125-1138.

Breslin FC, Mustard C. Factors influencing the impact of unemployment on mental health among young and older adults in a longitudinal, population-based survey. Scandinavian journal of work, environment & health 2003;29(1):5-14.

Briscoe, M. Sex differences in psychological well-being. Psychological Medicine 1982;1(Monograph Supplement):1-46.

British Household Panel Survey, ESRC Research Centre on Micro-social Change. Colchester: The Data Archive. 1991-2008 Data files and associated documentation.

Brown S, Taylor K, Wheatley Price S. Debt and distress: Evaluating the psychological cost of credit. Journal of Economic Psychology 2005;26(5):642-663.

Browne WJ, Goldstein H, Rasbash J. Multiple membership multiple classification (MMMC) models. Statistical Modelling 2001;1(2):103-124

Browne WJ. MCMC estimation in MLwiN Version 2.13. Centre for Multilevel Modelling, University of Bristol, Bristol. 2009

Burchell B. The effects of labour market position, job insecurity and unemployment on psychological health. In: Gallie D, Marsh C, Vogler C, editors. Social change and the experience of unemployment. Oxford: Oxford University Press;1994. 188-122.

Burchell B, Ladipo D, Wilkinson F (eds). Job Insecurity and Work Intensification. London: Routledge, 2002

Catalano R. The health effects of economic insecurity. American Journal of Public Health 1991;81(9):1148-1152.

Catalano R, Rook K, Dooley D. Labour markets and help-seeking: a test of the employment security hypothesis. Journal of Health and Social Behaviour 1986;27(3):277-287.

Clark AE. Unemployment as a social norm: Psychological evidence from panel data, Journal of Labour Economics 2003;21:323–351.

Clark AE, Oswald AJ. Unhappiness and unemployment. Economic Journal 1994;104:648–659.

Claussen B. Health and re-employment in a five-year follow-up of long-term unemployed. Scandinavian journal of public health 1999;27(2):94-100.

Cooperstock R. Sex differences in the use of mood-modifying drugs: an explanatory model. Journal of Health and Social Behaviour 1971;12:238-244.

Cooperstock R. Sex differences in psychotropic drug use. Social Science and Medicine 1978;12(3B):179-186.

Creed PA, Macintyre SR. The relative effects of deprivation of the latent and manifest benefits of employment on the well-being of unemployed people. Journal of Occupational Health Psychology 2001;6(4):324-331.

Creed PA, Muller J, Machin MA. The role of satisfaction with occupational status, neuroticism, financial strain and categories of experience in predicting mental health in the unemployed. Personality & Individual Differences 2001;30:435-447

Creed PA. Predisposing factors and consequences of occupational status for long-term unemployed youth: A longitudinal examination. Journal of Adolescence 1999;22:81–89

Cummins S, Curtis S, Diez-Roux AV, Macintyre S. Understanding and representing 'place' in health research: a relational approach. Social Science & Medicine 2007;65(9):1825-1838.

Daniel W. A National Survey of the Unemployed. London: P.E.P, 1974

De Masi P. IMF Estimates of Potential Output: Theory and Practice (EPub). International Monetary Fund, Research Department, Washington D.C. 1997

Delong JB, Olney ML. Macroeconomics, Second Edition. McGraw-Hill Higher Education, 2006

Dew MA. Effects of unemployment on mental health in the contemporary family. Behavioural Modification 1991;15(4):501-544.

Dohrenwend BP, Dohrenwend BS. Sex differences and psychiatric disorders. American Journal of Sociology 1976;81:1447-5

Dooley D. Unemployment, Underemployment, and Mental Health: Conceptualizing Employment Status as a Continuum. American Journal of Community Psychology 2003;32(1):9-20.

Dooley D, Catalano R, Wilson G. Depression and unemployment: Panel findings from the Epidemiologic Catchment Area study. American Journal of Community Psychology 1994;22(6):745-765.

Dooley D, Rook K, Catalano R. Jon and non-job stressors and their moderators. Journal of Occupational Psychology 1987;60(115):132.

Drentea.P. Age, Debt and Anxiety. Journal of Health and Social Behaviour 2000;41(4):437-450.

Duncan K, Jones K, Moon G. Psychiatric morbidity: a multilevel approach to regional variations in the UK. Journal of Epidemiology and Community Health 1995;49:290-295.

Duncan C, Jones K, Moon G. Health-related behaviour in context: A multilevel modelling approach. Social Science & Medicine 1996;42(6):817-883

Duncan C, Jones K, Moon G. Context, composition and heterogeneity: Using multilevel models in health research. Social Science & Medicine 1998;46(1):97-11.

DWP Information Directorate: Work and Pensions Longitudinal Study. Causes of incapacity, August 1999, based on the WHO International Classification of Diseases, downloaded from DWP tabulation tool (http://83.244.183.180/100pc/ib/tabtool_ib.html) on 23/08/2011.

Eisenberg P, Lazarsfeld PF. The psychological effects of unemployment. Psychological Bulletin 1938;35(6):358-390

Eyer J. Prosperity as a cause of death. International Journal of Health Services 1977;7:125-150.

Fagin L, Little M. The Forsaken Families. Harmondsworth, Middlesex: Penguin, 1984.

Ferrie J. Labour Market Changes and Job Insecurity: A Challenge for Social Welfare and Health Promotion. In: Ferrie J, Marmot M, Griffiths J, Ziglio E, editors. WHO Regional Publications. Copenhagen: WHO, 1999.

Ferrie J. Is Job insecurity harmful to health? Journal of the Royal Society of Medicine, 2001;94(2):71-76.

Ferrie J, Shipley MJ, Stansfeld S. Effects of chronic flexible employment and change in job security on self-reported health, minor psychiatric morbidity, physicological measures and health related behaviours of British civil servants: the Whitehall study. Journal of Epidemiology and Community Health 2002;56:450-454.

Ferrie JE, Shipley MJ, Marmot MG, Stansfeld S, Davey Smith G. Health effects of anticipation of job change and non-employment: longitudinal data from the Whitehall II study. British Medical Journal 1995;311:1264

Finlay-Jones R, Eckhardt, B. A Social and Psychiatric Survey of Unemployment among Young People. Australian and New Zealand Journal of Psychiatry 1984;18(2):135-143

Fox A, Shewry M. New longitudinal insights into relationships between unemployment and mortality. Stress Medicine 1988;4(1):11-19.

Fryer D, Payne R. Proactive behaviour in unemployment: findings and implications. Leisure studies 1984;3:273-295.

Fryer D. Employment deprivation and personal agency during unemployment: A critical discussion of Jahoda's explanation of the psychological effects of unemployment. Social Behaviour 1986;1(1):3-23.

Gartner M. Macroeconomics. Essex, UK: Pearson Education Limited, 2003.

Gerdtham U-G, Ruhm CJ. Deaths rise in good economic times: Evidence from the OECD. Economics & Human Biology 2006;4(3):298-316.

Goldberg DP, Gater R, Sartorius N, Ustun TB, Piccinelli M, Gureje O, Rutter C. The validity of two versions of the GHQ in the WHO study of mental illness in general health care. Psychological Medicine 1997;27(1):191-7

Goldberg DP. Manual of the General Health Questionnaire. Windsor, England: NFER Publishing, 1978

Goldberg DP. The detection of psychiatric illness by questionnaire. London: Oxford University Press, 1972

Goldstein H. Multilevel mixed linear model analysis using iterative generalized least squares. Biometrika 1986;73(1):43-56.

Goodchild ME, Duncan-Jones P. Chronicity and the General Health Questionnaire. British Journal of Psychiatry 1985;146:55-61

Goodman CR, Shippy RA. Is it contagious? Affect similarity among spouses. Aging and Mental Health 2002;6(3):266–274

Gore S. The effect of social support in moderating the health consequences of unemployment. Journal of Health and Social Behaviour 1978;19:157–165.

Gove WR, McGorkel, J, Fain T, Hughes M. Response bias in community surveys of mental health: systematic bias and random noise. Social Science and Medicine 1976;10:497-502.

Gravelle HSE, Huchinson G, Stern J. Mortality and unemployment: a critique of Brenner's time-series analysis. Lancet 1981;318(8248):675-679.

Gurin G, Veroff J, Feld S. How Americans View Their Mental Health. New York: Basic Books, I960

Hagenaars AJM, De Vos K, Zaidi A. Poverty statistics in the late 1980s: Research based on micro-data. Luxembourg: Office for official publications of the European Union, 1994

Hamilton V, Broman C, Hoffman W, Renner D. Hard Times and Vulnerable People: Initial Effects of Plant Closing on Autoworkers' Mental Health. Journal of Health and Social Behaviour 1990;31(2):123-140.

Hamilton V, Hoffman W, Broman C, Rauma D. Unemployment, distress and coping: a panel study of autoworkers. Journal of Personality and Social Psychology 1993;65:234-237.

Hanisch KA. Job Loss and Unemployment Research from 1994 to 1998: A Review and Recommendations for Research and Intervention. Journal of Vocational Behaviour 1999;55(2):188-220

Happiness: Lessons from a New Science. Layard R. London: Penguin, 2005

Hartley J, Jacobson D, Klandermans B, Van Vuuren T. Job insecurity: coping with jobs at risk. London: Sage Publications, 1991.

Harvey D. From Space to Place and back again. In: Bird J, editor. Mapping the Futures: Local Cultures, Global Change. London: Routledge, 1993.

Harvey D. The Condition of Postmodernity: An Enquiry Into the Origins of Cultural Change. Oxford: Blackwell, 1989.

Hausman JA. Specification Tests in Econometrics. Econometrica 1978;46(6):1251–1271.

Henderson C, Diez Roux AV, Jacobs Jr DR. Neighbourhood characteristics, individual level socioeconomic factors, and depressive symptoms in young adults: the CARDIA study. Journal of Epidemiology and Community Health 2005;59:322-328.

Hepworth SJ. Moderating factors of the psychological impact of unemployment. Journal of Occupational Psychology 1980;53:139-146.

Hepworth SJ. Moderating factors of the psychological impact of unemployment. Journal of Occupational Psychology 1980;53:139–146.

Hintikka J. Suicide mortality in Finland during an economic cycle, 1985 -1995. Scandinavian Journal of Public Health 1999;27(2):85-88.

Hobfoll SE, Freedy JR, Green BL, Solomon SD. Coping in reaction to extreme stress: The roles of resource loss and resource availability. In, Zeidner M (ed), Endler NS (ed). Handbook of coping: Theory, research, applications. Oxford: John Wiley & Sons, 1996

International Labour Organisation, Bureau of Statistics. Resolution concerning statistics of the economically active population, employment, unemployment and underemployment, adopted by the Thirteenth International Conference of Labour Statisticians, October 1982. Accessed 17/09/11: http://www.ilo.org/public/english /bureau/stat/download/res/ecacpop.pdf

Iversen L, Sabroe S, Damsgaard MT. Hospital Admissions before and after Shipyard Closure. British Medical Journal 1989;299(6707):1073-1076.

Jackson C. The General Health Questionnaire. Occupational Medicine 2007;57:59.

Jackson PR, Warr P. Mental health of unemployed men in different parts of England and Wales, British Medical Journal 1987;295(6):525.

Jackson PR, Warr P. Unemployment and psychological ill-health: the moderating role of duration and age. Psychological Medicine 1984;14:605-614.

Jahoda M, Lazarsfeld PF, Zeisel H. Marienthal: The Sociology of an Unemployed Community. Chicago: Aldine-Atherton, 1933.

Jahoda M. Employment and Unemployment: A Social-psychological Analysis. Cambridge: Cambridge University Press, 1982.

Jahoda M. Work, employment, and unemployment: Values, theories, and approaches in social research. American Psychologist 1981;36(2):184-191

Jenkins R, Bhugra D, Bebbington P, Brugha T, Farrell M, Coid J et al. Debt, income and mental disorder in the general population. Psychological Medicine 2008;38(10):1485-1493.

Jenkins R, Lewis G, Bebbington P, Brugha T, Farrell M, Gill B et al. The national psychiatric morbidity surveys of Great Britain - initial findings from the household survey. Psychological Medicine 1997;27(4):775-789.

Joelson L, Wahlquist L. The psychological meaning of flexible employment and job loss: results of a longitudinal study. Social Science & Medicine 1987;25(2):179-182.

Jones K. Multilevel Analysis with Applications 2G Part 1. Course notes, Essex Summer School in SSDA, University of Essex 2010.

Jones K, Subramanian SV. Developing multilevel models using MLwiN 2.1: A training manual. June 2010. Acquired on Multilevel Analysis with Applications 2G Part 1 course, Essex Summer School in SSDA, University of Essex 2010.

Jones L. Specifying the temporal relationship between job loss and consequences: Implication for service delivery. Journal of Applied Social Sciences 1991-1992;16(1):37-62.

Kathol RG, Petty F. Relationship of depression to medical illness: A critical review. Journal of Affective Disorders 1981;3(2):111-121

Keefe V, Reid P, Ormsby C, Robson B, Purdie G, Baxter J et al. Serious health events following involuntary job loss in New Zealand meat processing workers. International Journal of Epidemiology 2002;31(6):1155-1161.

Kemp NJ, Mercer A. Unemployment, disability and rehabilitation centres and their effects on mental health. Journal of Occupational Psychology 1983;56:37-48

Kessler RC, Andrews G, Colpe LJ, Hiripi E, Mroczek DK, Normand SL, Walters EE, Zaslavsky AM. Short screening scales to monitor population prevalences and trends in non-specific psychological distress. Psychological Medicine 2002;32:959-976

Kessler RC, House JS, Turner JB. Unemployment and Health in a Community Sample. Journal of Health and Social Behaviour 1987;28(1):51-59

Kessler RC, Turner JB, House JS. Unemployment, Reemployment, and Emotional Functioning in a Community Sample. American Sociological Review 1989;54(4):648-657

Kessler RC. A disaggregation of the relationship between socioeconomic status and psychological distress. American Sociological Review 1982;17:752-764.

Khang YH, Lynch JW, Kaplan GA. Impact of economic crisis on cause-specific mortality in South Korea. International Journal of Epidemiology 2005;34(6):1291-1301.

Kinicki AJ, Prussia GE, McKee-Ryan FM. A Panel Study of Coping with Involuntary Job Loss. The Academy of Management Journal 2000;43(1):90-100

Kirkwood BR, Sterne JAC. Essential Medical Statistics, Second Edition. Oxford: Blackwell, 2003.

Kivimaki M, Vahtera J, Pentti J, Ferrie J. Factors underlying the effect of organisational downsizing on health of employees: longitudinal cohort study. British Medical Journal 2000;320(7240):971-975.

Kohn R, Dohrenwend BP, Mirotznik J, Dohrenwend BP (ed). Adversity, stress, and psychopathology. New York: Oxford University Press, 1998

Kohn R, White K (eds.). Health Care – An International Study: Report of the World Health Organisation/International Collaborative Study of Medical Care Utilization. London: Oxford University Press, 1976.

Kuh D, Hardy R, Rodgers B, Wadsworth MEJ. Lifetime risk factors for women's psychological distress in midlife. Social Science and Medicine 2002;55(11):1957-1973

Labour Market Statistics, Statistical Bulletin, Office for National Statistics, released: 16/11/11. Accessed 20/11/11: http://www.ons.gov.uk/ons/dcp171778_241735.pdf

Langner TS, Michael ST. Life stress and mental health: The midtown Manhattan study. Oxford: Free Press Glencoe, 1963

Laporte A. Do economic cycles have a permanent effect on population health? Revisiting the Brenner hypothesis. Health Economics 2004;13(8):767-779.

Leana CR, Feldman DC. Gender differences in responses to unemployment. Journal of Vocational Behaviour 1991;38(1):65-77

Lee S, Colditz GA, Berkman LF, Kawachi I. Prospective study of job insecurity and coronary heart disease in US women. Annals of Epidemiology 2004;14(1):24-30.

Lewis G, Booth M. Regional differences in mental health in Great Britain. Journal of Epidemiology and Community Health 1992;42(608):611.

Lewis G, Wilkinson G. Another British disease? A recent increase in the prevalence of psychiatric morbidity. Journal of Epidemiology and Community Health 1993;47:358-361

Lowenthal M, Thurnher M, Chiriboga, D. Four Stages of Life. San Francisco: Jossey-Bass, 1975.

Luoto R, Poikolainen K, Uutela A. Unemployment, sociodemographic background and consumption of alcohol before and during the economic recession of the 1990s in Finland. International Journal of Epidemiology 1998;27(4):623.

Lynn P (ed.), Buck N, Burton J, Laurie H, Lynn P, Uhrig SCN. Quality Profile: British Household Panel Survey Version 2.0: Waves 1 to 13: 1991-2003. Institute for Social and Economic Research, University of Essex, 2006

Machin A. Comparisons between unemployment and the claimant count. Labour Market Trends, Office for National Statistics 2004;112(2):59-62

Macky KA. Unemployed school leavers: Their mental health and work involvement. Community Mental Health in New Zealand 1984;1:40-45.

Martikainen P, Mäki N, Jäntti M. The Effects of Unemployment on Mortality following Workplace Downsizing and Workplace Closure: A Register-based Follow-up Study of Finnish Men and Women during Economic Boom and Recession. American Journal of Epidemiology 2007;165(9):1070-1075.

Martikainen P, Valkonen T. Excess mortality of unemployed men and women during a period of rapidly increasing unemployment. Lancet 1996;348(9032):909-912.

Martin RL, Morrison PS (eds). The geographies of labour market inequality: some emergent issues and challenges. London: Routledge, 2003

Martin RL, Townroe P. Changing trends and pressures in regional development. In: Martin RL, Townnroe P (eds). Regional Development in the 1990s. London: Routledge, 1992.

Massey D. Space, Place, and Gender. Minneapolis: University of Minnesota Press, 1994

Macintyre S, Ellaway A, Cummins S. Place effects on health: how can we conceptualise, operationalise and measure them? Social Science & Medicine 2002;55:125–139

McCulloch A. Ward-level deprivation and individual social and economic outcomes in the British household panel study. Environment and Planning A 2001;33:667-684.

McFadyn RG. Coping with threatened identities: Unemployed people's self-categorizations. Current Psychology 1995;14(3):233-256

McKee-Ryan F, Song Z, Wanberg CR, Kinicki AJ. Psychological and Physical Well-Being During Unemployment: A Meta-Analytic Study. Journal of Applied Psychology 2005;90(1):53-76.

McMunn A, Bartley M, Hardy R, Kuh D. Life course social roles and women's health in mid-life: causation or selection? Journal of Epidemiology and Community Health 2006;60:484-489.

Meyler D, Stimpson JP, Peek MK. Health concordance within couples: A systematic review, Social Science & Medicine 2007;64(11):2297-2310

MLwiN Help version 2.02.03. Section: 'Weights'

Montgomery SM, Cook D, Bartley M, Wadsworth ME. Unemployment pre-dates symptoms of depression and anxiety resulting in medical consultation in young men. International Journal of Epidemiology 1999;28(1):95-100.

Moser K, Goldblatt P, Fox A, Jones D. Unemployment and Mortality. Longitudinal Study: mortality and social organisation. London: HMSO;1990.

Neff JA, Husaini BA, McCorkel J. Psychiatric and medical problems in rural communities. Social Science & Medicine 1980;14(4):331-336

Nettleton S, Burows R. Mortgage debt, insecure home ownership and health: and exploratory analysis. Sociology of Health & Illness 1998;20(5):731-753.

Neumayer E. Recessions lower (some) mortality rates: evidence from Germany. Social Science & Medicine 2003;58(6):1037-1047.

Nomis: Peter Dodds and Peter Henderson, personal correspondence 10/11/10 and 24/11/10

Novo M, Hammarström A, Janlert U. Do high levels of unemployment influence the health of those who are not unemployed? A gendered comparison of young men and women during boom and recession. Social Science & Medicine 2001;53(3):293-303.

Novo M, Hammarstrom A, Janlert U. Health hazards of unemployment - only a boom phenomenon? A study of young men and women during times of prosperity and times of recession. Public Health 2000;114(1):25-29.

Ostamo A, Lönnqvist J. Attempted suicide rates and trends during a period of severe economic recession in Helsinki, 1989–1997. Social psychiatry and psychiatric epidemiology 2001; 36(7):354-360.

Oswald AJ, Powdthavee N. Obesity, unhappiness and the challenge of affluence: theory and evidence. Economic Journal 2007;117(521):441–454.

Parsons T. Illness and the role of the physician: a sociological perspective. American Journal of Orthopsychiatry 1951;21(3):452–460

Paul KI, Moser K. Unemployment impairs mental health: Meta-analyses. Journal of Vocational Behaviour 2009;74:264–282

Payne R, Hartley J. A test of a model for explaining the affective experience of unemployed men. Journal of Occupational Psychology 1987;60(1):31–47

Pevalin DJ. Multiple applications of the GHQ-12 in a general population sample: an investigation of long-term retest effects. Social Psychiatry and Psychiatric Epidemiology 2000;35(11):508-512.

Pickett KE, Pearl M. Multilevel analyses of neighbourhood socioeconomic context and health outcomes: a critical review. Journal of Epidemiology and Community Health 2001;55(111):122.

Platt S, Kreitman N. Long term trends in parasuicide and unemployment in Edinburgh, 1968–87. Social Psychiatry and Psychiatric Epidemiology 1990;25(1):56–61.

Platt S, Miccolo R, Tansella M. Suicide and unemployment in Italy: Description, analysis and interpretation of recent trends. Social Science and Medicine 1992;34(11):1191–1201.

Powdthavee N. Are There Geographical Variations in the Psychological Costs of Unemployment in South Africa? Social Indicators Research 2006;80(3):629-652

Pred A. Place as Historically Contingent Process: Structuration and the Time-Geography of Becoming Places. Annals of the Association of American Geographers 1984;74(2):279-297.

Ranzijn R, Carson E, Winefield AH, Price D. On the scrap-heap at 45: The human impact of mature-aged unemployment. Journal of Occupational and Organizational Psychology 2006;79(3):467–479

Rasbash J, Charlton C, Browne WJ, Healy M. and Cameron B. (2009) MLwiN Version 2.1. Centre for Multilevel Modelling, University of Bristol.

Rasbash J, Steele F, Browne WJ & Goldstein H. A User's Guide to MLwiN Version 2.10. Centre for Multilevel Modelling, University of Bristol, Bristol. 2008

Reijneveld SA, Schene AH. Higher prevalence of mental disorders in socioeconomically deprived areas in the Netherlands. Journal of Epidemiology & Community Health 1998;52:2-7.

Reynolds S, Gilbert P. Psychological impact of unemployment: Interactive effects of vulnerability and protective factors on depression. Journal of Counselling Psychology 1991;38:76-84

Ritzer G. The McDonaldization of Society (5th edition). Thousand Oaks, California: Pine Forge Press, 2007.

Robinson WS. Ecological Correlations and the Behavior of Individuals. American Sociological Review 1950;15(3):351–357

Ross CE. Neighbourhood disadvantage and adult depression. Journal of Health and Social Behaviour 2000;2000(41):177-187.

Rowley KM, Feather NT. The impact of unemployment in relation to age and length of unemployment. Journal of Occupational Psychology 1987;60(4):323–332

Ruhm CJ. Are Recessions Good for Your Health? The Quarterly Journal of Economics 2000;115(2):617-650.

Ruhm CJ. Good times make you sick. Journal of Health Economics 2003;22(4):637-658.

Rutter M, Tizard J, Whitmore K. Education, Health and Behaviour. London: Longmans 1970

Sacker A, Wiggins D. Age-period-cohort effects on inequalities in psychological distress, 1981-2000. Psychological Medicine 2002;32:977-990.

Schaufeli WB, Van Yperen NW. Success and failure in the labour market. Journal of Organizational Behaviour 1993;14:559–572

Shepherd M, Cooper B, Brown AC, Kalton, G. Psychiatric Illness in General Practice. London: Oxford University Press, 1966

Shields MA, Wheatley Price S. Exploring the economic and social determinants of psychological well-being and perceived social support in England. Journal of the Royal Statistical Society 2005;168(3):513–537

Sinfield A. What unemployment means. Oxford: Robertson, 1981.

Skapinakis P, Lewis G, Araya R, Jones K, Williams G. Mental health inequalities in Wales, UK: multi-level investigation of the effect of area deprivation. The British Journal of Psychiatry 2005;186:417-422.

Sloggett A, Joshi H. Higher mortality in deprived areas: community or personal disadvantage? British Medical Journal 1994;309:1470

Smith R. "I feel really ashamed": How does unemployment lead to poorer mental health? British Medical Journal 1985;291(1409):1412.

Smith SJ, Easterlow D. The strange geography of health inequalities. Transactions of the Institute of British Geographers 2005;30(2):173–190

Stafford M, Duke-Williams O, Shelton N. Small area inequalities in health: Are we underestimating them? Social Science & Medicine 2008;67(6):891-899

StataCorp. 2007. Stata Statistical Software: Release 10. College Station, TX: StataCorp LP.

StataCorp. 2009. Stata Statistical Software: Release 11. College Station, TX: StataCorp LP.

StataCorp. Stata Longitudinal Data/Panel Data Reference Manual Release 11. College Station, TX: StataCorp LP. 2009.

Strandh M. Different Exit Routes from Unemployment and their Impact on Mental Well-Being: The Role of the Economic Situation and the Predictability of the Lifecourse. Work Employment & Society 2000;14(3):459-479.

Sturgis P, Allum N, Brunton-Smith I. Attitudes Over Time: The Psychology of Panel Conditioning. In: Methodology of Longitudinal Surveys (ed Lynn P). Chichester: John Wiley & Sons Ltd, 2009

Tapia Granados JA. Increasing mortality during the expansions of the US economy, 1900–1996. International Journal of Epidemiology 2005;34(6):1194-1202.

Taris TW. Unemployment and Mental Health: A Longitudinal Perspective. International Journal of Stress Management 2002;9(1):43-57

Taylor, MF (ed), Brice J, Buck N, Prentice-Lane E. British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices. Colchester: University of Essex, 2010

Taylor MP, Pevalin DJ, Todd J. The psychological costs of unsustainable housing commitments. Psychological Medicine 2007;37(7):1027-1036.

Tennant R, Hiller L, Fishwick R, Platt S, Joseph S, Weich S, Parkinson J, Secker J, Stewart-Brown S. The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): development and UK validation. Health Qual Life Outcomes 2007;5(63)

The European Union Labour Force Survey, Methods and Definitions, 1998 edition, Eurostat. Accessed 09/09/11: http://circa.europa.eu/irc/dsis/employment/info/data/eu_lfs/lfs_main/ Related_documents /LFSmeth98.pdf

Theodossiou I. The effects of low-pay and unemployment on psychological well-being: A logistic regression approach. Journal of Health Economics 1998;17(1):85-104

Thomas C, Benzeval M, Stansfeld SA. Employment transitions and mental health: an analysis from the British household panel survey. Journal of Epidemiology and Community Health 2005;59:243-249

Thomas DS. Social Aspects of the Business Cycle. London: Routledge, 1925.

Thomas, R. How enlarged travel to work areas conceal inner city unemployment. Radical Statistics 1998;67:35-45

Troll EL. Continuations: Adult Development and Aging. Monterey: Brooks-Cole Publishing, 1982.

Ullah P. The association between income, financial strain and psychological well-being among unemployed youths. Journal of Occupational Psychology 1990;63:317-330.

Uppal S. Impact of the timing and severity of disability on the subjective well-being of individuals with disabilities. Social Science & Medicine 2006;63:525–539

Väänänen A, Buunk BP, Bram P, Kivimäki M, Pentti J, Vahtera, J. When It Is Better to Give Than to Receive: Long-Term Health Effects of Perceived Reciprocity in Support Exchange. Journal of Personality and Social Psychology 2005;89(2):176-193.

Valkonen T, Martikainen P. The association between unemployment and mortality: causation or selection? In: Lopez AD, Caselli G, Valkonen T, (eds). Adult mortality in developed countries: from description to explanation. Oxford: Clarendon Press, 1995.

Viinamäki H, Hintikka J, Kontula O, Niskanen L, Koskela K. Mental health at population level during an economic recession in Finland. Nordic Journal of Psychiatry 2000;54(3):177-182.

Vinokir AD, Price RH, Caplan RD. Hard times and hurtful partners: How financial strain affects depression and relationship satisfaction of unemployed persons and their spouses. Journal of Personality and Social Psychology 1996;71(1):166-179.

Vinokur AD, Schul Y. The web of coping resources and pathways to reemployment following a job loss. Journal of Occupational Health Psychology 2002;7(1):68-83

Vuori J, Silvonen J, Vinokur AD, Price RH. The Tyoehoen Job Search Program in Finland: Benefits for the unemployed with risk of depression or discouragement. Journal of Occupational Health Psychology 2002;7:5-19

Wadsworth ME, Montgomery SM, Bartley M. The persisting effect of unemployment on health and social wellbeing in men early in working life. Social Science and Medicine 1999;48:1491-1499.

Wagstaff A. Time series analysis of the relationship between unemployment and mortality: A survey of econometric critiques and replications of Brenner's studies. Social Science & Medicine 1985;21(9):985-996

Wainwright NWJ, Surtees PG. Area and individual circumstances and mood disorder prevalence. The British Journal of Psychiatry 2004;185:227-232.

Wainwright NWJ, Surtees PG. Places, people, and their physical and mental functional health. Journal of Epidemiology and Community Health 2004;58:333-339.

Wanberg CR, Carmichael HD, Downey RG. Satisfaction at last job and unemployment: A new look. Journal of Organizational Behaviour 1999;20:121–131

Wanberg CR. A Longitudinal Study of the Effects of Unemployment and Quality of Reemployment. Journal of Vocational Behaviour 1995;46(1):40-54

Wanberg CR. Antecedents and outcomes of coping behaviours among unemployed and reemployed individuals. Journal of Applied Psychology 1997;82:731-744.

Warr P, Jackson P. Adapting to the unemployed role: a longitudinal investigation. Social Science and Medicine 1987;25(11):1219-1224.

Weich S, Lewis G. Poverty, Unemployment and common mental disorders: Population-based cohort study. British Medical Journal 1998;314:591-595.

Warr P, Jackson P. Factors influencing the psychological impact of prolonged unemployment and of re-employment. Psychological Medicine 1985;15:795-807.

Warr P. Twelve questions about unemployment and health. In: Roberts B, Finnegan R, Gallie D, editors. New approaches to economic life. Manchester: Manchester University Press, 1985.

Warr P. Work, Jobs and Unemployment. Bulletin of the British Psychological Society 1983;36:305-311.

Warr P. Work, Unemployment and Mental Health. Oxford: Oxford University Press, 1987.

Webster D, Turok I. The Future of Local Unemployment Statistics: The Case for Replacing TTWAs. Fraser of Allander Institute Quarterly Economic Commentary 1997;22(2)

Weich S, Lewis, G. Material standard of living, social class, and the prevalence of the common mental disorders in Great Britain. Journal of Epidemiology and Community Health 1998;52:8-14.

Weich S, Twigg L, Holt G, Lewis G, Jones K. Contextual risk factors for the common mental disorders in Britain: a multilevel investigation of the effects of place. Journal of Epidemiology and Community Health 2003;57:616-621.

Weich S, Twigg L, Lewis G, Jones K. Geographical variation in rates of common mental disorders in Britain: prospective cohort study. The British Journal of Psychiatry 2005;187:29-34.

Weich S. Absence of spatial variation in rates of the common mental disorders. Journal of Epidemiology and Community Health 2005;59:254-257.

Wiener KKK, Oei TPS, Creed PA. Predicting job seeking frequency and psychological well-being in the unemployed. Journal of Employment Counselling 1999;36:67-81

Winefield AH, Tiggermann M, Winefield HR. The psychological impact of unemployment and unsatisfactory employment in young men and women: longitudinal and cross-sectional data. British Journal of Psychology 1991;82:473-486.

Winefield AH, Winefield HR, Tiggemann M, Goldney RD. A longitudinal study of the psychological effects of unemployment and unsatisfactory employment on young adults. Journal of Applied Psychology 1991;76(3):424-431.

Winefield AJ. Unemployment: Its psychological costs. In: Cooper CL, Robertson IT (eds). International Review of Industrial and Organizational Psychology. Chichester: Wiley, 1995

Winegardner D, Simonetti JL, Nykodym N. Unemployment: The living death? Journal of Employment Counselling 1984;21(4):149-155.

Winkelmann L, Winkelmann , R. Why Are the Unemployed So Unhappy? Evidence from Panel Data. Economica 1998;65(257):1–15

Winkelmann L, Winkelmann R. Why are the Unemployed So Unhappy? Evidence from Panel Data. Economica 1998;65(257):1-15.

www.statistics.gov.uk/geography/downloads/2001_TTWA_Methodology.pdf. Accessed 07/02/2011

www.statistics.gov.uk/geography/ttwa.asp. Accessed 07/02/2011

www.nomisweb.co.uk. Accessed 18/01/2011