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Working Hours Mismatch in Non-Standard Employment and Individuals' Mental Health

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Declaration

I hereby declare that this submission is my own work and any contributions or materials by other authors used in this thesis have been appropriately acknowledged. This thesis has not been previously submitted to any other university or institution as part of the requirements for another degree or award.

Claire Houssard

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Disclaimer

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Abstract

Mental health is inherent to individuals' well-being, and is an essential element in workplace productivity. Mental health has also been the focus of recent policy debate in Australia, as researchers and policy makers have paid particular attention to the link between labour market experiences and mental health. However, little empirical research has explored the full 24-hour time span available to individuals in their choice of working hours. This thesis extends previous studies to investigate the impact of a working hours' mismatch in non-standard employment on individuals' mental health in Australia.

The first eight waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey are used to estimate static and dynamic models. The persistence of mental health over time motivates the use of linear dynamic panel data models over static fixed effects models. Overall, the key findings reinforce existing studies, and are robust across the range of models estimated. We find a working hours' mismatch in non-standard employment to negatively affect men's mental health. In contrast, we find a positive effect for women. Although most of the key results lack precision, overemployment is significantly associated with poorer mental health for both genders. Notably, this effect seems to be driving the negative relationship observed between a working hours' mismatch in non-standard employment and better mental health for men.

1. Introduction

Since the mid 1970s, the Australian labour market has been subject to various changes. Enterprise bargaining, labour market deregulation and trading hour liberalisation have altogether revolutionised the workforce composition and working arrangements (Allan et al., 1998). In particular, there has been a shift away from 'traditional' to 'non-traditional' forms of employment (ABS, 2009a). With the advent of technologies and globalization, a push towards a '24/7 economy' has raised concerns over its implications for workers' mental health. Notably the disparity observed between individuals' desired and actual working hours has been the focus of recent studies.

While around-the-clock activity can increase efficiency and productivity, a substantial amount of pressure may be placed upon workers. As such, this thesis aims to assess the relationship between a working hours' mismatch in non-standard employment and individuals' mental health in Australia.

This thesis draws upon previous research conducted by Ulker (2006) on the relationship between non-standard work schedules and individuals' mental health. The release of five additional waves of data since Ulker (2006) allows for an extension of his results, as well as the possibility to investigate longer term effects. In addition, a longer time span will assist with two key points. Firstly, while the effects of non-standard work on mental health were imprecisely estimated in Ulker (2006), a richer set of observations may allow for more precise estimates. Secondly, additional waves of data will ascertain whether the positive relationship between non-standard employment and better mental health for women, as noted by Ulker (2006), has evolved over time.

Findings concur with Ulker (2006). Overall, a working hours' mismatch in non-standard employment is associated with poorer mental health for men. In contrast, a positive relationship emerges for women, on average. Although most focus variables are

imprecisely estimated, the negative and significant effects of overemployment seem to be driving the relationship noted for men.

This thesis contributes to the economic literature in two main aspects. Firstly, while atypical employment such as casual, fixed-term, contract, or part-time work has triggered a lot of attention from researchers and policy makers, little consideration has been given to the time of the day actually worked. In addition, it may not be the non-standard nature of the work in itself that affects individuals' mental health, but rather whether such working hours are in line with their preferences. Yet, interaction effects between working hours' mismatches and the timing of non-traditional work remain unexplored in Australia to date.

Secondly, while most of the literature has drawn upon cross-sectional data, a richer set of models can be estimated through longitudinal data. Indeed, Frijters and Ulker (2008) draw attention to the importance of controlling for individual unobserved traits that may otherwise render the observed relationship spurious. In particular, controlling for individual specific fixed effects has proven to make large differences in obtained estimates, in terms of signs, economic and statistical significance. In addition, panel data allows for the estimation of static and dynamic models, which provide a more complete picture of the relationship assessed over time.

Despite a lack of general consensus on the definition of 'traditional' or 'standard' working arrangements, Allan et al. (p.235, 1998) refer to a 'standard working time model'. In this case, a standard working week consists of the daily eight hours workload, five days a week from Monday to Friday, daylight time, up to forty hours weekly. To illustrate the extent of non-standard forms of employment, the Australian Bureau of Statistics (ABS) reveals many interesting facts. According to the ABS (p. 26, 2009a), in 2007 "41% of Australia's workers preferred to work some or all of their hours at night or on the weekend. An even larger proportion (51%) usually did work some or all of their hours at these 'non-

traditional' times". While little empirical research was conducted on non-standard work arrangements in Australia, discrepancies between individuals' actual and preferred working hours have been the focus of recent studies.

Wooden and Drago (p. 7, 2007) note the evidence of a 'time divide', whereby a sizeable share of the Australian workforce reveals its discontent over working hours. A working hours' mismatch occurs when individuals deem themselves to be either overemployed or underemployed. Overemployment refers to individuals willing, though unable, to work fewer hours, even if it implies a possible decline in their income. Similarly, underemployed individuals wish, though are unable, to work more hours, accounting for the possibility of a rise in their income. In 2007, although 65% of Australian workers were satisfied with their working hours, 14% reported to be underemployed, as opposed to 21% overemployed workers (ABS, 2009a).

A working hours' mismatch in non-standard employment can result from demand, supply and institutional factors. Institutional elements refer to regulations setting out workers' rights and entitlements. These subsequently shape demand and supply side factors (Productivity Commission, 2006).

On the one hand, demand side factors advocating the need for non-traditional employment are varied. In light of increased market competition, employers justify the expansion of non-standard work from an efficiency perspective. Indeed, extending working hours to evenings, nights and weekends allows for a greater production capacity utilisation (Allan et al., 1998). Furthermore, with the advent of technologies and globalisation, a sustained growth in the services, health, communication and energy sectors has intensified pushes towards a '24/7 economy'. On the other hand, supply side factors include workers' preferences and need for greater flexibility to balance their day-to-day activities. In

addition, non-standard work arrangements may act as a natural transition for unemployed individuals back into continuing employment (Productivity Commission, 2006).

Before turning to the policy implications of this study, it is important to understand what constitutes mental health. Mental health is not merely the absence of illness. A healthy mental state plays an inherent part in an individual's wellbeing, ability to integrate into the community and productivity within a working environment. According to the 2007 *National Survey of Mental Health and Wellbeing*, 3.2 million Australians, or 20% of the population aged between 16-85 were estimated to have a mental disorder in the year preceding the survey. Furthermore, mental health disorders were estimated to account for 13% of the total burden of disease in Australia in 2003, and are ranked third in terms of major disease groups (AIHW, 2009). A number of mental illnesses are recorded in Australia, such as depression and anxiety, which range in degrees of severity.

In 2005-06, Australia spent approximately $86.9 billion on health, which is equivalent to 9% of its gross domestic product (AIHW, 2008). Although the benefits from health care services may accrue to individuals in need, there may be a negative externality as the cost of these services may be borne by the society overall (Mendolia, 2009). Thus, providing assistance to individuals suffering from a mental illness constitutes one of several policy implications relevant to this study. In light of an ageing population and a decline in the share of working-age individuals, a departure from standard working arrangements has emerged as a way to encourage workforce participation in Australia. According to the 2010 *Intergenerational Report*, the ratio of working age individuals to those aged 65 years and above has been estimated to nearly halve by 2050 (Attorney-General's Department, 2010). Thus, a move to greater flexibility to meet the needs of those individuals was vindicated as a way to increase workforce participation and boost productivity.

Ultimately, further attention should be devoted to overemployed individuals, from a policy perspective. While greater labour force utilisation generates benefits to employers, it may come at the expense of poorer mental health outcomes for workers. Overall, this study supports further research regarding the health implications of a working hours' mismatch.

2. Literature review

2.1. Theoretical framework

Under the conventional assumptions of rational behaviour, ordered preferences and perfect markets, individuals should be able to freely adjust their working hours in line with their preferences (Kaufman, 1999). In practice, mismatches in working patterns are observed, as often, individuals' working hours do not coincide with their preferences.

On the one hand, such individuals may be faced with a number of extrinsic constraints. These include job mobility costs, contract terms, job insecurity, as well as information asymmetries between employers and employees. At a broader level, distortions in taxation systems and institutional factors can contribute to a mismatch in working hours (Otterbach, 2010; Sousa-Poza and Ziegler, 2003).

On the other hand, intrinsic elements can also influence one's working patterns. Notably, part of the existing literature criticizes the conventional rational choice model for its failure to account for endogenous factors inherent in agents' decision-making process. Kaufman (1999) argues the need to incorporate psychological concepts to the conventional behavioural process of economic agents. In short, an individual's decision making process could be the result of a change in a person's taste, preference, or environment. Even social norms can also contribute to this process.

Aside from the neoclassical economic theory, a growing body of literature has focused on the full 24-hour time span available to individuals in their decision of when to supply their labour. In particular, Hamermesh (1999) emphasizes that the time of the day during which individuals exert work effort has implications from both a firm's perspective (as firms wish to maximize their profits), as well as from an economic welfare perspective. Indeed, heterogeneity in an individual's decision over which time of the day to work will have

repercussions on their overall well-being. For instance, individuals working over evenings may benefit from access to a greater range of activities during the day. However, these individuals may be deprived of valuable time spent with their family and friends who may work during daylight hours.

Since individuals place different values on temporal variety in their labour supply decision (Hamermesh, 2005), a number of papers have studied its health implications. In particular, negative life events and experiences are considered in a broader context of a theory on stress. Initially, a working hours' mismatch can be viewed as a source of stress, or 'stressor'. Effectively, overemployed individuals may face the burden of increased work expectations, while those underemployed may feel deprived of responsibilities (Pearlin et al., 1981). In addition, such 'stressors' can exacerbate individuals' health when combined with a lack of social support or interactions, especially for those who work non-standard hours. 'Stressors' can manifest themselves in a number of ways, including depression, psychological disorders, disruption of circadian rhythms, and overall, mental illnesses. Mastery and self-esteem can mediate stress arising from a mismatch in non-standard working hours. Mastery refers to one's sense of control over a range of events. Self-esteem is defined as one's perception of self-worth or self-merit. For instance, underemployed men may experience low self-esteem levels or sense of mastery, should they perceive themselves as the sole breadwinner of the family.

Notably, Avison and Turner (1988) highlight the importance of distinguishing short-term from long-term health effects, with varying degrees of severity. The persistence in stress outcomes over time can be divided in two effects: acute 'stressors' and chronic 'stressors'. Acute or eventful 'stressors' have short-lived effects on individuals' health outcomes. Chronic 'stressors' can have a long lasting and detrimental impact on one's overall health.

In the context of mental health outcomes, the effect of a working hours' mismatch is ambiguous. Both over and under employment could negatively affect one's mental health. On the one hand, such individuals may feel frustrated, as a result of a low bargaining power to resolve a working hours' mismatch with their employer (Kaufman, 1999). Furthermore, overemployment could be perceived as a signaling device to employers. In effect, employers may rely on longer, yet inefficient working hours to sort out more productive workers (Sousa-Poza and Ziegler, 2003).

On the other hand, a working hours' mismatch could positively affect one's mental health. According to a theory of norms (Kaufman, 1999), overemployment may not forcibly induce a decline in one's mental health levels. Norms refer to expectations placed upon individuals' actions, and are enforced through a system of rewards or punishments in accordance with an observed outcome (Kaufman, 1999). Thus, long working hours can be perceived as a norm, and are therefore nurtured within one's working environment. In a similar fashion, the effect of underemployment on mental health could be positive. Effectively, it may reflect individuals' satisfaction with their work characteristics and willingness to work more hours. Furthermore, longer working hours may be perceived as intrinsically self-fulfilling.

As previously discussed, it remains unclear whether a mismatch in non-traditional working hours could affect an individual's mental health levels positively or negatively. However, an insight into behavioural processes provides a more complete picture of economic agents' labour supply decision.

From a macroeconomic perspective, work experience and education have traditionally been considered as an inherent part of an individual's human capital stock. However, health also constitutes a key element of human capital accumulation. Both mentally and physically healthier individuals are endowed with higher energy and well-being levels.

These individuals may record lower work absenteeism rates, and subsequently have a greater capacity to be productive and efficient. Consequently, health has been discussed as an essential input to an aggregate production function. This function expresses a country's Gross Domestic Product (GDP) as a function of labour, physical and human capital (Bloom et al., 2004). As such, not only does health play a fundamental role on how individuals acclimatize themselves to various environments, but it also contributes more broadly to economic growth.

2.2. Empirical approaches

In most cross-sectional studies, pooled ordinary least squares (OLS) regressions remain the starting point. Nevertheless, unobserved heterogeneity, such as individuals' preferences or ability, motivates the use of fixed effects regressions, in light of available panel datasets. In particular, Frijters and Ulker (2008) note that results in the context of health outcomes are very sensitive to unobserved effects. While random effects regressions are occasionally estimated, those mainly serve as a comparison between pooled OLS and fixed effects results (Scutella and Wooden, 2008; Ulker, 2006). Indeed, the assumption of orthogonality between fixed effects and the set of covariates can be restrictive, and unlikely to hold in a number of cases. An alternative approach to fixed effects is the use of first-differencing. While Adam and Flatau (2006) use first-differencing in assessing the possible impacts of job insecurity on mental health, this regression approach remains 'unpopular' in comparison to fixed effects.

Furthermore, probit, ordered probit or ordered logit regressions are also commonly estimated. Nevertheless, while it seems intuitive to apply such methods to self-rated health, their use in the context of other health outcomes is debated. Some researchers favour non-linear estimations, and argue that health measures should be treated as ordinal, as

individuals have different perceptions of a given health level (Clark, 2003). However, others prefer to adopt linear models for two main reasons. Firstly, thresholds for poor, good and excellent health for instance, are disputable as a number of papers arbitrarily decide on such cut-offs. Secondly, while the use of non-linear models is facilitated in cross-sectional analyses, linear models are frequently estimated in longitudinal studies, for ease of modeling and interpretation (Frijters and Ulker, 2008).

Despite the range of theories on labour supply, time use and health associations, it provides with little guidance in terms of most empirical approaches adopted. Clark's (2003) study stands out for empirically testing a theory of norms within households, where unemployment is referred as a norm. Aside from Clark's (2003) approach, a number of papers appeal to the economic and psychological literature to uncover behavioural processes underlying economic agents' decisions.

2.3. Empirical evidence

A number of studies have empirically addressed the links between labour market experiences and mental health. In particular, a growing body of economic literature has been exploring the possible impacts of a working hours' mismatch, or atypical employment, on health outcomes. Nevertheless, considerable attention has traditionally been given to the impacts of unemployment on individuals' mental health. Notably, recent developments have focused on possible effects at a household level, though such studies remain sparse. Mendolia (2009) examined the impact of job loss, consisting of redundancies and dismissals, on family mental well-being, using the first fourteen waves of the British Household Panel Survey (BHPS). Her findings indicate that both redundancies and dismissals have a positive effect on the probability of individuals' poorer mental well-being.

Likewise, Clark (2003) tested the possible implications of job loss on psychological well-being, in relation to a theory of social norms. In this context, norms were defined as beliefs shared amongst a group of people. In particular, while unemployment has been shown to have a detrimental impact on individuals' psychological well-being, such a shock may be mitigated when shared within a group of individuals nurturing the same norm. This study used the first seven waves of the BHPS. Overall, Clark's (2003) results converge to those predicted by theories of norms. The negative effect of unemployment on well-being is lessened when shared amongst a group of unemployed individuals.

Scutella and Wooden (2008) used the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, to investigate whether Clark's (2003) results could be generalized to Australia. They assessed whether unemployed individuals living in a jobless household suffered from poorer mental health than their unemployed counterparts living in a household in which at least one person was employed. Following Clark's (2003) study, one may assume a reduced impact of unemployment on individuals' mental health when such a norm is shared within a jobless household. However, no significant differences between jobless households and those including at least one employed individual were found with regards to individuals' mental health levels.

Aside from unemployment associations, a number of studies have focused on the relationship between labour force transitions and mental health, in light of the availability of longitudinal datasets. LIena-Nozal (2009) explored the relationship between work status and working conditions, and individuals' mental health. More specifically, she focused on changes in labour market activity, changes in types of employment and transitions from unemployment to various types of employment. Her study drew on a combination of four panel data surveys covering Australia, Canada, Switzerland and England. Overall, men were found to suffer to a greater extent than women from being out of the workforce. In

addition, transitions from unemployment or inactivity back into the labour force were shown to positively affect individuals' mental health. In contrast, transitions into non-standard forms of employment were associated with poorer mental health levels. Dockery (2006) also addressed the impacts of labour market experiences, such as job loss and transitions into and out of the labour force on individuals' mental health. Overall, his findings compare well with those of LIena-Nozal (2009).

In a similar fashion, Bardasi and Francesconi (2003) used the first ten waves of the BHPS in order to assess the relationship between atypical employment and four subjective individual outcomes: mental health, general health, job and life satisfaction. In their paper, atypical employment referred to temporary work - fixed-term contracts, casual or seasonal work – and part-time work. Overall, atypical employment was not found to entail long-lasting and detrimental effects on health outcomes. Nevertheless, individuals in seasonal and casual jobs appeared to suffer from poorer mental health than their counterparts in permanent work. In spite of gender effects in mental health outcomes, changes in employment status over a three year span did not impact on changes in men's mental health.

While unemployment and labour market transitions have been the subject of considerable research, little consideration has been given to the possible impacts of working conditions on health outcomes. Working conditions include the level of job intensity, complexity and autonomy. Cottini and Lucifora (2009) have contributed to this gap in the literature by assessing the relationship between employment provisions, working conditions and individuals' mental health. Their analysis was conducted across fifteen European countries, using three waves of the European Working Conditions Survey (EWCS). Despite the degree of heterogeneity observed across countries, adverse working conditions were associated with increased levels of mental health distress overall.

Correspondingly, Fletcher et al. (2010) observe supporting evidence of a negative relationship between working characteristics and environmental conditions, and individuals' self-reported health. In particular, using data from the Dictionary of Occupational Titles and the Panel Study of Income Dynamics (PSID) between 1984 and 1999, the cumulative effects of those work characteristics were analysed throughout a five-year window. Overall, women were shown to suffer to a greater extent from harsher working conditions than men. Indeed, while the estimates obtained on cumulative working hours were positive and economically insignificant for males, large negative effects were displayed for females.

There are a number of cross sectional studies conducted on the relationship between working hours and mental health. Nonetheless, there is to date little empirical evidence of the impact of the irregularity of those working hours or non-standard work on mental health, exploiting longitudinal data. Given preconceptions of atypical work as an 'inferior' form of employment, when compared to traditional arrangements, policy makers and researchers alike have mostly focused on casual work, part-time work and fixed terms contracts (Wooden and Warren, 2004). Notably, part-time, shift work, and other forms of atypical work were found to negatively affect individuals' mental health. Yet, the timing of one's work schedule has only been comprehensively addressed by Ulker (2006) in an Australian study.

Ulker (2006) examined the effects of non-standard work schedules on individuals' mental and physical health, using the first three waves of the HILDA survey. Interestingly, although men exhibited a negative relationship between non-standard work schedules and better mental health, a positive relationship emerged for females overall. Although imprecisely estimated, this relationship proved to be robust across various specifications, including the progressive addition of controls.

In light of a rise in weekly working hours, there has been growing evidence of a 'time divide'. Despite half of the Australian population working in accordance with their preferred hours, a sizeable share of the workforce has revealed their discontent over those (Wooden and Drago, 2007). Wilkins (2007) investigated the possible impacts of underemployment on subjective well-being, using a cross-section from the HILDA survey. Underemployed individuals displayed lower well-being levels, on average. Notably, while part-time underemployment was found to have a negative impact on subjective well-being for both males and females, this effect was not far short of the one observed for unemployed individuals.

Conversely, Adam and Flatau (2006) found little evidence of an effect of underemployment on mental well-being. However, a marked negative relationship was observed between the level of overemployment and individuals' mental health status. They used the first two waves of the HILDA survey, in studying the relationship between job insecurity and individuals' mental health. In a similar fashion, an Australian study from Dockery (2006) also uncovered an inverse relationship between the level of overemployment and better mental health. More recently, Wooden et al. (2009) reinforced the prevalence of over and under employment in Australia, as accounting for roughly 28% and 17% of individuals in paid employment, respectively. Their results suggest a significant and negative relationship between both over and under employment, and job and life satisfaction outcomes. Despite the relatively small magnitude of those effects once accounting for unobserved heterogeneity; relative to the impacts of a severe disability, the effects of overemployment appear to be sizeable.

In an international context, Australia's working patterns were not shown to differ significantly from other developed nations. Wooden and Drago (2007) assessed Australia's weekly share of working hours in comparison to a group of twenty OECD countries, using

the HILDA survey. Overall, Australia was shown to have an above average proportion of long-hours workers (45 hours or more weekly) and short-hours workers (less than 20 hours weekly). These results hold in spite of some discrepancies in measuring working hours across OECD nations.

In regards to working hours' mismatches, Reynolds (2004) stresses the importance of considering broader factors. He investigated the potential factors underlying the emergence of working hours' mismatches in the context of a cross-national study between the United States, Japan, Sweden and Germany. While many workers appear to be underemployed, there is considerable disparity in working hours' mismatches across these countries. Reynolds (2004) notes these findings to reflect institutional, economic, social and political elements within the respective countries.

From the previous discussion, it is clear that a growing body of literature has been focusing on the relationship between a working hours' mismatch and mental health. In addition, a number of papers have addressed the link between atypical employment and mental health. Yet, Ulker (2006) stands out, as explicitly accounting for the timing of individuals' work schedules. This thesis combines research from Ulker (2006) and Wooden et al. (2009) in assessing the effects of a working hours' mismatch in non-standard employment on individuals' mental health.

3. Data

3.1. Data source

The Household, Income and Labour Dynamics in Australia (HILDA) survey is a nationally representative longitudinal survey of Australian households. It was established in 2001 and presently consists of eight waves. The first wave in 2001 comprised a sample of 19,914 individuals interviewed from 7,682 households. The data were predominantly collected through face-to-face interviews and in some instances by telephone or assisted interviews, given individuals' circumstances (Watson, 2010).

The reference population consists of all household members occupying private dwellings as a primary residence in wave 1. The sample selection is based at the household level, defined as 'a group of people who usually reside and eat together', according to the ABS (Watson, p.98, 2010). As an indefinite panel survey, shifts in the composition of households are tracked over time. Indeed, all household members interviewed in wave 1 are subsequently followed in later waves, as Continuing Sample Members (CSM). Furthermore, any born or adopted children within a given household in a given wave are then converted to CSMs.

In the first wave, four distinct forms were used in collecting household and individual level information: the Household Form (HF), the Household Questionnaire (HQ), the Person Questionnaire (PQ) and the Self-Completion Questionnaire (SCQ). In following waves, the Person Questionnaire (PQ) was subsequently replaced by the Continuing Person Questionnaire (CPQ) for household members interviewed in earlier years and the New Person Questionnaire (NPQ) for entrants in the survey (Watson, 2010).

While attrition plagues a number of surveys, the attrition rate in the HILDA survey has been declining over waves. Attrition occurs when respondents do not participate in the

survey in one or more waves. It ranges from 13.2 per cent in wave 1 to 4.8 per cent in wave 8, and compares fairly well with the attrition rate noted in the BHPS (Watson, 2010). Attrition can be considered random in the event of the death of respondents, or should they move overseas. In contrast, difficulties in locating respondents or refusal to participate in the survey often lead to non-random attrition. While longitudinal weights are provided to alleviate attrition, those will not be used in this study. Weights are based on a range of characteristics, many of which are controlled for in this research (Watson and Wooden, 2004). In addition, the use of an unbalanced sample will assist in mitigating non-random attrition.

3.2. Sample selection

An unbalanced sample of individuals aged between 25 and 64 years and who were employed at the first wave was studied. This implies that individuals would not be in full-time education, neither retired from the workforce. In addition, individuals who were still studying full-time were excluded from this analysis.

After pooling the eight waves of data, the initial sample consisted of a total of 41,882 observations. Once missing values due to non-respondents (PQ) and not returned self-completion questionnaires (SCQ) were removed, a total of 38,936 observations were retained. In regards to non-standard work schedules, 5 observations were removed as non-identified, and a total of 253 observations were deleted from the category ‘other’, as meaningless for the analysis. Once deleting 164 observations which had not identified their mental health status, the sample consisted of a total of 38,514 observations. The final sample comprises 36,674 observations after removing all partial non-responses and individuals absent at wave 1.

3.3. Approach to missing data

A sensitivity test to missing data was conducted as follows:

- If missing values occurred in an ordered variable from which a set of dummy variables was generated; those dummies were set to zero in the presence of missing values, and a separate dummy variable was created to capture missing values.
- If a continuous variable had missing values, this variable was set to zero in the presence of missing values, and a separate dummy variable was created to capture this.

The obtained results changed very little quantitatively and the interpretation remained qualitatively the same, when compared to an analysis whereby all missing values were removed. As such, for ease of interpretation, all missing values were excluded from the reported set of results, as not significantly affecting our estimates.

3.4. Dependent variable

The outcome variable consists of individuals' mental health levels, and originates from the Self-Completion Questionnaire (SCQ). In particular, individuals' mental health status is derived from an index of health variables, commonly denoted as the Short-Form survey health indicators (SF-36). The SF-36 health indicators are an assortment of 36 items, covering eight main health subscales. These health subscales encompass four physical health scales (physical functioning, role-physical, bodily pain and general health) and four mental health scales (vitality, social functioning, role-emotional and mental health) (Ware et al., 1993). Physical component summary (PCS) scores and mental component summary (MCS) scores are subsequently derived from a factor component analysis of those eight

health subscales and from the Varimax method, transformed to be orthogonal to each other (Ware et al., 1995).

The MCS measure used in this research ranges from 0 (poor mental health) to 100 (optimal mental health), which facilitates any associated interpretations, when compared to the full-range of health index variables (Ware and Kosinski, 2001). Furthermore, the derived MCS measure was shown to be robust and reliable in a range of analyses (Ware and Kosinski, 2001; Ware et al., 1995). Ware et al. (1995) compared the use of MCS and PCS scores to the use of eight health subscales, using the Medical Outcomes Study. While the use of health subscales may help in narrowing down the focus of the analysis; it comes at the expense of added complexity in the scoring and interpretations. In three out of four tests conducted, the derived mental component summary (MCS) measure proved to be superior to the 'best' health subscale.

While some may argue in favour of the treatment of health outcomes as ordinal given different individuals' perceptions, two key considerations support the opposite case.

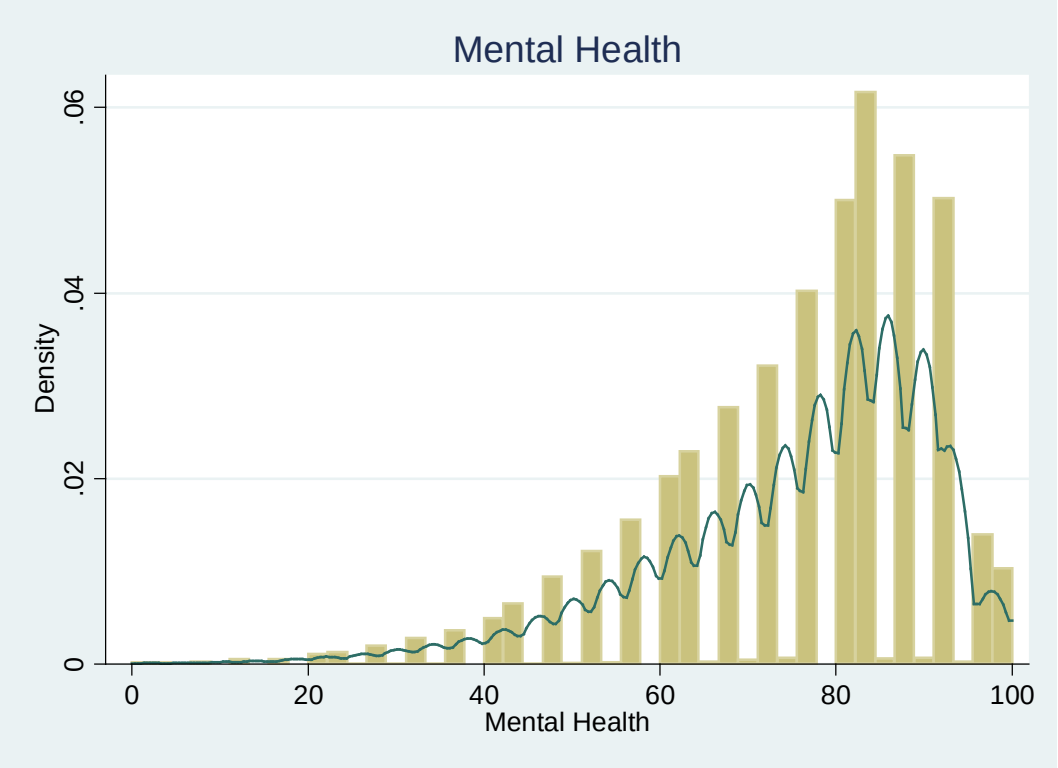
Firstly, dealing with mental health as a cardinal measure facilitates the modeling approaches undertaken. The treatment of health outcomes as ordinal is widespread in cross-sectional studies, where it is more common to estimate ordered probit or logit models. Nevertheless, when it comes to longitudinal analyses, cardinalisation is often imposed on health outcomes, so as to minimize the level of complexity associated with multinomial or ordered models (Frijters and Ulker, 2008).

Secondly, whether the health dependent variable is treated as cardinal or ordinal was not shown to significantly affect the sensitivity of main results (Frijters and Ulker, 2008; Ferrer-i-Carbonell and Frijters, 2004). While shadow prices or monetary tradeoffs were shown to differ to a large extent in Frijters and Ulker (2008), those effects do not relate to

the topic examined here. As such, for the purpose of this thesis, the dependent variable shall be treated as cardinal, for ease of modeling and interpretation.

Figure 1 presents a histogram of the dependent variable, along with an epanechnikov kernel density distribution. The mental health measure is skewed to the left, and although not strictly continuous, ranges fairly widely, with a mean of 76 per cent and a standard deviation of 16.

Figure 1: Mental health histogram



3.5. Key explanatory variables

The HILDA dataset provides a rich set of variables. As such, the approach of a number of empirical studies was followed to select a set of key variables. Demographics and socio-economic characteristics - including age, state of residence, ethnicity, immigration status, children, marital status and education - were discussed in a range of papers as likely to affect individuals' mental health. These variables are intended to capture changes to an

individual's environment, as well as socio-economic status, all prone to affect one's mental health. Notably, as pointed by Kennedy and McDonald (2006), Australian immigrants may suffer from poorer mental health from increased pressure to cope with a different environment. In addition, a number of studies find a relationship between individuals' age and mental health, as well as married individuals exhibiting improved mental health levels when compared to their single counterparts (Scutella and Wooden, 2008; Kennedy and McDonald, 2006; Adam and Flatau, 2006). While one may expect mental health to improve with the level of education attained, such a link remains blurred as contradicted in some studies (Clark, 2003). Furthermore, controlling for individuals' state of residence assists in capturing differences in access and quality of psychiatric services provided across Australia.

Moreover, long-term health conditions and disabilities are accounted for, whereby such conditions have persisted for or are likely to persist for six months or more, and restrict an individual's set of daily activities (HILDA, 2010). In particular, a dummy variable was generated, so as to capture whether such conditions limited the amount or type of work undertaken by those individuals. Finally, yearly household disposable income, home ownership and a set of occupation and job characteristics are also controlled for, as likely to influence one's mental health. Notably, the inclusion of occupation variables assists in mitigating a possible selection in non-standard forms of employment. However, there may also be time varying unobserved individual traits inducing a self-selection process. For further information, the full list of covariates is provided in *Appendix 1A*.

3.5.1. Non-standard work schedules

For the purpose of this thesis, seven dummy variables are used in capturing differences in work timing: regular daytime schedules, regular evening shifts, regular night shifts, rotating shifts, split shifts, on call and irregular schedules. A regular daytime work

schedule is referred to as standard work, while the six other work schedules represent non-standard work. As displayed in question C10 from the Person Questionnaire, respondents are required to describe which of these seven work schedules best fits with their current work status in their main job (HILDA, 2010). The ABS (2009b) categorizes the six forms of non-traditional work schedules as follows:

- Regular evening and regular night shifts include individuals working in between the hours of 5 pm and 6 am.
- Rotating shifts are characterised by an alternating pattern, where for instance, individuals may be occasionally required to swap a morning shift for an evening shift.
- Split shifts are marked by two or more distinct periods during the day, where shifts not worked at remain unpaid.
- On call work schedules are arrangements in which employees may be contacted to return to work, outside the range of standard working hours. In addition, employees may be provided with an allowance when undertaking such arrangements.
- Individuals working irregular schedules are prone to an uncertain pattern in working hours.

As displayed in *table 1*, while over half of all individuals in our sample work regular daytime schedules, nearly a quarter work non-standard schedules. Noticeably, the largest proportion of individuals falls into rotating shifts and irregular work schedules. As opposed to Ulker's (2006) prediction, the share of individuals in most non-standard work schedules has declined slightly over time; at the expense of a rise in standard work (Appendix 1B).

Table 1: Current work schedule in main job

Pooled employed population	Males		Females	
Current work schedule	**Frequency**	**Percent**	**Frequency**	**Percent**
Regular daytime	13,876	76.71	12,086	77.11
Regular evenings	292	1.61	304	1.94
Regular nights	256	1.42	281	1.79
Rotating shifts	1,412	7.81	1,020	6.51
Split shifts	177	0.98	199	1.27
On Call	391	2.16	328	2.09
Irregular	1,685	9.32	1,456	9.29
Total	*18,089*	*100.00*	*15,674*	*100.00*

3.5.2. Working hours' mismatch

In the survey, respondents are initially asked to fill in the Person Questionnaire with the number of their usual weekly hours of work in all jobs, both at work and at home. Subsequently, respondents are queried on their preferred working hours. In particular, working hours' mismatches are derived from question C4 of the Person Questionnaire, where respondents are asked the following:

'If you could choose the number of hours you work each week, *and taking into account how that would affect your income,* would you prefer to work…fewer hours than you do now? About the same hours as you do now? Or more hours than you do now?' (HILDA, 2010).

A similar measure is available in the BHPS, asking respondents the following:

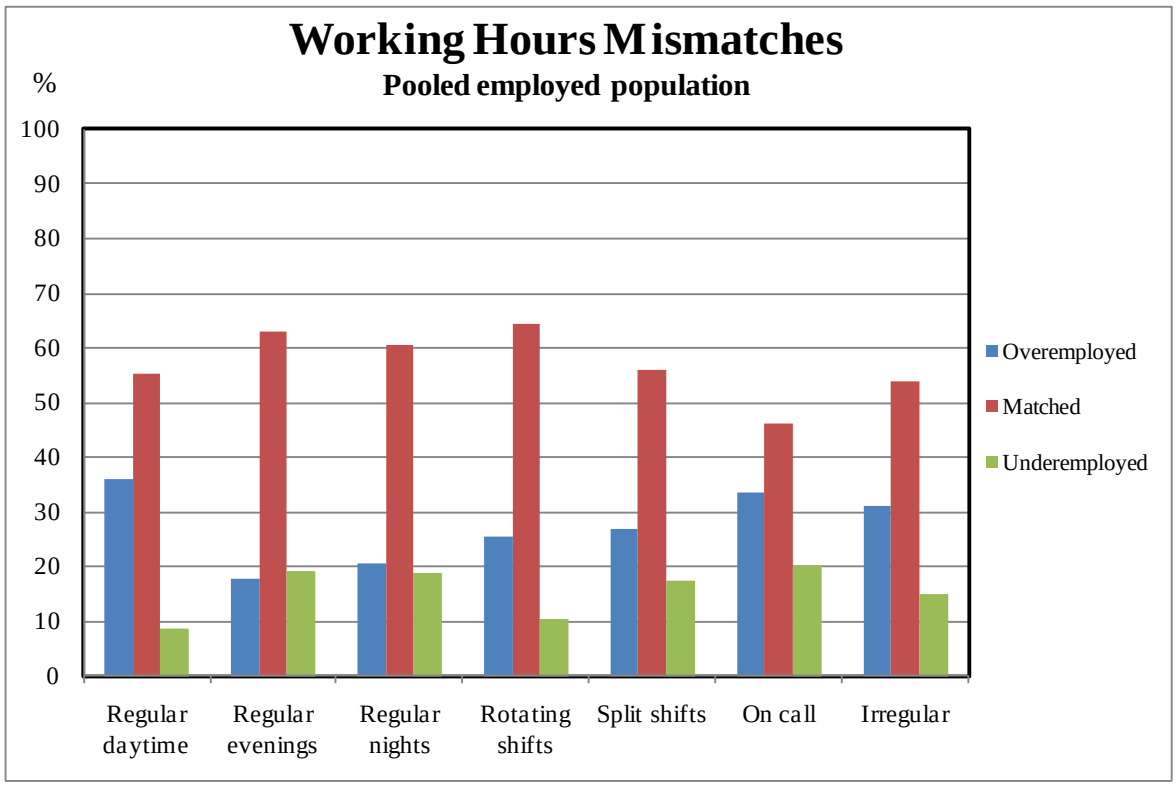
'Thinking about the hours you work, *assuming that you would be paid the same amount per hour,* would you prefer to work fewer hours than you do now? work more hours than you do now? or carry on working the same number of hours?' [author's emphasis] (BHPS, 2010).

In contrast to the HILDA survey, the working hours' mismatch question in the BHPS does not require respondents to consider the possible implications on their income. Böheim and Taylor (2004) note that such a measure can be restrictive as individuals' perceptions of a working hours' mismatch can differ should they account for variations in their income.

Although respondents are also queried on the number of hours they would prefer to work each week, this information is solely used for sensitivity checks. Indeed, some discrepancies may arise in the construction of working hours' mismatches. By definition, one would assume individuals reporting matched preferences to work the exact same amount of hours in reality. While this may not hold in practice, there are no sizeable differences between actual and preferred working hours for individuals reporting matched preferences in our sample (Appendix 1C).

On average, overemployment is more prevalent across respondents than underemployment. Effectively, nearly 32% of employed men are overemployed, while 13% are underemployed. This compares with approximately 23% overemployed and 19% underemployed women overall. Interestingly, aside from on call and irregular work schedules, a greater proportion of individuals report matched preferences in non-standard work schedules, when compared to regular daytime schedules (Figure 2).

Figure 2: Working hours mismatches – pooled employed population



3.6. Summary statistics

Table 2 presents means in dummy variables for both males and females. The majority of the sample comprises middle-aged individuals and over one in two individuals are either married or in a de facto relationship. In addition, over one in five individuals were born overseas; and both respondents who arrived less than ten years ago and individuals of Aboriginal or Torres Strait Islander origin represent a mere 1% of the sample**.** Despite some level of heterogeneity across gender, over 50% of the sample either holds a Certificate/Diploma or a Bachelor degree, and around 80% of respondents own their house. While nearly a fifth of individuals suffer from a long-term health condition or disability, only half of those live with a limiting condition. Around 90% of individuals are employed, with a slightly higher fraction of employed men (94.87%). While over one fifth of employed individuals work non-standard schedules, these are mostly concentrated within rotating shifts and irregular work schedules. Further, overemployment is much more

prevalent for both males and females than underemployment. A greater proportion of employed males are technicians and trades workers (20%), machinery operators and drivers (10%) and labourers (8%) when compared to females. Nevertheless, on average, females account for a larger share of all other occupations than males. Finally, an overwhelming proportion of the sample solely holds one job and is categorized as employees.

Table 3 provides a separate set of descriptive statistics for males and females in continuous explanatory variables. On average, individuals exhibit good mental health levels, though slightly lower for females (74.82% compared to 76.42%). Additionally, when compared to women, men usually work more hours each week, and tend to stay for a longer duration with their current employer and within their occupation. Furthermore, men earn a higher level of disposable income than women, on average.

Table 2: Descriptive statistics - dummy variables

Variables	Mean Males	Mean Females	Variables	Mean Males	Mean Females
age_25to34	0.189	0.186	regular_evening_wk	0.015	0.017
age_50to64	0.286	0.296	regular_night_wk	0.013	0.016
aboriginal_torres	0.009	0.012	rotating_shift	0.074	0.058
arrived_less_than_10yrs	0.013	0.012	split_shift	0.009	0.011
state_vic	0.258	0.258	on_call_wk	0.021	0.019
state_qld	0.192	0.197	irregular_wk	0.088	0.083
state_sa	0.095	0.091	over_employed	0.347	0.278
state_wa	0.108	0.097	under_employed	0.081	0.106
state_tas	0.029	0.035	reg_evening_over	0.004	0.002
state_nt	0.008	0.009	reg_evening_under	0.003	0.004
state_act	0.025	0.024	reg_night_over	0.003	0.003
bounded_locality	0.030	0.027	reg_night_under	0.003	0.003
rural_balance	0.146	0.146	rot_shift_over	0.019	0.014
other_urban	0.217	0.218	rot_shift_under	0.007	0.007
children_age_0to4	0.190	0.150	split_shift_over	0.003	0.002
children_age_5to14	0.352	0.337	split_shift_under	0.001	0.003
children_age_15to24	0.160	0.179	on_call_over	0.008	0.005
overseasborn_english	0.125	0.107	on_call_under	0.003	0.005
overseasborn_other	0.101	0.110	irregular_over	0.034	0.019
separated	0.033	0.040	irregular_under	0.010	0.016
divorced	0.053	0.093	professionals	0.215	0.272
widowed	0.004	0.019	tech_trade_wk	0.199	0.034
never_married	0.115	0.097	community_wk	0.047	0.108
university	0.267	0.310	clerical_admin_wk	0.076	0.235
tertiary	0.422	0.269	sales_wk	0.040	0.065
year12	0.103	0.133	machinery_wk	0.101	0.011
hlth_cond	0.184	0.171	labourers	0.080	0.062
limit_hlth_cond	0.101	0.110	more1job	0.072	0.087
homeowner	0.790	0.802	employer	0.041	0.027
unemployed	0.012	0.010	own_acct_wk	0.100	0.058
nilf	0.040	0.100	contr_family_mbr	0.001	0.006
			casual	0.081	0.157

Table 3: Descriptive statistics - continuous variables

Males				
Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
mental_hlth	76.416	15.51	0	100
hhpers	3.120	1.45	1	14
income[1] ($'000)	72.488	43.98	0.025	583.26
hours_worked[2] (weekly)	42.386	15.50	0	130
tenure_curr_occupation (years)	11.994	10.70	0	55
tenure_curr_employer (years)	8.798	9.09	0	49

Females				
Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
mental_hlth	74.820	16.31	0	100
hhpers	2.997	1.34	1	8
income ($'000)	71.969	45.46	0.025	583.26
hours_worked (weekly)	28.803	16.64	0	119
tenure_curr_occupation (years)	9.545	9.57	0	48
tenure_curr_employer (years)	7.041	7.75	0	48

[1]Negative or zero values of income were imputed with mean of income

[2]Hours worked weekly in main job

4. Empirical Modeling

4.1. Preliminary empirical approach

The set of pooled ordinary least squares (OLS), fixed effects and random effects regressions conducted in Ulker (2006) form the basis of this research. However, the approach adopted in this study goes beyond Ulker (2006). Interaction effects between working hours' mismatches and non-standard employment are modeled for each specification. For each modeling approach, three specifications were estimated to assess the robustness of the results to a range of controls.

1. Regressing individuals' mental health levels on a set of focus variables only. These include six dummies for non-standard work schedules, two dummies for over and under employment and a set of interaction dummies between non-standard work schedules and working hours' mismatches. For the remainder of this thesis, the interaction dummies shall be referred to as 'interaction terms'.
2. Regressing individuals' mental health levels on the set of focus variables and a set of occupation controls.
3. Regressing individuals' mental health levels on the complete set of covariates.

In addition, the standard errors are clustered for each model, where a cluster denotes a household. It is meaningful to adopt this approach in this study, as it allows for some unknown form of correlation in the errors within clusters. However, it is still assumed that the errors are not correlated across clusters (Wooldridge, 2009).

To begin with, a pooled OLS model of the following form is considered:

$$MH_{it} = Z_{it}\beta + X_{it}\gamma + v_{it} \qquad i = 1,2 \dots, N \;\; t = 1,2 \dots, T \qquad [4.1]$$

$$v_{it} = \delta_i + \mu_{it}$$

MH_{it} denotes mental health for individual *i* at time *t*. Z_{it} encompasses the set of focus variables; while X_{it} stands for the remaining set of covariates. For simplicity, the intercept is subsumed into X_{it}. Finally, v_{it} is a composite error term, consisting of both individual specific effects δ_i and an idiosyncratic error term $\mu_{it.}$ In addition to the first three classical linear model assumptions, one must be willing to assume orthogonality between the composite error term and the regressors, so as to obtain consistent and unbiased coefficient estimates (Wooldridge, 2009). Even if the idiosyncratic error term μ_{it} is not correlated with the independent variables, any correlation between individual specific fixed effects δ_i and the regressors would produce biased and inconsistent estimates. Due to the availability of eight years of data, a within transformation commonly referred to as fixed effects, would allow for the set of time varying covariates to be correlated with individual specific fixed effects. Indeed, any time invariant explanatory variable and individual specific unobserved effects subsequently get swept away from the time demeaning process.

Correspondingly, we consider the following fixed effects model:

$$MH_{it} = Z_{it}\beta + X_{it}\gamma + \delta_i + \mu_{it} \qquad i = 1,2 \dots, N \;\; t = 1,2 \dots, T \qquad [4.2]$$

Aside from X_{it} now encompassing a set of time varying covariates, each variable remains as previously defined. It is to be noted that this model does not display a composite error term, but rather explicitly allows individual unobserved effects δ_i to be correlated with the set of covariates. The strict exogeneity assumption requiring orthogonality between the idiosyncratic error term μ_{it}, and all regressors and unobserved effects in all time periods is key to ensure unbiasedness and consistency (equation [4.3]). Recall, consistency refers to the number of observations $N \to \infty$ with a fixed number of time periods T (Wooldridge, 2009).

$$E(\mu_{it}|Z_{it}, X_{it}, \delta_i) = 0 \qquad [4.3]$$

Under a set of assumptions, the obtained coefficient estimates are normally distributed and exact inference t and F tests can be used. These assumptions include a constant variance and no serial correlation in the error term (μ_{it}), as well as the disturbances being identically and independently distributed (i.i.d), given the regressors and unobserved effects (Wooldridge, 2009).

Finally, a random effects model was conducted, mainly as a comparison between fixed effects and pooled OLS estimates. In addition to the assumptions associated with a fixed effects model, orthogonality between the unobserved effects δ_i and the set of covariates is now required so as to get consistent and unbiased estimates (equation [4.4]). Naturally, should all of these assumptions be satisfied, the use of a random effects model would produce more efficient estimates than that of a fixed effects (Wooldridge, 2009).

$$E(\delta_i|Z_{it}, X_{it}) = 0 \qquad [4.4]$$

As a natural starting point, a reproduction of Ulker (2006) was undertaken, since the HILDA survey data was used. While little guidance was provided in regards to the derivation of his sample, a reproduced version was closely approximated, and supported from a comparative set of descriptive statistics. While Ulker's (2006) sample amounted to 14,442 pooled observations, a sample of a total of 15,036 observations was reproduced. Since Ulker (2006), the release of five additional waves of data provided an opportunity to extend his analysis. His specification was subsequently extended to the pooled eight waves of data, and similar findings emerged. A negative relationship is still observed between non-standard work and better mental health for men. Furthermore, the positive effects noted for females still persist[1].

[1] Reproduction and extension results are available upon request.

4.2. Extending to a linear dynamic panel data (DPD) model

In comparison to Ulker (2006), additional waves of data allow for the study of long term effects, as well as considering the persistence of mental health over time. Notably, LIena-Nozal (2009) and Friedland and Price (2003) stress the importance of controlling for pre-existing mental health conditions. Past mental health levels can account for a fair share of the variation in one's current mental health, and should not be ignored.

While adding a lag of the dependent variable to the set of covariates allows controlling for pre-existing mental health conditions; it comes at the expense of complicating the production of consistent estimates. Indeed, let us consider the following autoregressive model, including both fixed effects δ_i, as well as a lag of the dependent variable $MH_{i,t-1}$:

$$MH_{it} = MH_{i,t-1}\alpha + Z_{it}\beta + X_{it}\gamma + \delta_i + \mu_{it} \qquad i = 1,2 \dots, N \quad t = 2,3 \dots, T \quad [4.5]$$

As clearly expressed by Angrist and Pischke (p. 245, 2009), taking first differences 'kills' the fixed effects δ_i, which may be correlated with the time-varying covariates:

$$\Delta MH_{it} = \Delta MH_{i,t-1}\alpha + \Delta Z_{it}\beta + \Delta X_{it}\gamma + \Delta\mu_{it} \qquad i = 1,2 \dots, N \quad t = 3,4 \dots, T \quad [4.6]$$

where Δ is the first difference operator.

However, both differenced disturbances $\Delta\mu_{it}$ and the differenced lag of the dependent variable $\Delta MH_{i,t-1}$ become correlated, as both are functions of the previous level of the disturbances $\mu_{i,t-1}$. One cannot hope to use OLS to obtain consistent estimates of the parameters under the set of assumptions associated with fixed effects, as the strict exogeneity assumption is now violated (Kennedy, 2008).

As initially proposed by Anderson and Hsiao (1981), with fixed T and $N \to \infty$, a second lag of the dependent variable can be used to instrument the endogenous first-differenced lag of

the dependent variable. In the context of a linear DPD model (or dynamic unobserved effects panel data model), Arellano and Bond (1991) suggest another possible combination of instruments. Such instruments may be used under the following set of assumptions.

From *equation [4.5]* we assume a random sample of cross-sections over time, where a small number of time periods T and a large number of observations N are available. Naturally the stability condition $0 < |\alpha| < 1$ is required under a stationary process. In addition, we assume the unobserved effects δ_i and the idiosyncratic error term μ_{it} to be independently and identically distributed (i.i.d) across individuals *i;* and the disturbances μ_{it} to be serially uncorrelated as follows:

$$E(\delta_i) = 0, E(\mu_{it}) = 0, E(\delta_i \mu_{it}) = 0 \quad \text{for } i = 1,2 \dots, N \quad t = 2,3 \dots, T \qquad [4.7]$$

$$E(\mu_{it}\mu_{is}) = 0 \quad \text{for } i = 1,2 \dots, N \text{ and } t \neq s \qquad [4.8]$$

And the initial condition assumption

$$E(MH_{i1}, \mu_{it}) = 0 \quad \text{for i} = 1,2 \dots, N \quad t = 2,3 \dots, T \qquad [4.9]$$

From assumptions [4.7], [4.8] and [4.9], first-differenced lags of the covariates $\Delta X_{i,t-p,}$ $\Delta Z_{i,t-p}$ (with $p \geq 1$) and lags of two or more time periods of the dependent variable $MH_{i,t-s}$ (with $s \geq 2$) may be used to instrument the endogenous first-differenced lag of the dependent variable $\Delta MH_{i,t-1}$. The default of T-p-2 lags of the dependent variable and T-p-1 lags of the differenced covariates is used in instrumenting $\Delta MH_{i,t-1.}$ As we include p=1 lag of the dependent variable in the model, with eight waves of data, this translates into 5 lags of MH_{it} and 6 lags of $\Delta X_{i,t-p}$ and $\Delta Z_{i,t-p}$ as instruments.

In a linear DPD model, Arellano and Bond (1991) appeal to the Generalized Method of Moments (GMM) in order to derive consistent estimates of the parameters. Specifically,

the use of a linear DPD model will assist in gauging the persistence in mental health over time. In addition, the robustness of the results obtained in a linear DPD model will be assessed when compared to those obtained in a fixed effects specification. In particular, Wooldridge (2001) notes that in the presence of serial correlation or heteroskedasticity, a GMM approach can produce more efficient estimates of the parameters than fixed effects. However, the extent of such efficiency gains remains largely unknown.

On the basis of the discussion of the initial condition and assumptions of the error components structure, with three or more time periods ($T \geq 3$), Arellano and Bond (1991) note the following m = (T-2)(T-1)/2 or m = 21 linear moment restrictions to be valid:

$$E\left[MH_{i(t-j)}\Delta\mu_{it}\right] = 0 \quad \text{for } j = 2 \dots, (t-1) \text{ and } t = 3,4 \dots, T \qquad [4.10]$$

$$where\ \Delta\mu_{it} = \mu_{it} - \mu_{i,t-1} = \Delta MH_{it} - \Delta MH_{i,t-1}\alpha - \Delta Z_{it}\beta - \Delta X_{it}\gamma$$

Implicitly, as the number of time periods T increases, the number of linear moment restrictions rapidly rises (Bowsher, 2002).

Equation [4.10] refers to the exogeneity assumption, as lags of two or more periods of the dependent variable are assumed to be uncorrelated with the first-differenced disturbances. Intuitively, while the model is just identified with three waves of data, Sargan tests of overidentifying restrictions can be conducted with T > 3 time periods. In addition, serial correlation tests can be performed and will be discussed in the next section.

5. Empirical Results

As noted in *Section 4*, three specifications were run for each model. As control variables are of secondary interest, results on the set of focus variables will form part of the main discussion. Estimates on the focus variables are fairly robust across the progressive addition of controls (Appendix 2A). Thus, only the third specification is reported, as displaying effects persisting throughout. The interested reader can refer to the full set of results obtained with *Stata 10 SE* provided in *Appendix 2C* for further information. For ease of reporting and interpretation, results on the set of interaction terms only are presented in a graphical way. It is to be noted that separate regressions were conducted for males and females.

5.1. Primary analysis

Ulker's (2006) approach was closely followed in deciding over the final set of control variables. However, lifestyle variables were excluded from our analysis, as likely to be endogenous. Furthermore, instead of controlling for the total number of children ever had, the number of dependent children aged 0-4, 5-14 and 15-24 were considered. It is more intuitive to expect dependent children within a certain age range to have an effect on mental health, rather than children who may not require any parental assistance. Finally, adding industry variables to the third specification was not shown to significantly affect the focus variables. Thus, industry controls were excluded from the third specification for parsimony, as consisting of 19 dummies at a 1-digit level[2].

Functional form specification tests were conducted for the three specifications with the command *linktest* available in *Stata 10 SE*. Under the null hypothesis, higher powers of the regressors should be statistically insignificant. We fail to reject the null that the model is

[2] Alternative specifications including the set of industry variables are available upon request.

correctly specified under conventional levels of significance in the first two specifications. However, we reject the null at a 1% level in the third specification, for both males and females. The failure of the test seems to be attributed to *hlth_cond, limit_hlth_cond* and the state dummies in the females' regression. Indeed, we fail to reject the null hypothesis once excluding those controls (p-value > 46%). The source of misspecification is more difficult to pin down in the case of males. Among a number of alternatives, specifications expressing age, tenure in current occupation and employer in quadratic terms did not improve tests. Nevertheless, the robustness of key results across the range of specifications and models provide the basis of the third specification chosen.

Under Breusch-Pagan tests, we consistently reject the null of homoskedasticity in all three specifications for both genders. Thus, all estimates discussed in the following sections were estimated along with heteroskedasticity-robust standard errors.

5.2. Preliminary results

Figures 3 and 4 present the coefficient estimates on the interaction terms for men in pooled OLS and fixed effects models, respectively. F*igures 5 and 6* display pooled OLS and fixed effects results for women, respectively. For each graph, the vertical axis displays the magnitude of the coefficient estimate for each interaction term, while the seven work schedules lie on the horizontal axis. As respondents may report being either overemployed, satisfied with their working hours, or underemployed, each work schedule can correspondingly be interacted three times. This gives rise to a total set of 21 interaction terms. It is important to note that each interaction term is compared against the base group, being an individual working a regular daytime schedule in accordance with his/her preferences.

Overall, results support the Ulker (2006) and Wooden et al. (2009) findings. A negative relationship emerges between a working hours' mismatch in non-standard employment and better mental health for men (figures 3 and 4). In contrast, a large number of interaction terms are positively related to women's mental health (figures 5 and 6). While most effects are mitigated when switching from a pooled OLS to a fixed effects model, some are robust across the three specifications. Although most focus variables are imprecisely estimated in both models, a few interaction terms are statistically significant throughout. In particular, the negative and statistically significant (1% level) effects of overemployment on mental health seem to be driving the negative relationship noted for men (Appendix 2B).

Both over and under employment affect men's mental health negatively in all work schedules (figure 3). Yet, the effects of overemployment appear to dominate, especially after accounting for unobserved heterogeneity (figure 4). These effects are in accordance with Wooden et al. (2009). In particular, the negative impacts of a working hours' mismatch in regular daytime, regular nights, split shifts, and irregular work schedules remain economically significant in both pooled OLS and fixed effects models.

However, only the estimates obtained on overemployment in regular daytime and irregular work schedules remain statistically significant at a 1% level in both models (Appendix 2B). While imprecise estimates should be interpreted with caution, the negative effects of a working hours' mismatch in regular night schedules and split shifts may not be negligible. Indeed, these estimates are comparable to the impact of a limiting long-term health condition or disability on men's mental health. On average, men suffering from a limiting health condition are predicted to experience a 2.2 points decline in their mental health, in comparison to men without any condition. Furthermore, this effect is statistically significant at a 1% level in both models (Appendix 2C).

Individuals' abilities and motivation can be assumed to be time-invariant and removed from the fixed effects model. However, other effects such as self-esteem and appraisal deserve further consideration in the negative relationship observed (Waters and Moore, 2002). In particular, Bird and Fremont (1991) partly attribute changes in men's mental health to their sense of obligations or duties. Men may perceive themselves as the sole breadwinner of the family, and fulfill this role in two ways. While income and occupation act as direct channels, how men place themselves relative to their peers in the society indirectly affects their mental health. Not only may working non-standard schedules be seen as precarious, but it may also exacerbate men's mental health through a working hours' mismatch.

While weekly working hours have not increased dramatically since the mid 1980s, Green (2001) indicates an increasing feeling of a working hours' burden among employees. Specifically, a rising pressure within the workplace, working conditions and expectations placed upon workers in comparison to their peers all contribute to this burden. These factors are likely to vary over time and influence the deterioration observed in men's mental health when their work schedules are not in accordance with their preferences. Unfortunately, these elements are difficult to capture.

In contrast to males, the relationship between a working hours' mismatch in non-standard work and females' mental health is ambiguous. Although a pooled OLS model reveals a negative relationship (figure 5), positive effects dominate in fixed effects (figure 6). This supports the importance of unobserved effects in the females' regressions. Similarly to men, overemployment seems to have larger effects on women's mental health than underemployment. Further, this relationship is more pronounced after accounting for unobserved heterogeneity. Overemployed women working regular daytime, regular

evening shifts, on call and irregular schedules display lower mental health levels, on average.

A loss of economic significance is observed when moving from a pooled OLS to a fixed effects model (figures 5 and 6). Yet, the negative effects of overemployment in regular daytime and underemployment in irregular work schedules remain statistically significant at a 1% and 5% level respectively for both models (Appendix 2B). As noted for men, while mostly statistically insignificant, other estimates can be compared with the impact of a limiting long-term health condition or disability on mental health for women (Appendix 2C).

Although social roles are evolving from women's increasing labour force participation, time spent in child care and housework still influences their choice of working hours (Bird and Fremont, 1991). These factors may contribute to the negative associations observed between a working hours' mismatch and women's mental health. Conversely to working hours' mismatches, the interaction terms in most schedules indicate improved mental health for females working in accordance with their preferences (figure 6).

In light of the contrasting relationships noted for males and females, an insight into behavioural processes can provide some intuition. Hamermesh (2005) suggests a theory of temporal routine, defining routine as performing the same activity over two distinct periods. His findings indicate that men engage in more temporal routine behaviour than women, as they allocate a greater share of their time to routine market work. This may explain the negative relationship observed for men, as opposed to women.

Thus, factors such as individuals' preferences, perceptions of social status, self-esteem and the value placed on temporal variety can all play an essential role in the disparity of the results for both genders.

Figure 3: Pooled OLS results – specification (3) - males

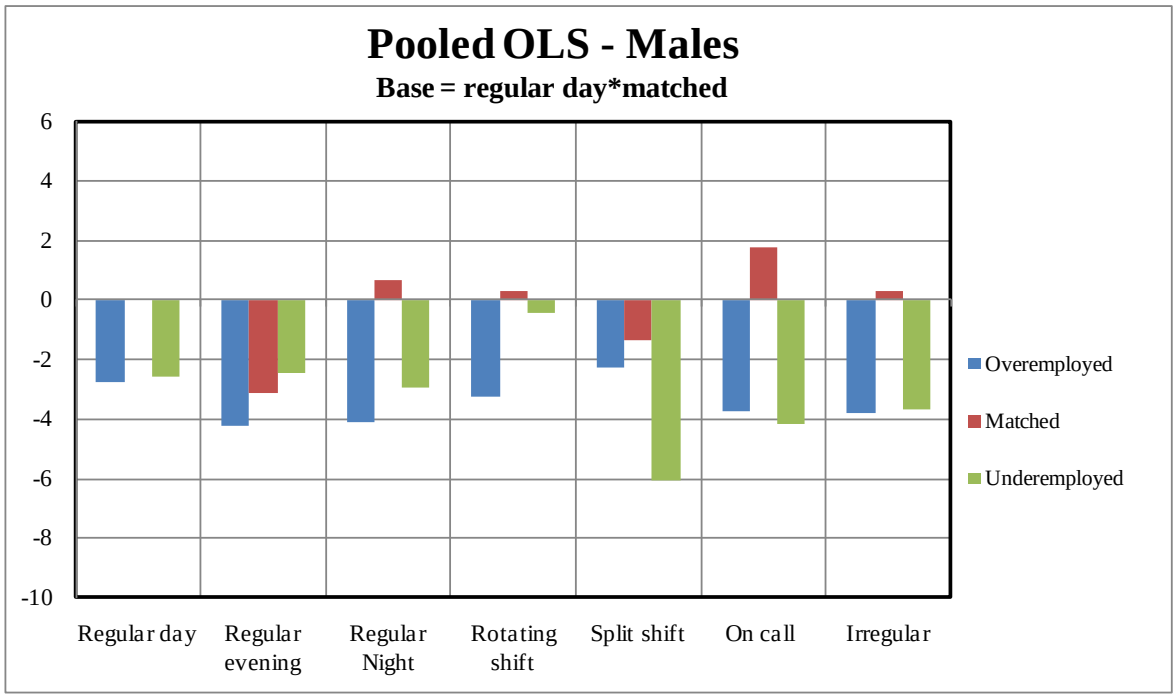


Figure 4: Fixed effects results – specification (3) - males

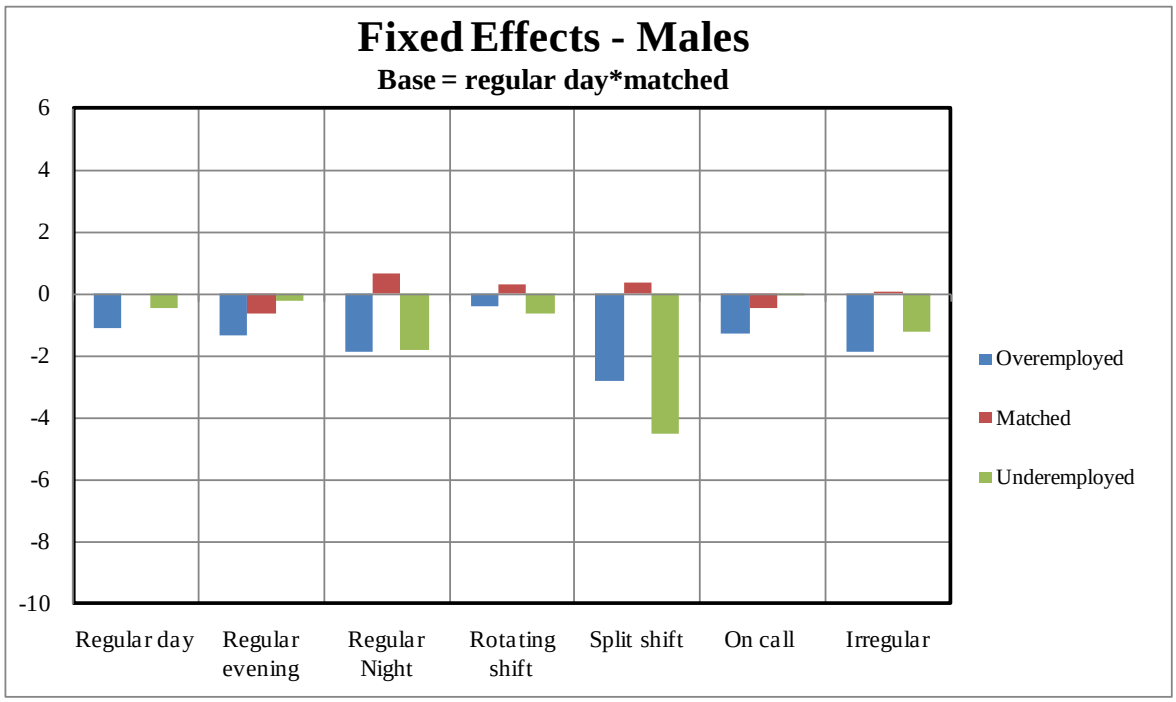


Figure 5: Pooled OLS results – specification (3) - females

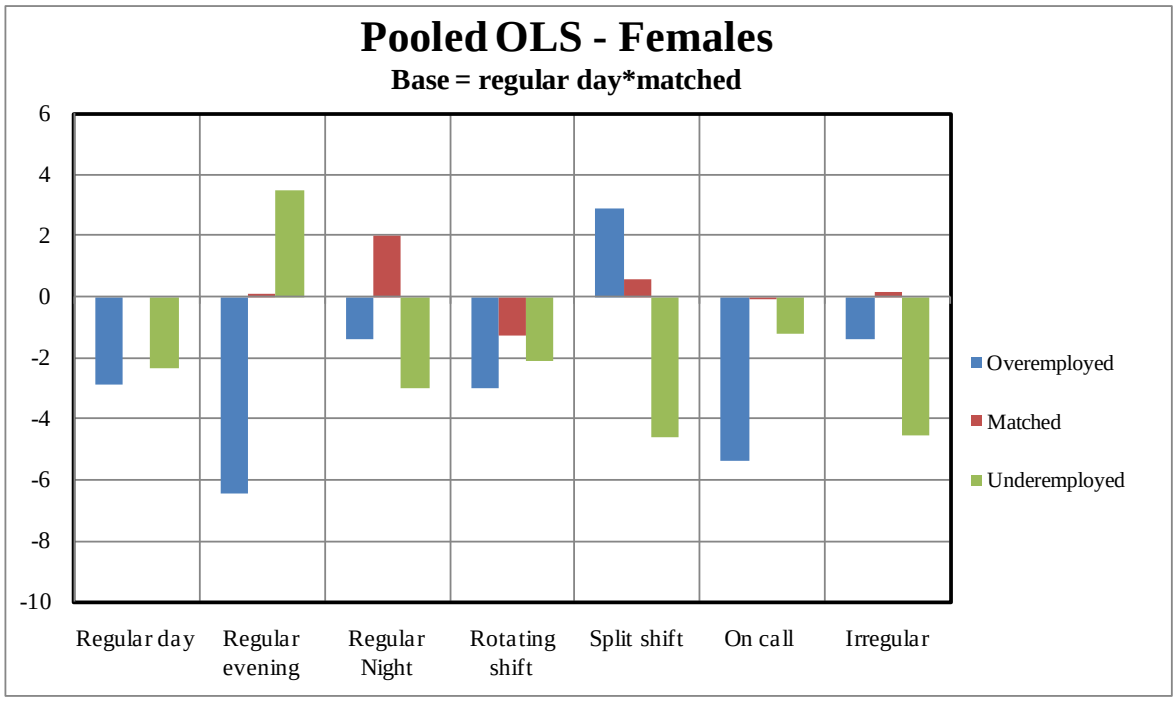
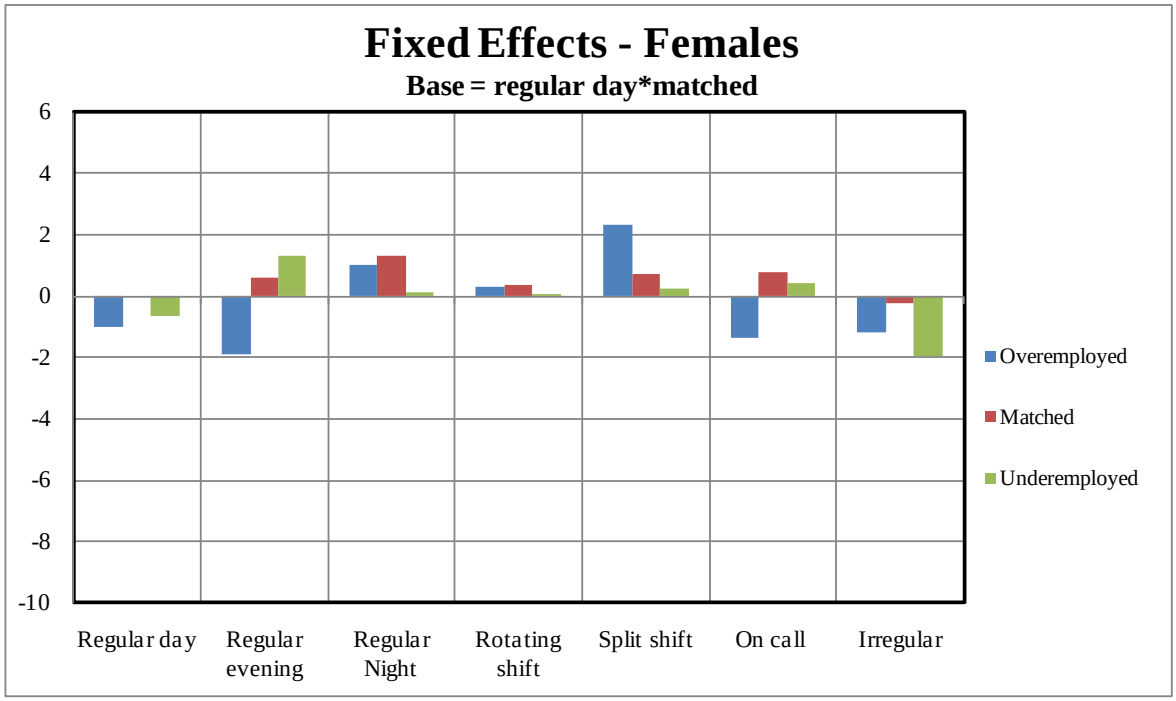


Figure 6: Fixed effects results – specification (3) - females



5.3. Extension: linear dynamic panel data (DPD) results

While a static relationship is obtained from a fixed effects model, the longitudinal aspect of the dataset is exploited in incorporating dynamic effects. A linear DPD model addresses this gap in Ulker (2006), from the availability of a longer time span. When running *equation [4.5]*, we find a positive and statistically significant (1% level) estimate on past mental health, providing evidence of persistence in mental health. Yet, a small positive magnitude (between 0 and 0.2) indicates there will only be small differences between the immediate short-run effects and ultimate long-run effects of variable changes (Appendix 2C).

Furthermore, a statistically significant estimate on lagged mental health supports the use of a linear DPD model over static fixed effects. This result is intuitive, as one would expect pre-existing mental health conditions to be a good predictor of future mental health. In addition, this effect holds across all three specifications. A note of caution is warranted should one account for previous mental health in a fixed effects model. A negative and statistically significant (1% level) estimate is obtained on its coefficient when running a fixed effects regression. Other than obtaining inconsistent estimates of the parameters, a negative relationship seems counterintuitive.

Figures 7 and 8 display coefficient estimates on the short-run response of the interaction terms in linear DPD models for males and females, respectively. Again, only the third specification is reported, as key findings are robust throughout (Appendix 2A). One may refer to *Appendix 2C* for the full set of results. It is to be noted that the short-run response on interaction terms does not differ much from their long-run response (Appendix 2B). This is to be expected from the small coefficient estimate obtained on $MH_{i,t-1.}$

Despite some changes, the key results noted in fixed effects regressions remain unchanged. Overall, a negative relationship is observed between a working hours'

mismatch in non-standard work and better mental health for men (figure 7). In contrast, a number of positive effects persist for women, on average (figure 8).

The negative effects of overemployment in regular daytime and irregular work schedules on men's mental health remain precisely estimated, at 1% and 5% levels of significance respectively. Conversely to the fixed effects' results, men overemployed in regular evening and regular night shifts display improved mental health levels. However, these estimates are both economically and statistically insignificant. Similar effects are observed for underemployed men in regular daytime schedules and on call (figure 7). While both over and under employed men in rotating shifts suffered from poorer mental health in fixed effects, these associations are exacerbated in a linear DPD model (figure 7). Although imprecise, estimates on these parameters are not far short of the effect of limiting health conditions on men's mental health (Appendix 2C).

Despite a similar relationship observed across fixed effects and linear DPD models for females, some changes are worth noting. Firstly, the negative health associations of overemployment in regular evening shifts are not only exacerbated, but also statistically significant at a 1% level (figure 8). This contrasts with an imprecise estimate on this coefficient in the fixed effects (Appendix 2B). Secondly, the effects of a working hours' mismatch in regular night schedules on females' mental health are also exacerbated in a linear DPD model. Finally, while the effects of overemployment in standard work remain precisely estimated (1% level), those of underemployment in irregular work turn statistically insignificant (Appendix 2B).

From the previous discussion, we note some robust estimates on interaction terms across both fixed effects and linear DPD models. In particular, the negative and statistically significant (1% level) coefficient estimate on overemployment persists throughout. This provides further evidence that most effects seem to be driven by those of overemployment

on mental health. The changes observed on some of the focus variables confirm the importance of controlling for past levels of mental health, as affecting key interaction terms for both males and females.

Figure 7: Linear DPD results – specification (3) - males

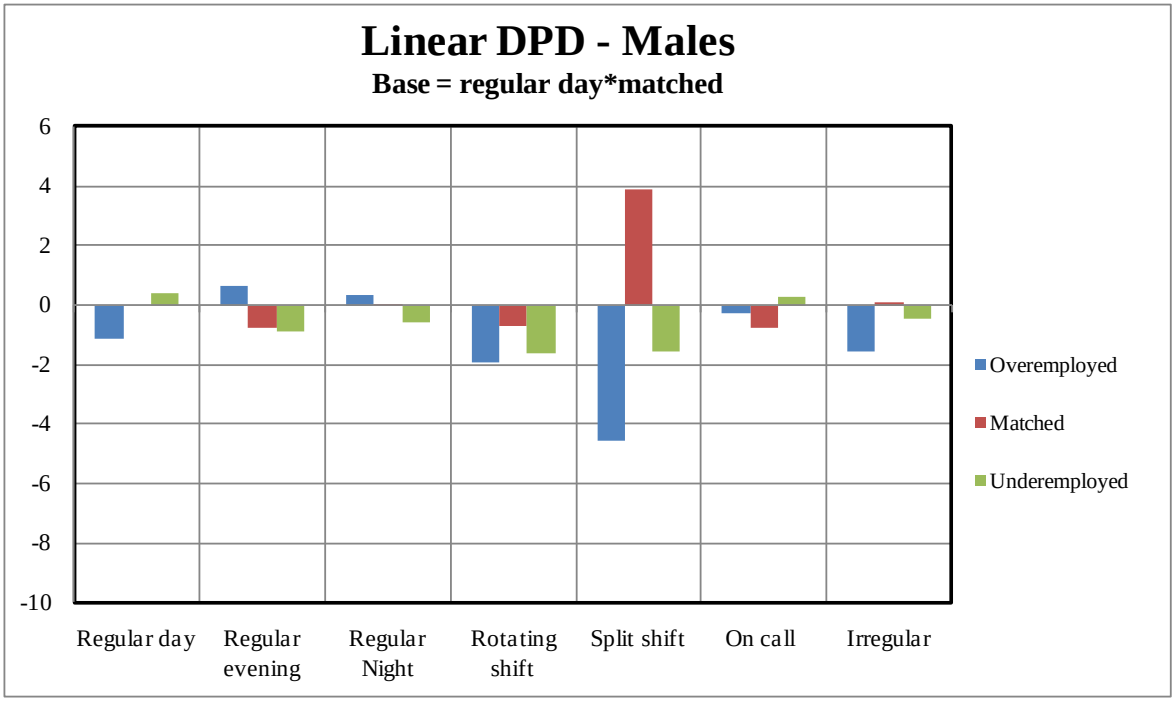
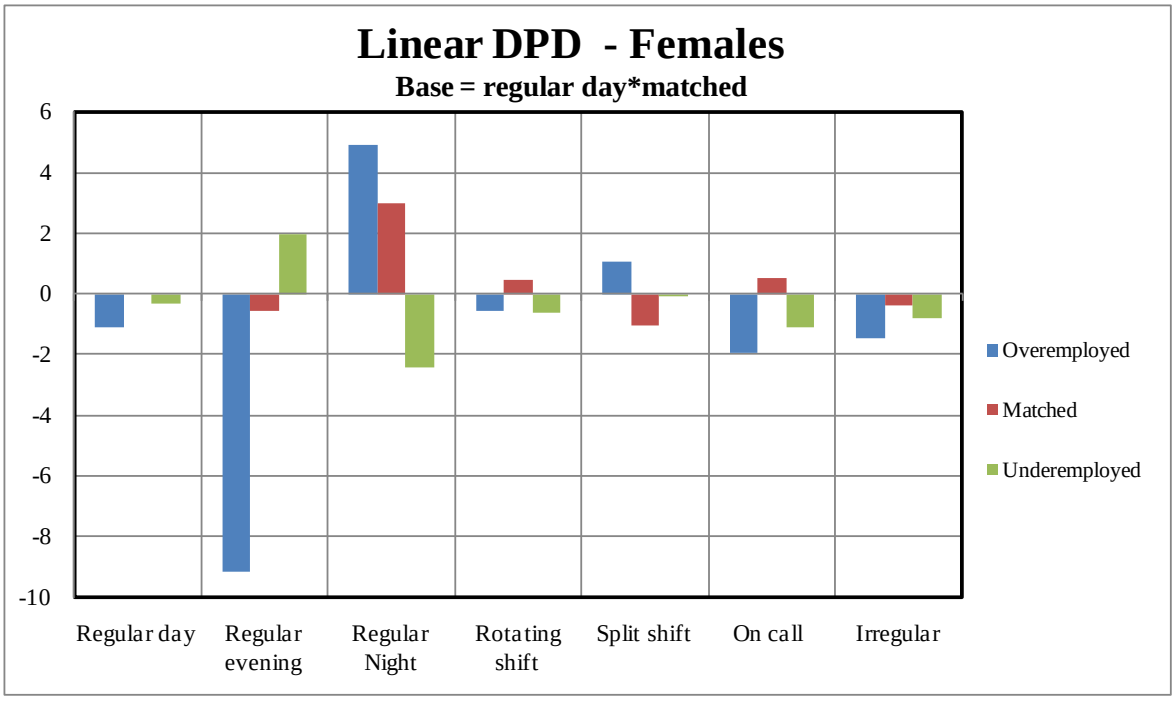


Figure 8: Linear DPD results – specification (3) - females



5.4. Discussion of explanatory variables

The fixed effects and linear DPD models provide reliable estimates compared with pooled OLS regressions, as they account for unobserved heterogeneity across individuals. As such, this section will only discuss key inferences on control variables estimated in fixed effects and linear DPD models (Appendix 2C).

An increasing number of household members negatively impacts on both males and females' mental health in both models. While statistically significant at a 1% and 10% level in fixed effects for males and females respectively, imprecise estimates are obtained in the linear DPD model. Yet, those effects remain economically insignificant throughout.

The presence of children aged 0-4 years is positively associated with better mental health for men and women and this effect is statistically significant at a 1% level in fixed effects. However, these effects dissipate in the linear DPD model. Statistically and economically insignificant estimates on children aged 5-14 and children aged 15-24 provide little evidence of a relationship with mental health for males. Yet, an economically and statistically significant (1% level) estimate is obtained on the coefficient of children aged 5-14 years for females in the linear DPD model. The findings for men are in line with those of Mendolia (2009) in that mental health does not appear to be influenced by the presence of children. Mental health may be improved in the initial years of childhood, though positive associations are shown to dissipate over time.

Single individuals exhibit higher levels of mental health distress than their counterparts married or in a de facto relationship. In particular, these effects are largest for separated males and females; with economically and statistically significant (1% level) estimates. These effects concur with a number of empirical studies, suggesting enhanced well-being levels for married individuals (Cottini and Lucifora, 2009; Scutella and Wooden, 2008).

The estimated coefficients on education variables are mostly statistically and economically insignificant across genders. This weak association has also been found in studies by Adam and Flatau (2006) and Dockery (2006). While we expect mental health levels to improve in the level of education attained, Clark (2003) notes a negative relationship. He contends that fastidious individuals may self-select themselves in higher levels of education, which in turn influences this negative association.

Similarly to Clark (2003) and Scutella and Wooden (2008), unemployed individuals suffer from poorer mental health than those employed. These negative estimates are both economically and statistically significant in fixed effects models. Yet for females, these effects lose statistical significance in linear DPD regressions. Most estimates on occupation variables are consistent across specifications in fixed effects and linear DPD models. However, there is little evidence of a relationship between occupation and mental health for males, as most effects are imprecisely estimated. This is in line with a study from Dockery (2006). A similar story emerges for females, though the estimate on labourers is positive, economically and statistically significant at a 5% level in fixed effects. In linear DPD, while the coefficient on labourers loses statistical significance, that on professionals turns statistically significant at a 1% level.

Interestingly, the number of weekly hours worked does not seem to influence one's mental health. In contrast, holding more than one job positively affects one's mental health and is economically and statistically significant at a 5% level in the males' linear DPD regressions. This positive estimate matches with Dockery's (2006) research. Holding more than one job may signal an ability to multitask and a need for temporal variety. Thus, such individuals may experience improved mental health levels. While a longer duration with one's current employer negatively affects mental health, this effect remains economically

insignificant across both models and genders. However, the estimate on the tenure with current employer for males remains statistically significant at a 5% level throughout.

A positive relationship between income and mental health is found. This is expected, given the large body of empirical literature supporting this positive link (Mendolia, 2009; Scutella and Wooden, 2008). However, across both fixed effects and linear DPD regressions, the estimates on income are both economically and statistically insignificant. It may well reflect that it is income in relative - and not absolute - terms which has an effect (Mendolia, 2009; Clark, 2003).

5.5. Diagnostics

5.5.1. Model fit and tests of joint statistical significance

Despite the range of covariates controlled for, the overall fit remains low in all models and specifications (Appendix 2C). It is likely to reflect time varying unobserved individual traits which can affect the variation in one's mental health, though difficult to account for.

While most of the focus variables are individually statistically insignificant, a series of Wald tests were run to assess their joint statistical significance. Wald statistics have an asymptotic chi-squared distribution with q restrictions as the degrees of freedom (Wooldridge, 2009). These tests were conducted separately for males and females, for each specification and model (Appendix 2D). The null hypothesis consists of a set of jointly statistically insignificant variables. The joint significance of different sets of focus variables were assessed in turn: non-standard work dummies, working hours' mismatch dummies, interaction terms, and the full set of focus variables. Both non-standard work dummy variables and interaction terms are mostly jointly statistically insignificant for both genders. However working hours' mismatch dummies are highly jointly statistically significant for both males and females across all specifications and models. These tests

confirm the large effects of a working hours' mismatch in driving the overall relationship, as statistically significant when tested jointly with the full set of focus variables.

5.5.2. Key diagnostics in linear DPD models

A number of potential issues are to be considered in regards to the use of linear DPD models. The stability condition, no serial correlation in the disturbances, and the validity of instruments used are all required to obtain consistent estimates of the parameters (Arellano and Bond, 1991). While one-step estimates are discussed in main results, two-step estimates were also computed for comparison purposes (Appendix 2C). Two-step estimates are generated from a second round of iterations, potentially producing more precise estimates.

The stability condition holds in all three specifications for both males and females. We obtain a coefficient estimate in the range of 0 to 0.2 on the first-differenced lag of mental health (Appendix 2C). As noted in *section 4*, we assume the disturbances to be i.i.d. However, taking first-differences in a model with well behaved errors induces a first-order moving average process, and hence autocorrelation in the differenced error term. Autocorrelation tests can be computed in *Stata 10 SE*, in which the null hypothesis consists of zero autocorrelation in the differenced disturbances at order m. While tests at m=1 are not informative, the rejection of the null at m=2 indicates serial correlation in the levels of the disturbances. We strongly reject the null hypothesis of zero autocorrelation at order m=1 in all males' and females' regressions (p-value < .001). However, large p-values in the second-order (m=2) differenced disturbances provide strong evidence against serial correlation in the disturbances for males. Notably, in all three males' regressions, p-values on autocorrelation tests at m=2 exceed 36%. In contrast, there only appears to be serial correlation in the third specification for the females' regression, with a p-value of 5% at m=2. This is problematic, as the GMM approach used to derive consistent estimates of the

parameters is no longer valid. While there may be serial correlation in the females' regression, the test may also be sensitive to endogeneity.

As such, additional regressions were run with the full set of covariates only. However, it was no longer assumed that all regressors were strictly exogenous, as some were explicitly instrumented along with the first-differenced lag of mental health.

$$Cov(\Delta x_{it}, \Delta \mu_{it}) \neq 0 \quad and \quad Cov(\Delta z_{it}, \Delta \mu_{it}) \neq 0 \quad with\, x \in X \, and \, z \in Z \qquad [5.1]$$

Sargan tests of overidentifying restrictions were conducted, to assess the exogeneity of instruments used. The null hypothesis consists of an exogenous set of instruments, or exclusion restrictions:

$$H_o: E\left(\Delta \mu_{it} \middle| \Delta X_{i,t-p}\right) = 0 \; and \; E\left(\Delta \mu_{it} \middle| \Delta Z_{i,t-p}\right) = 0$$

$$and \; E\left(\Delta \mu_{it} \middle| MH_{i,t-s}\right) = 0 \quad with \; p \geq 1 \; and \; s \geq 2 \qquad [5.2]$$

$$H_1: H_0 \; is \; false$$

A rejection of the null hypothesis indicates potentially endogenous instruments. A note of caution is warranted in interpreting this test. Under the assumption of homoskedastic disturbances, the Sargan test has an asymptotic chi-squared distribution. However, this test cannot be conducted under robust standard errors, as the form of heteroskedasticity is unknown. Thus, Sargan tests on one-step estimates tend to over-reject the null hypothesis in the presence of heteroskedasticity. Conversely, Sargan tests on two-step estimates tend to under-reject the null under heteroskedasticity. This often leads to higher p-values for two-step estimates, when compared to those of one-step estimates (Arellano and Bond, 1991). As such, rejection of the null may either be attributed to some endogenous instruments, or merely the presence of heteroskedasticity. We anticipate instruments to be predictive of the first-differenced lag of mental health, $\Delta MH_{i,t-1.}$ Yet, given no readily

available command to test instrument relevance, brute force estimation would have been cumbersome and was not pursued.

Sargan tests on one-step estimates are rejected at a 1% level for males and 5% level for females (Appendix 2E). As suspected, we fail to reject the null on two-step estimates, as large p-values were obtained for both genders. Base Sargan tests on one and two step estimates provide supporting evidence of potential heteroskedasticity in the errors. Although Sargan tests on one-step estimates indicate the failure of one or more instruments, it cannot be clear which one fails. As such, various specifications may assist in narrowing down endogenous instruments. There is little evidence of a reverse causation between non-standard work and mental health, as most non-standard work dummies are individually and jointly statistically insignificant. From the economic literature, we suspect unemployment, a working hours' mismatch and long-term health or disability conditions as potential endogenous candidates.

Unemployment is found to negatively affect individuals' mental health in a number of studies. Yet, those suffering from poorer mental health may be more likely to be unemployed (Mendolia, 2009; Kennedy and McDonald, 2006). Accounting for this possibility in the three specifications did not improve the Sargan tests for males and females. Kennedy and McDonald's (2006) paper provides a similar link. They did not find a reverse causation between unemployment and individuals' mental health in a study of Australian immigrants.

Furthermore, Friedland and Price (2003) caution against inferences made on the direction of the causal effect between working hours' mismatches and health. Over and under employment may not only affect one's mental health, but individuals' mental health may also affect whether individuals work more or less hours than they wish. As discussed in *section 2*, overemployed individuals may be endowed with higher mental health levels to

begin with; and this may signal a greater level of productivity and efficiency to their employers (Sousa-Poza and Ziegler, 2003).

The null of exogenous instruments was rejected when instrumenting both over and under employment and the first-differenced lag of mental health as endogenous. Underemployment does not seem to be subject to reverse causation, as statistically insignificant for both males and females (Appendix 2C). However, the link between overemployment and mental health remains blurred, as a statistically significant estimate (5% level) is obtained for both genders on overemployment. A study by Geyer and Myck (2010) provides reasons to question the direction of causation between overemployment and mental health. They investigated the influence of health on a mismatch between actual and desired weekly working hours in Germany. A significant relationship is found in that employees suffering from poor health wish to work fewer hours weekly.

In addition to overemployment, we suspect health conditions or disability to be endogenous. Currie and Madrian (1999) note reporting of limiting health or disability conditions can be subject to biases and measurement error. Firstly, individuals suffering from limiting health conditions may be prone to poorer mental health levels to begin with. Secondly, some respondents may be inclined to under-report the extent of their health conditions. As such, the final specification reported in *Appendix 2E* instruments overemployment, long-term health conditions and limiting disabilities, as well as the first-differenced lag of mental health. We fail to reject the null hypothesis of exogenous instruments at conventional levels of significance for both genders.

Finally, instead of using five lags of the dependent variable to instrument the first-differenced lag of mental health, only two lags were used. As suggested by Wooldridge (2002), many overidentifying restrictions may lead to poor finite sample properties, and the failure of Sargan tests. While restricting the number of lags on the dependent variable

improved Sargan tests for the males' regression, results obtained for females barely changed (Appendix 2E). Further, restricting the number of lags on the first-differenced covariates was not shown to improve Sargan tests statistics for both genders. It is to be noted that key inferences on the set of focus variables are robust across the specifications previously discussed.

5.6. Sensitivity analysis

Although the mental health associations observed for both males and females persist in a number of specifications, they remain mostly statistically insignificant. A working hours' mismatch seems to be driving most effects when interacted with non-standard employment. In particular, overemployment is the only effect to be economically and statistically significant (1% level) across all specifications and models. To ascertain this, further robustness checks were conducted and are summarized below. More details are available upon request.

5.6.1. A comparison to Ulker's study

In addition to the reproduction and extension of the Ulker (2006) results, pooled OLS and fixed effects regressions were run for our sample with the first three waves only. The coefficient estimates from this subsample were compared to those obtained with the full sample. This comparison aimed to assess whether similar results would have been obtained with our sample at the time of Ulker (2006). Overall, a consistent story is obtained when evaluated against the full sample. Across both pooled OLS and fixed effects, a working hours' mismatch in non-standard employment is mostly associated with negative effects on men's mental health. In contrast, a greater number of positive estimates are obtained for

females, especially after accounting for unobserved effect; which concurs with Ulker (2006).

Conversely to the full sample findings, underemployed men working split shifts do not display large declines in their mental health levels. Interestingly, the negative effects of a working hours' mismatch in both regular nights and rotating shifts are more sizeable in the case of the subsample for men. In regard to females, similar associations emerge to the full sample. However, the negative effects of overemployment in regular evening work schedules on women's mental health are diminished.

Aside from subsample analyses, random effects regressions were run separately for males and females, for all three specifications. A large number of estimates are closer to those of fixed effects regressions than in pooled OLS. Nevertheless, a set of Hausman tests consistently rejects the null of no systematic difference in the coefficients between fixed and random effects (1% level). These tests are rejected for both males and females, and in all three specifications.

5.6.2. Lag distribution and cumulative effects

To ensure that the model dynamics were fully captured, two sensitivity analyses were conducted. Firstly, a finite distributed lag distribution of order one was estimated across all three models and specifications.

For pooled OLS and fixed effects regressions:

$$E\left(MH_{it}\middle|Z_{it}, Z_{i,t-1}, \dots, X_{it}, X_{i,t-1,} \dots\right) = E(MH_{it}|Z_{it}, Z_{i,t-1}, X_{it}, X_{i,t-1}) \qquad [5.3]$$

The above equation states that once X and Z variables have been controlled for, at most one lag of the focus and control variables affect current mental health.

For linear DPD regressions:

$$E\left(MH_{it}\middle|MH_{i,t-1}, Z_{it}, Z_{i,t-1}, \dots, X_{it}, X_{i,t-1}, \dots\right) =$$

$$E(MH_{it}|MH_{i,t-1}, Z_{it}, Z_{i,t-1}, X_{it}, X_{i,t-1}) \qquad [5.4]$$

Equation [5.4] expresses a dynamically complete model. Once accounting for contemporaneous effects in X and Z variables, at most one lag of mental health, and one lag in the focus and control variables could affect current mental health. In particular, accounting for the lag structure of the covariates provides a more flexible specification compared with the linear DPD model. The variation in current mental health may not only be influenced by past mental health levels, but also by lagged effects of some covariates.

Despite a few statistically significant estimates obtained on the lagged focus variables in pooled OLS regressions, those effects do not persist over a year. While both lagged over and under employment turn statistically significant (1% level) in all pooled OLS specifications, these effects dissipate in fixed effects, and vanish completely in linear DPD estimations. In addition, lags on key interaction terms for both males and females fade away within a year, as not statistically significant. In contrast, the contemporaneous effects of overemployment on mental health remain negative, economically and statistically significant (1% level) across all models and specifications.

Secondly, the approach of Fletcher et al. (2010) was followed in assessing whether a working hours' mismatch had any cumulative effects within a three-year window. As such, both over and under employment were lagged three years back, and scores were subsequently aggregated across those three years to obtain the cumulative effects.

As an example, we consider this specification in a linear DPD model:

$$MH_{it} = MH_{i,t-1}\alpha + Z_{it}\beta + X_{it}\gamma + (\sum_{k=t-3}^{t} over_{ik})\theta_1 + (\sum_{k=t-3}^{t} under_{ik})\theta_2 + \delta_i + \mu_{it}$$

$$for\ \ i = 1,2 \dots, N \quad t = 2,3 \dots, T \qquad [5.5]$$

over and *under* denote overemployment and underemployment, respectively. All other covariates remain as discussed in *section 4.*

For both males and females, while there seems to be cumulative effects in pooled OLS specifications, these tend to dissipate in fixed effects. Similarly to the lag distribution analysis, both over and under employment do not have cumulative effects on mental health in all three specifications of a linear DPD model.

5.6.3. Potential endogeneity issues

A final set of sensitivity checks was conducted in an attempt to address the issue of reverse causation discussed in *section 5.5.2*. The availability of longitudinal data lends itself to Granger tests of causality, in regard to our set of focus variables. If one-way causality runs from Z_{it} to MH_{it}, then past values of Z_{it} should be predictive of MH_{it}. Conversely, past values of MH_{it} should not be predictive of Z_{it}. If they were, this would indicate Granger causality running from MH_{it} to Z_{it} (Wooldridge, 2009; Fiebig, 1980).

Regressions of future and past values of mental health on the set of focus variables produce a story consistent with Granger causation from Z_{it} to MH_{it}. These estimates are especially robust across the three specifications in fixed effects and linear DPD models. Of particular interest are the robust estimates obtained on both over and under employment in regressions of past values of mental health on the set of focus variables. In this case, estimates on a working hours' mismatch are not only statistically insignificant, but also

economically insignificant in both fixed effects and linear DPD models, for males and females. However, while we can rule out one-way causation, we cannot rule out two-way causation. Given the number of focus variables, it remains unclear how one would regress Z_{it} on mental health, MH_{it}.

Aside from reverse causation, the issue of self-selection in non-standard forms of employment could be addressed if we could look at a particular subset of individuals in our sample. These individuals would need to be subject to an exogenous shock, to randomly sort out workers in non-standard forms of employment. Yet, it was difficult to come up with such a shock in the HILDA survey data. Thus, the self-selection issue could only be mitigated by controlling for occupation and industry in our study.

6. Conclusion

This thesis investigated the influence of a working hours' mismatch in non-standard employment on individuals' mental health. The gap in Ulker (2006) was addressed in exploiting a longer time span to estimate static and dynamic models. Overall, the key findings concur with Ulker (2006) and Wooden et al. (2009), and are robust across various specifications.

A negative relationship emerges between a working hours' mismatch in non-standard employment and better mental health for men. In contrast, positive associations are found for women, on average. Despite the lack of precision in key estimates, the negative and significant effects of overemployment on mental health appear to be driving the relationship noted for men.

Although non-standard work was not shown to significantly affect one's mental health, the effects of a working hours' mismatch deserve further consideration. Policy makers typically focus on underemployment, as a measure of labour force underutilisation (ABS, 2010). Yet, a number of studies found overemployment to negatively affect health outcomes, in line with our results (Adam and Flatau, 2006). Overemployment can conceal a number of factors. These include asymmetries in bargaining powers between workers and employers, as well as heterogeneity in individuals' work/life balance preferences. Thus, policies targeted at working arrangements and conditions may need to be revised to accommodate the needs of those individuals.

Although a consistent story emerges across various specifications, this study is subject to a number of threats. Results are to be interpreted with caution, as the direction of the causation remains blurred. While there is little evidence of a reverse causation between non-standard work and mental health, this cannot be ascertained in the context of working hours' mismatches. Overemployed individuals may be endowed with higher mental health

levels to begin with, and signal higher productivity levels to their employers (Sousa-Poza and Ziegler, 2003). The onset of the 2008 Global Financial Crisis provides a valuable natural experiment. Recessions can be used as a source of exogeneity in inferring the direction of the causation between a working hours' mismatch and mental health. Employers may retain their skilled labour force by putting their employees on fewer hours of work, leading to underemployment. Alternatively, some employees may find themselves overemployed in the case of lay-offs, since faced with a greater number of tasks to perform.

Furthermore, results may be subject to measurement error from the self-reporting nature of the dependent variable. Respondents may be inclined to overstate their mental health levels. In addition, there may be a coping process, whereby it may take one or two attempts before respondents feel comfortable in answering self-completion questionnaires. However, consistent findings between subsample and full sample analyses provide little evidence of measurement error in mental health. Finally, possible interactions at a household level in working hours' mismatch remain unexplored, and may assist in uncovering factors underlying conflicts between actual and desired working hours.

Despite these limitations, this thesis contributed in two main aspects. Firstly, incorporating dynamics in estimations provide a more complete picture of health outcomes over time. Indeed, we find persistence in mental health over time, motivating the use of linear DPD models over those of static fixed effects. Secondly, the findings reinforce the lack of relationship between non-standard work schedules and mental health. While Ulker (2006) anticipated a rise in the proportion of individuals in non-standard employment, our analysis indicates a rise in standard work over time. Nevertheless, the negative and significant effects of overemployment on mental health provide room for further research in this area.

7. Appendices

Appendix 1A: Variable definitions

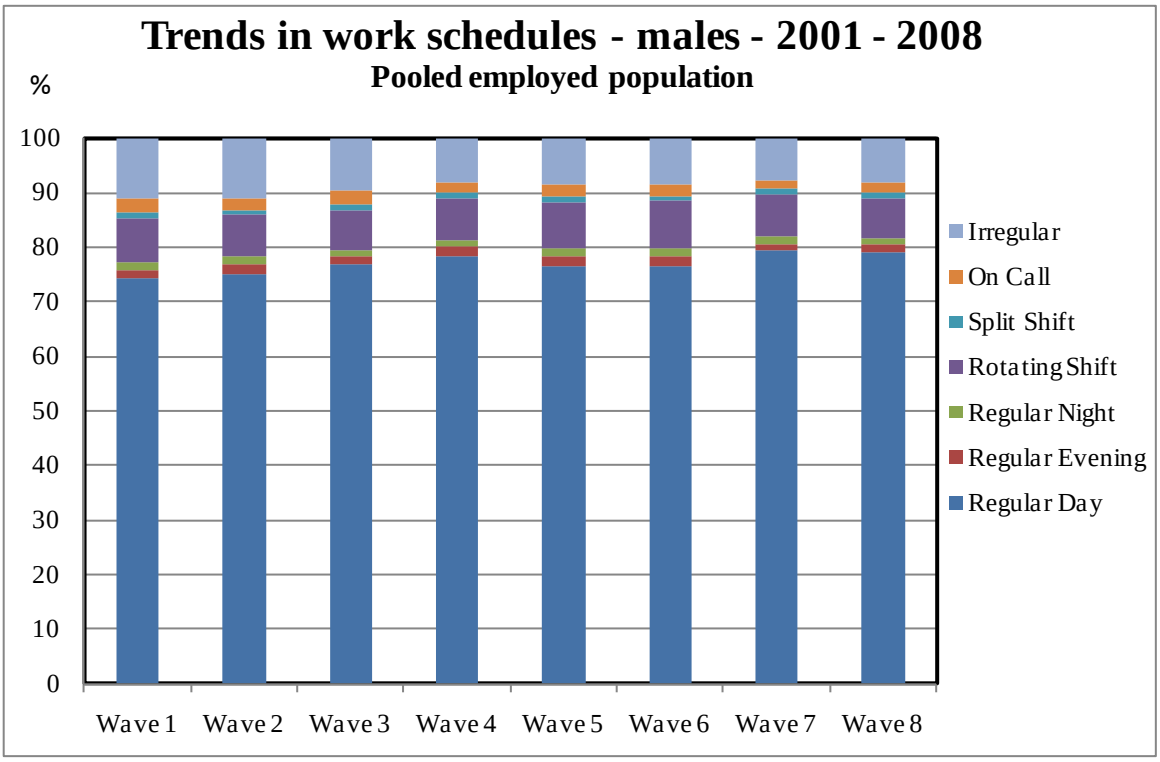
Variable	Source*	Definition
Personal characteristics and education		
age_25to34	*hgage*	1 if individual is between 25 to 34 years of age, 0 otherwise
age_50to64	*hgage*	1 if individual is between 50 to 64 years of age, 0 otherwise
Base category for above dummies is *age_35to49* for individuals aged between 35 and 49 years		
hhpers	*hhpers*	Number of in-scope persons in the household (household size)
aboriginal_torres	*anatsi*	1 if individual is of Aboriginal or Torres Strait Islander origin, 0 ot herwise
arrived_less_than_10yrs	*anyoa*	1 if individual came to live in Australia less than 10 years ago (anyoa-1998>0), 0 otherwise
state_vic	*hhstate*	1 if individual resides in Victoria, 0 ot herwise
state_qld	*hhstate*	1 if individual resides in Queensland, 0 ot herwise
state_sa	*hhstate*	1 if individual resides in South Australia, 0 ot herwise
state_wa	*hhstate*	1 if individual resides in Western Australia, 0 ot herwise
state_tas	*hhstate*	1 if individual resides in Tasmania, 0 ot herwise
state_nt	*hhstate*	1 if individual resides in Northern Territory, 0 ot herwise
state_act	*hhstate*	1 if individual resides in Australian Capital Territory, 0 ot herwise
Base category for state is *state_nsw* for individuals residing in New South Wales		
bounded_locality	*hhsos*	1 if individual's section of state is a bounded locality, 0 otherwise
rural_balance	*hhsos*	1 if individual's section of state is rural balance, 0 otherwise
other_urban	*hhsos*	1 if individual's section of state is other urban, 0 otherwise
Base category for section of state is *major_urban*		
children_age_0to4	*hhd0_4*	1 if individual has dependent children aged 0-4 (includes partner's children), 0 otherwise
children_age_5to14	*hhd5_9, hhd1014*	1 if individual has dependent children aged 5-14 (includes partner's children), 0 otherwise
children_age_15to24	*hhd1524*	1 if individual has dependent children aged 15-24 (includes partner's children), 0 otherwise
Base category for children is *no dependent children aged 0-24*		
overseasborn_english	*anbcob*	1 if individual was born outside of Australia - in a main english speaking country, 0 ot herwise
overseasborn_other	*anbcob*	1 if individual was born outside of Australia - in a non-English speaking country, 0 ot herwise
Base category for country of birth is *australian_born* for Australian born		
separated	*mrcurr*	1 if individual is separated, 0 otherwise
divorced	*mrcurr*	1 if individual is divorced, 0 otherwise
widowed	*mrcurr*	1 if individual is widowed, 0 otherwise
never_married	*mrcurr*	1 if individual has never been married, 0 otherwise
Base category for marital status is *married_defacto* for individuals married or in a de facto relationship		
university	*edhigh*	1 if highest level of education is postgraduate, graduate diploma, graduate certificate or bachelors degree, 0 otherwise
tertiary	*edhigh*	1 if highest level of education is an advanced diploma, diploma or certificate, 0 otherwise
year12	*edhigh*	1 if highest level of education is year 12, 0 otherwise
Base category for education variables is *year11* for highest level of education below year12		

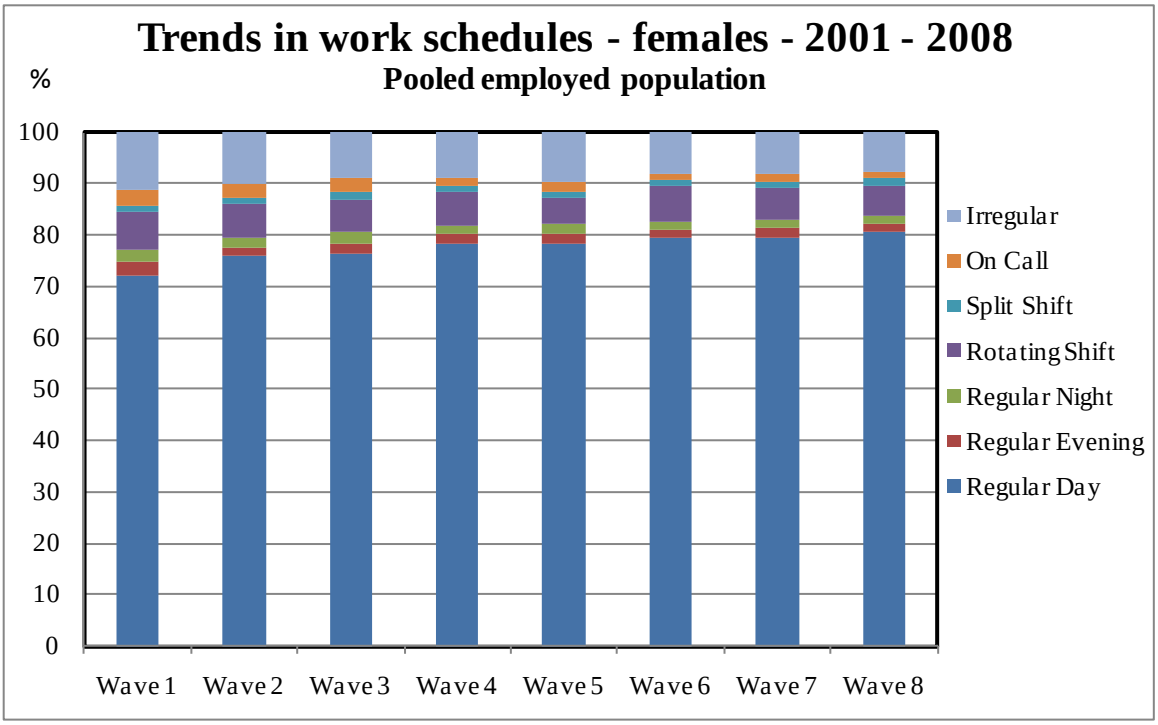
Variable	Source*	Definition
Health		
mental_hlth	*ghmh*	Individual's self-reported level of mental health (SF-36 derived variable)
hlth_cond	*helth*	1 if individual suffers from a long term health condition or disability, 0 otherwise
Base category for above dummy is *no_hlth_cond* for no long-term health/disability condition		
limit_hlth_cond	*helthwk*	1 if individual suffers from a long term health condition or disability that limits or prevents the amount/type of work, 0 otherwise
Base category for above dummy is *no_limit_hlth_cond* for no limit/impact on amount/type of work or individuals not suffering from a long term health condition		
Income and assets		
income	*hifdip, hifdin*	Household financial year disposable income - missing values are imputed and the variable is top-coded
homeowner	*hstenur, hstenr*	1 if individual owns a house or is currently paying off a mortgage, 0 otherwise
Employment		
hours_worked	*jbmhruc*	Hours per week usually worked in main job
unemployed	*esbrd*	1 if individual is unempoyed, 0 otherwise
nilf	*esbrd*	1 if individual is not in the labour force, 0 otherwise
Base category for employment status is *employed*		
regular_evening_wk	*jbmsch*	1 if individuals works on regular evenings, 0 otherwise
regular_night_wk	*jbmsch*	1 if individual works on regular nights, 0 otherwise
rotating_shift	*jbmsch*	1 if individual works rotating shifts, 0 otherwise
split_shift	*jbmsch*	1 if individual works split shifts, 0 otherwise
on_call_wk	*jbmsch*	1 if individual works on call, 0 otherwise
irregular_wk	*jbmsch*	1 if individual works irregular schedules, 0 otherwise
Base category for non-standard schedules is *regular_day_wk*		
over_employed	*jbhrcpr*	1 if individual would like to work fewer hours per week, 0 otherwise
under_employed	*jbhrcpr*	1 if individual would like to work more hours per week, 0 otherwise
Base category is *matched* for matched working preferences		
Occupation and job characteristics		
professionals	*jbmo61*	1 if individual's occupation is classified as professionals, 0 otherwise
tech_trade_wk	*jbmo61*	1 if individual's occupation is classified as technicians and trades workers, 0 otherwise
community_wk	*jbmo61*	1 if individual's occupation is classified as community and personal service workers, 0 otherwise
clerical_admin_wk	*jbmo61*	1 if individual's occupation is classified as clerical and administrative workers, 0 otherwise
sales_wk	*jbmo61*	1 if individual's occupation is classified as sales workers, 0 otherwise
machinery_wk	*jbmo61*	1 if individual's occupation is classified as machinery operators and drivers, 0 otherwise
labourers	*jbmo61*	1 if individual's occupation is classified as labourers, 0 otherwise
Base category for occupations is *managers*		

Variable	Source*	Definition
more1job	*jbn*	1 if individual has more than one job, 0 otherwise
Base category for job status is *only1job* if individual has only one job		
employer	*es*	1 if individual's current employment status is classified as employer (ABS defined), 0 otherwise
own_acct_wk	*es*	1 if individual's current employment status is classified as own account worker (ABS defined), 0 otherwise
contr_family_mbr	*es*	1 if individual's current employment status is classified as contributing family member (ABS defined), 0 otherwise
Base category for above dummies is *employee (* ABS defined)		
casual	*jbcasab*	1 if individual is a casual worker, 0 ot herwise
Base category for above dummy is *permanent*		
tenure_curr_occupation	*jbocct*	individual's tenure in current occupation (years)
tenure_curr_employer	*jbempt*	individual's tenure with current employer (years)

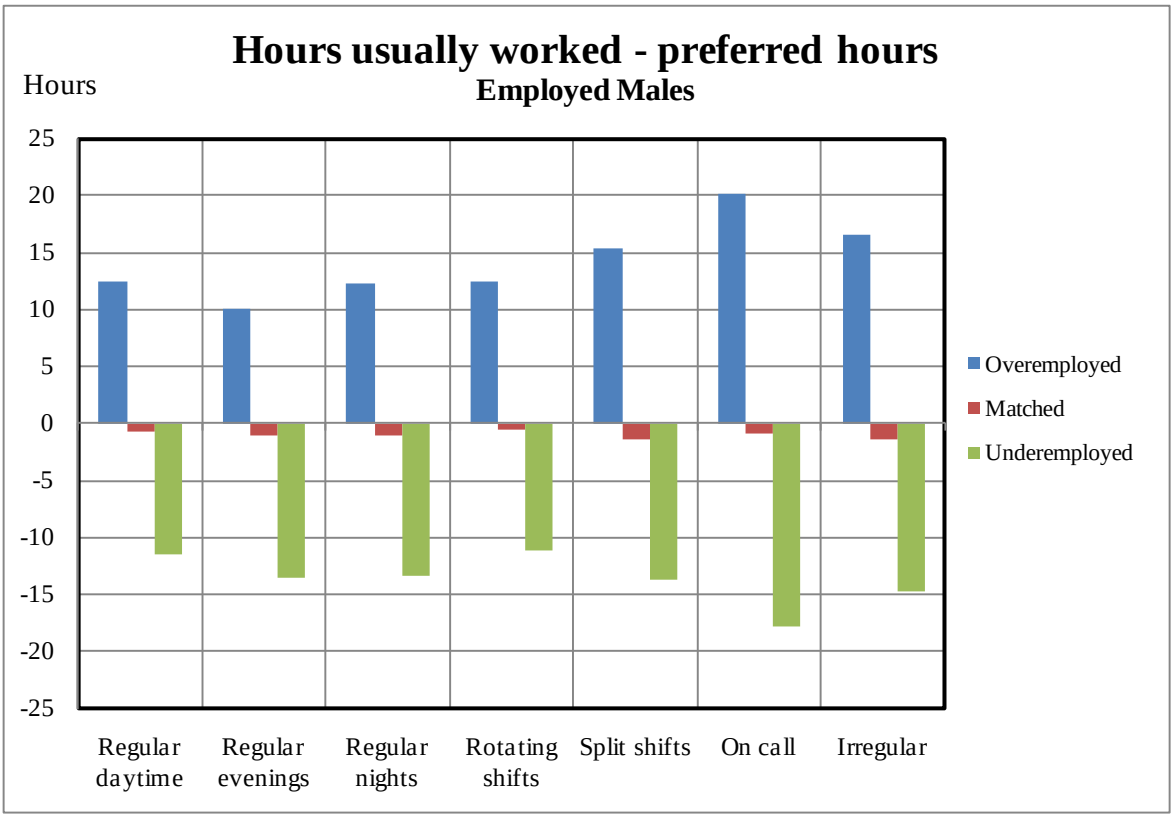
*Source refers to the variable name provided in the HILDA survey

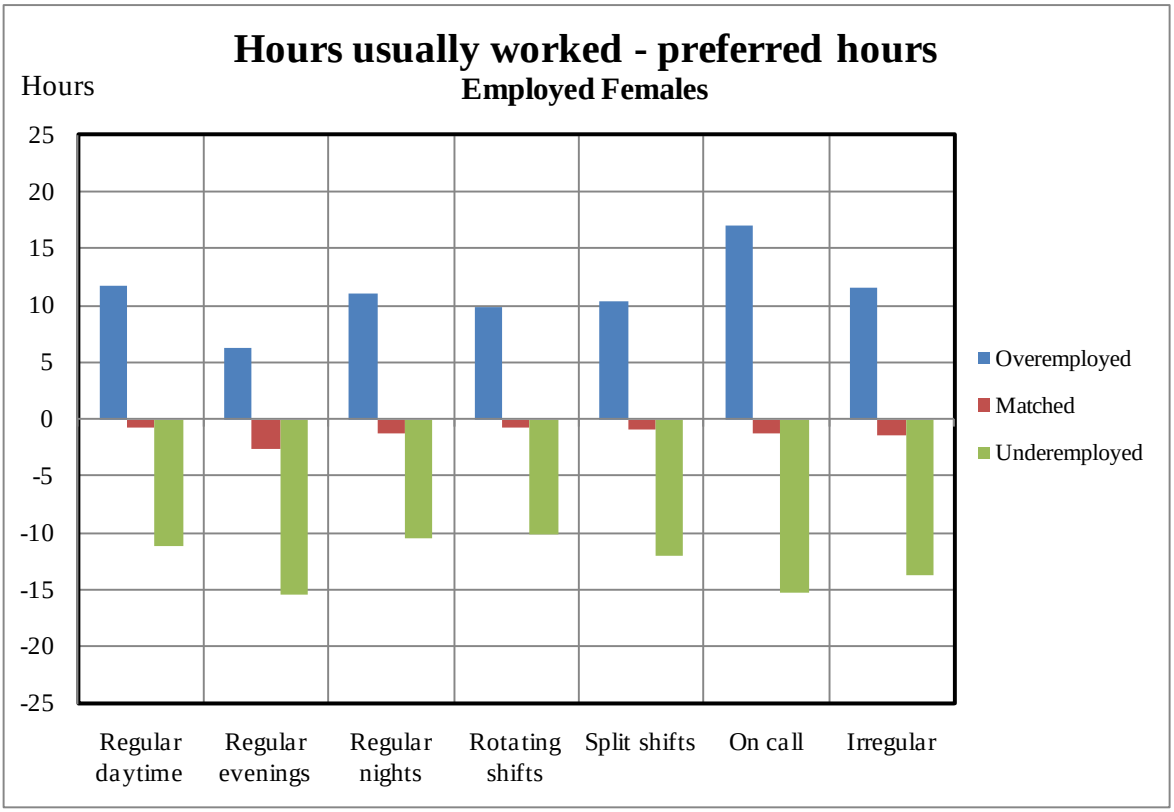
Appendix 1B: Trends in work schedules – 2001-2008





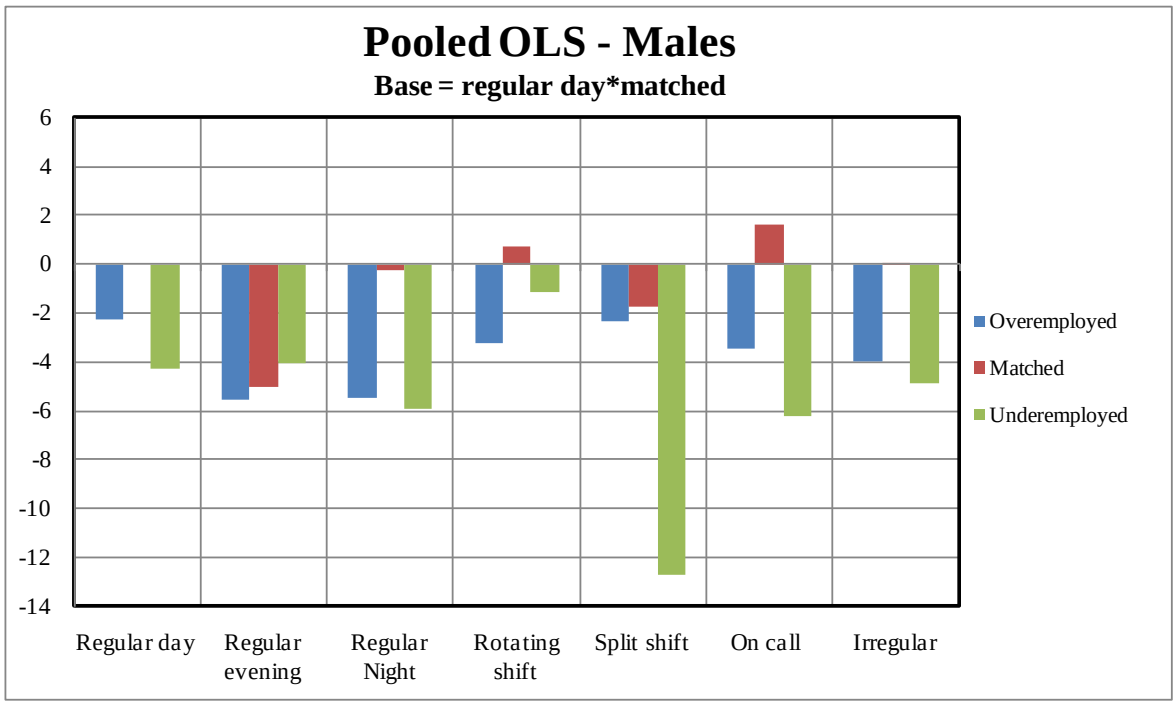
Appendix 1C: Hours usually worked – preferred hours

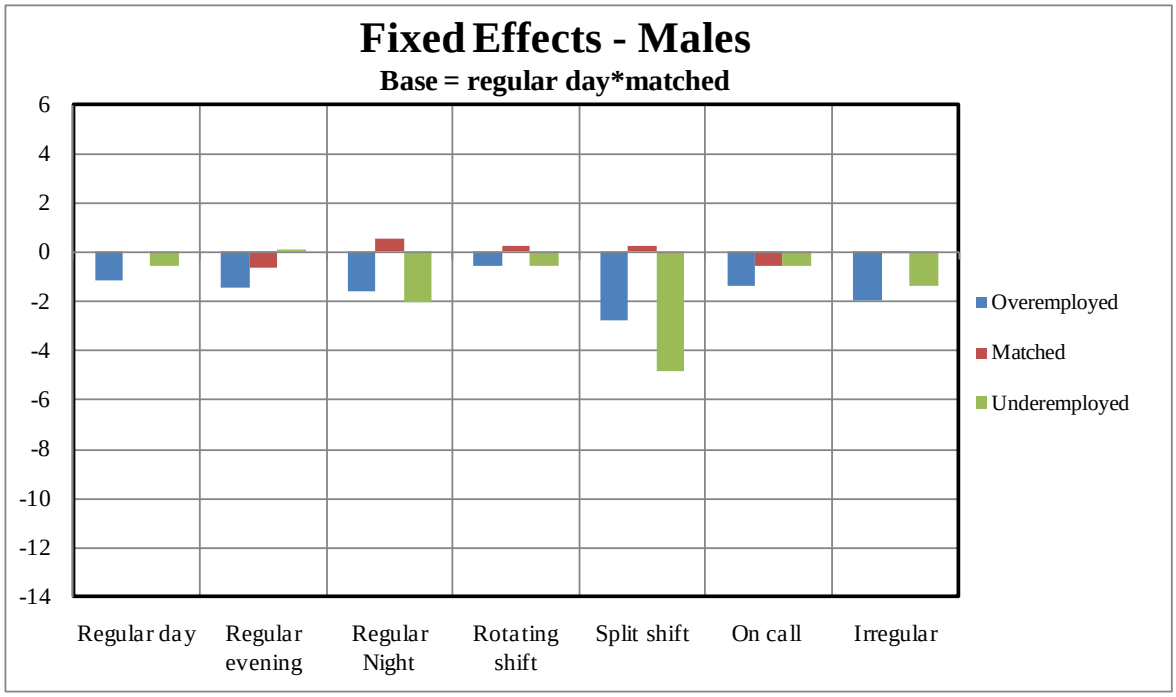




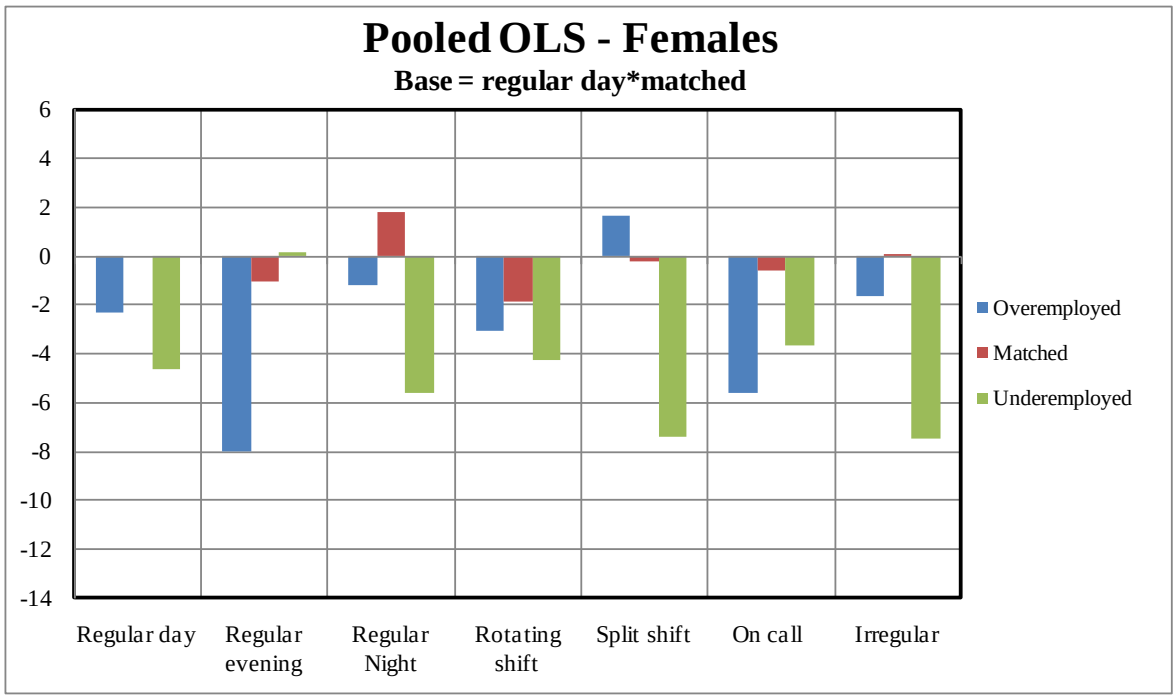
Appendix 2A: Results: Specification (1) – focus variables solely

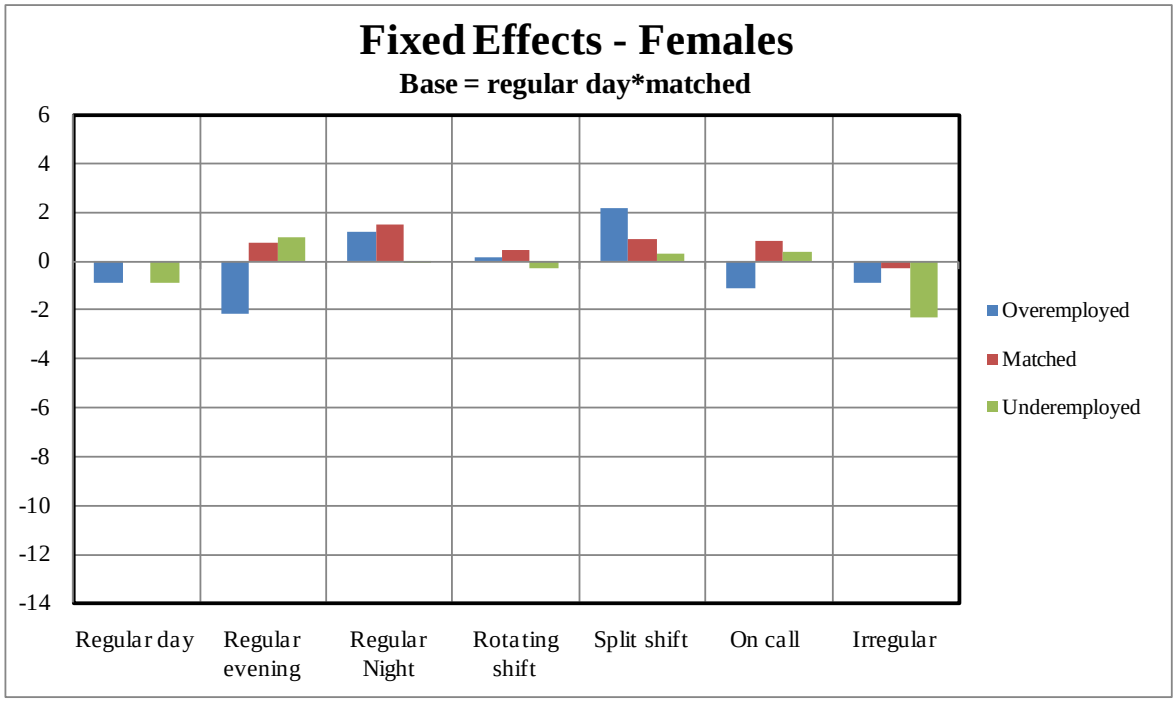
Males



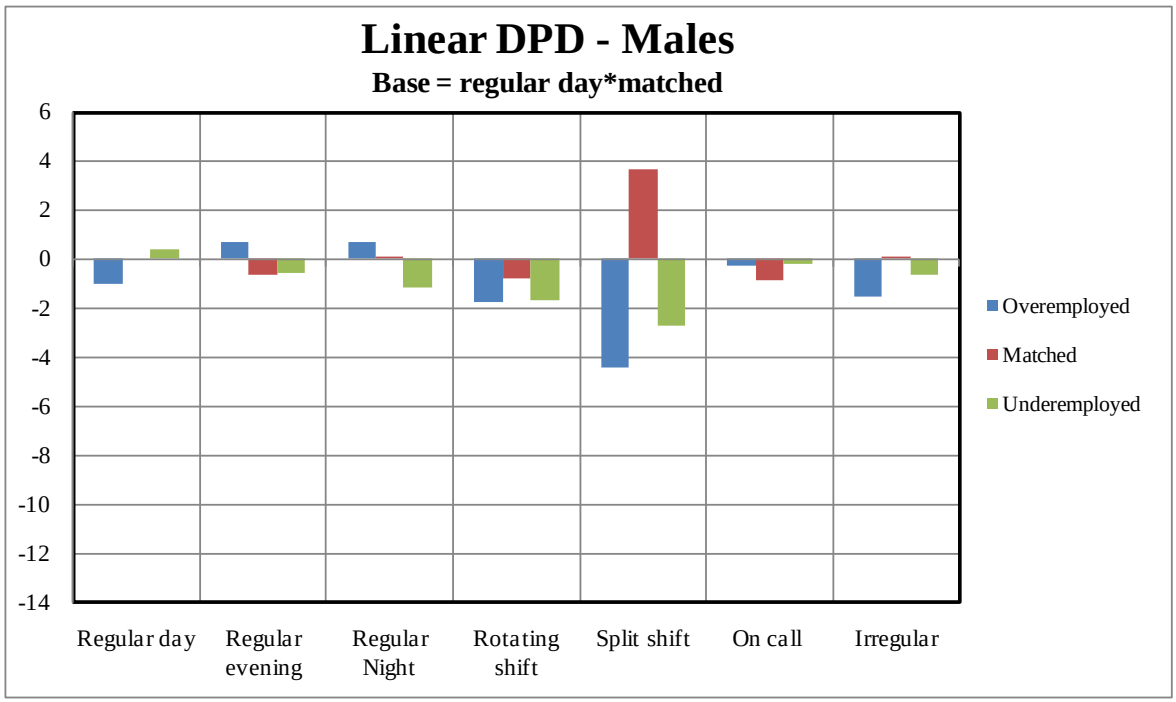


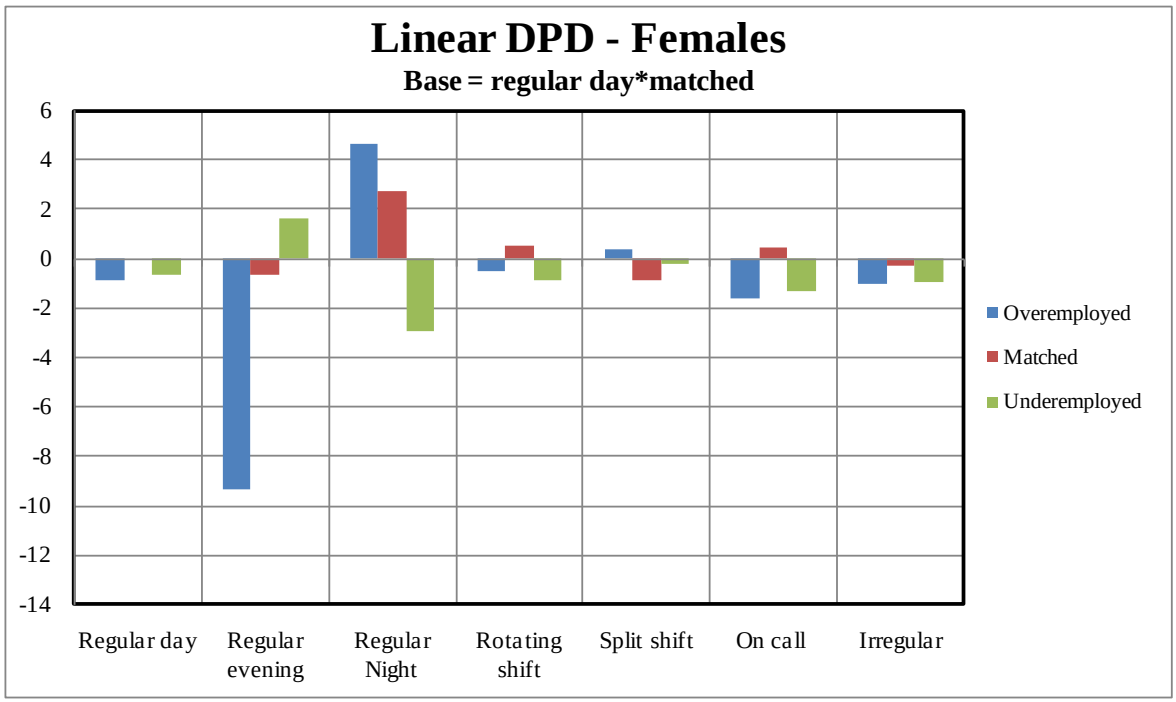
Females


Pooled OLS - Females
Base = regular day*matched
6
4
2
0
-2
-4
-6
-8
-10
-12
-14
Regular day
Regular evening
Regular Night
Rotating shift
Split shift
On call
Irregular
Overemployed
Matched
Underemployed


Fixed Effects - Females
Base = regular day*matched
6
4
2
0
-2
-4
-6
-8
-10
-12
-14
Regular day
Regular evening
Regular Night
Rotating shift
Split shift
On call
Irregular
Overemployed
Matched
Underemployed

Linear DPD results





Appendix 2B: Results on interaction terms

Specification (3) only

Males				Females			
Pooled OLS - (3)				**Pooled OLS - (3)**			
	Overemployed	Matched	Underemployed		Overemployed	Matched	Underemployed
Regular day	-2.732 (0.36) ***	-	-2.567 (0.64) ***	Regular day	-2.877 (0.41) ***	-	-2.329 (0.68) ***
Regular evening	-4.237 (2.33) *	-3.106 (1.92)	-2.465 (2.39)	Regular evening	-6.419 (2.65) **	0.067 (1.45)	3.478 (2.29)
Regular Night	-4.101 (3.13)	0.668 (1.57)	-2.967 (2.51)	Regular Night	-1.413 (3.42)	2.020 (1.69)	-2.977 (3.13)
Rotating shift	-3.258 (1.10) ***	0.278 (0.76)	-0.418 (1.51)	Rotating shift	-2.988 (1.19) **	-1.287 (0.90)	-2.080 (1.59)
Split shift	-2.263 (2.81)	-1.328 (1.57)	-6.069 (5.56)	Split shift	2.896 (2.46)	0.580 (1.77)	-4.597 (3.45)
On call	-3.726 (1.49) **	1.785 (1.31)	-4.136 (2.42) *	On call	-5.399 (2.06) ***	-0.055 (1.38)	-1.225 (2.20)
Irregular	-3.807 (0.73) ***	0.294 (0.65)	-3.649 (1.34) ***	Irregular	-1.398 (1.10)	0.160 (0.70)	-4.546 (1.31) ***
Fixed Effects - (3)				**Fixed Effects - (3)**			
	Overemployed	Matched	Underemployed		Overemployed	Matched	Underemployed
Regular day	-1.119 (0.27) ***	-	-0.488 (0.45)	Regular day	-1.020 (0.30) ***	-	-0.640 (0.45)
Regular evening	-1.322 (1.76)	-0.641 (1.11)	-0.201 (1.75)	Regular evening	-1.872 (2.19)	0.610 (1.09)	1.304 (1.76)
Regular Night	-1.895 (1.68)	0.675 (1.16)	-1.837 (2.10)	Regular Night	1.017 (1.94)	1.335 (1.10)	0.112 (1.61)
Rotating shift	-0.406 (0.77)	0.297 (0.61)	-0.630 (1.12)	Rotating shift	0.296 (1.07)	0.337 (0.67)	0.022 (1.07)
Split shift	-2.815 (1.90)	0.366 (1.32)	-4.524 (4.56)	Split shift	2.333 (1.33) *	0.737 (1.41)	0.239 (1.72)
On call	-1.306 (0.94)	-0.450 (0.73)	-0.068 (1.66)	On call	-1.390 (1.42)	0.789 (1.03)	0.394 (1.64)
Irregular	-1.858 (0.55) ***	0.083 (0.46)	-1.253 (1.03)	Irregular	-1.164 (0.75)	-0.244 (0.50)	-1.978 (0.96) **
Short-run responses				**Short-run responses**			
Linear DPD (3)				**Linear DPD (3)**			
	Overemployed	Matched	Underemployed		Overemployed	Matched	Underemployed
Regular day	-1.135 (0.33) ***	-	0.385 (0.60)	Regular day	-1.096 (0.39) ***	-	-0.344 (0.63)
Regular evening	0.627 (1.79)	-0.736 (1.76)	-0.915 (2.52)	Regular evening	-9.149 (2.85) ***	-0.543 (1.71)	1.973 (1.53)
Regular Night	0.340 (2.40)	0.040 (1.37)	-0.597 (2.09)	Regular Night	4.940 (2.81) *	2.999 (1.52) **	-2.450 (2.85)
Rotating shift	-1.930 (1.18)	-0.702 (0.82)	-1.615 (1.58)	Rotating shift	-0.586 (1.26)	0.473 (0.93)	-0.613 (1.60)
Split shift	-4.532 (2.89)	3.880 (1.81) **	-1.541 (4.63)	Split shift	1.083 (2.33)	-1.045 (1.75)	-0.0529 (2.69)
On call	-0.261 (1.33)	-0.755 (1.25)	0.293 (2.44)	On call	-1.955 (1.87)	0.503 (1.63)	-1.111 (2.36)
Irregular	-1.555 (0.76) **	0.080 (0.67)	-0.480 (1.26)	Irregular	-1.432 (1.10)	-0.353 (0.73)	-0.807 (1.23)
Long-run responses				**Long-run responses**			
Linear DPD (3)				**Linear DPD (3)**			
	Overemployed	Matched	Underemployed		Overemployed	Matched	Underemployed
Regular day	-1.255 (0.37) ***	-	0.425 (0.66)	Regular day	-1.219 (0.44) ***	-	-0.382 (0.70)
Regular evening	0.693 (1.98)	-0.814 (1.95)	-1.012 (2.79)	Regular evening	-10.173 (3.17) ***	-0.603 (1.90)	2.194 (1.71)
Regular Night	0.376 (2.65)	0.045 (1.52)	-0.661 (2.31)	Regular Night	5.493 (3.13) *	3.335 (1.69) **	-2.724 (3.18)
Rotating shift	-2.135 (1.31)	-0.776 (0.91)	-1.786 (1.74)	Rotating shift	-0.653 (1.40)	0.525 (1.03)	-0.682 (1.78)
Split shift	-5.012 (3.20)	4.291 (2.01) **	-1.704 (5.12)	Split shift	1.205 (2.60)	-1.162 (1.94)	-0.059 (2.99)
On call	-0.289 (1.47)	-0.835 (1.39)	0.324 (2.71)	On call	-2.174 (2.08)	0.559 (1.82)	-1.236 (2.62)
Irregular	-1.720 (0.84) **	0.089 (0.74)	-0.531 (1.39)	Irregular	-1.593 (1.22)	-0.393 (0.81)	-0.898 (1.37)

Heteroskedasticity-robust standard errors in parentheses

* p-value<0.10 ** p-value<0.05 *** p-value<0.01

Appendix 2C: Detailed results

Pooled OLS and fixed effects - males

Males

Mental Health	**Pooled OLS**			**Fixed Effects**		
	(1)	(2)	(3)	(1)	(2)	(3)
regular_evening_wk	-5.011 (2.06)**	-4.354 (2.01)**	-3.106 (1.92)	-0.659 (1.13)	-0.724 (1.13)	-0.641 (1.11)
regular_night_wk	-0.208 (1.44)	0.210 (1.48)	0.668 (1.57)	0.524 (1.16)	0.489 (1.16)	0.675 (1.16)
rotating_shift	0.727 (0.75)	0.872 (0.77)	0.278 (0.76)	0.241 (0.61)	0.176 (0.61)	0.297 (0.61)
split_shift	-1.699 (1.67)	-1.535 (1.64)	-1.328 (1.57)	0.276 (1.32)	0.250 (1.31)	0.366 (1.32)
on_call_wk	1.644 (1.40)	1.769 (1.41)	1.785 (1.31)	-0.545 (0.74)	-0.539 (0.74)	-0.450 (0.73)
irregular_wk	0.090 (0.67)	0.010 (0.68)	0.294 (0.65)	-0.039 (0.46)	-0.046 (0.46)	0.083 (0.46)
over_employed	-2.291 (0.37)***	-2.486 (0.37)***	-2.732 (0.36)***	-1.168 (0.26)***	-1.157 (0.26)***	-1.119 (0.27)***
under_employed	-4.281 (0.68)***	-3.850 (0.67)***	-2.567 (0.64)***	-0.548 (0.45)	-0.570 (0.45)	-0.488 (0.45)
reg_evening_over	1.792 (2.96)	1.810 (2.94)	1.601 (2.75)	0.360 (1.79)	0.400 (1.78)	0.438 (1.75)
reg_evening_under	5.267 (3.16)*	4.834 (3.13)	3.208 (2.82)	1.311 (1.98)	1.437 (1.99)	0.928 (1.90)
reg_night_over	-2.981 (3.06)	-2.947 (3.04)	-2.037 (3.09)	-0.937 (1.83)	-1.001 (1.82)	-1.451 (1.88)
reg_night_under	-1.432 (2.87)	-1.741 (2.88)	-1.068 (2.81)	-1.978 (2.38)	-2.027 (2.40)	-2.024 (2.39)
rot_shift_over	-1.632 (1.26)	-1.414 (1.27)	-0.804 (1.18)	0.360 (0.85)	0.385 (0.85)	0.416 (0.85)
rot_shift_under	2.412 (1.73)	2.001 (1.70)	1.871 (1.62)	-0.280 (1.22)	-0.335 (1.23)	-0.439 (1.22)
split_shift_over	1.627 (3.10)	1.630 (3.09)	1.797 (3.02)	-1.887 (2.09)	-1.905 (2.09)	-2.062 (2.06)
split_shift_under	-6.739 (6.42)	-5.925 (6.30)	-2.174 (5.74)	-4.539 (4.59)	-4.607 (4.59)	-4.402 (4.53)
on_call_over	-2.771 (1.91)	-2.910 (1.92)	-2.779 (1.81)	0.347 (1.10)	0.336 (1.10)	0.263 (1.09)
on_call_under	-3.574 (2.72)	-3.499 (2.71)	-3.354 (2.65)	0.512 (1.75)	0.542 (1.75)	0.870 (1.74)
irregular_over	-1.767 (0.93)*	-1.701 (0.93)*	-1.369 (0.89)	-0.748 (0.65)	-0.759 (0.65)	-0.822 (0.65)
irregular_under	-0.707 (1.53)	-0.875 (1.52)	-1.376 (1.47)	-0.775 (1.15)	-0.759 (1.15)	-0.848 (1.11)
unemployed	-10.198 (1.53)***	-11.002 (1.57)***	-7.560 (1.66)***	-3.206 (0.91)***	-3.021 (0.96)***	-2.974 (1.13)***
nilf	-9.154 (1.47)***	-9.958 (1.52)***	-5.917 (1.49)***	-3.198 (0.84)***	-3.011 (0.87)***	-3.212 (1.03)***
professionals		-0.675 (0.55)	-0.528 (0.55)		-0.161 (0.41)	-0.256 (0.41)
tech_trade_wk		-0.517 (0.56)	0.007 (0.56)		0.403 (0.47)	0.296 (0.47)
community_wk		-0.296 (1.05)	0.666 (0.98)		1.101 (0.99)	0.996 (0.97)
clerical_admin_wk		-0.799 (0.70)	-0.247 (0.69)		0.274 (0.45)	0.178 (0.44)
sales_wk		-0.830 (0.91)	-0.227 (0.87)		0.370 (0.67)	0.193 (0.67)
machinery_wk		-1.711 (0.75)**	-1.336 (0.73)*		-0.027 (0.61)	-0.327 (0.61)
labourers		-2.807 (0.78)***	-1.555 (0.74)**		0.285 (0.59)	-0.015 (0.58)
age_25to34			-0.263 (0.53)			-0.434 (0.47)
age_50to64			3.166 (0.51)***			-0.289 (0.47)
hhpers			-0.363 (0.22)			-0.717 (0.19)***
aboriginal_torres			-1.550 (2.69)			-
overseasborn_english			-0.614 (0.66)			-
overseasborn_other			-1.175 (0.71)*			-
arrived_less_than_10yrs			1.391 (1.86)			-

Detailed results: pooled OLS and fixed effects - males

Males

Mental Health	**Pooled OLS**			**Fixed Effects**		
	(1)	(2)	(3)	(1)	(2)	(3)
children_age_0to4			1.199 (0.49)**			1.244 (0.40)***
children_age_5to14			-0.544 (0.49)			-0.180 (0.37)
children_age_15to24			-0.461 (0.48)			-0.055 (0.34)
separated			-6.515 (1.25)***			-4.965 (0.88)***
divorced			-2.778 (1.03)***			-2.759 (0.96)***
widowed			-3.117 (4.76)			-7.513 (2.80)***
never_married			-3.660 (0.76)***			-3.175 (0.79)***
university			-0.487 (0.72)			0.189 (1.46)
tertiary			0.380 (0.62)			0.032 (1.17)
year12			0.587 (0.86)			1.900 (1.71)
hlth_cond			-3.966 (0.54)***			-0.908 (0.36)**
limit_hlth_cond			-5.792 (0.83)***			-2.231 (0.54)***
lnincome			0.894 (0.34)***			0.168 (0.26)
homeowner			1.732 (0.52)***			0.176 (0.41)
hours_worked			0.005 (0.02)			-0.001 (0.01)
tenure_curr_occupation			0.014 (0.02)			-0.011 (0.01)
tenure_curr_employer			0.010 (0.03)			-0.038 (0.02)**
more1job			0.812 (0.57)			0.656 (0.46)
employer			0.304 (0.75)			0.760 (0.65)
own_acct_wk			0.287 (0.61)			0.625 (0.48)
contr_family_mbr			-3.347 (3.33)			-2.537 (2.41)
casual			-0.584 (0.63)			0.515 (0.45)
Time dummies	No	No	Yes	No	No	Yes
State and section of state dummies	No	No	Yes	No	No	Yes
_cons	78.148 (0.28)***	78.952 (0.43)***	68.401 (3.86)***	77.064 (0.13)***	76.906 (0.29)***	76.022 (3.12)***
N	19067	19067	19067	19067	19067	19067
R-squared	0.025	0.027	0.095	0.005	0.005	0.019
Adjusted R-squared	0.024	0.025	0.092	0.004	0.004	0.015
Root MSE	15.33	15.31	14.78	-	-	-

Heteroskedasticity-robust and clustered standard errors in parentheses

* p-value<0.10 ** p-value<0.05 *** p-value<0.01

Detailed results: pooled OLS and fixed effects - females

Females

Mental Health	**Pooled OLS**			**Fixed Effects**		
	(1)	(2)	(3)	(1)	(2)	(3)
regular_evening_wk	-1.021 (1.52)	-0.538 (1.50)	0.067 (1.45)	0.743 (1.10)	0.643 (1.10)	0.610 (1.09)
regular_night_wk	1.774 (1.77)	2.060 (1.78)	2.020 (1.69)	1.470 (1.09)	1.241 (1.09)	1.335 (1.10)
rotating_shift	-1.831 (0.94)*	-1.706 (0.95)*	-1.287 (0.90)	0.419 (0.68)	0.392 (0.67)	0.337 (0.67)
split_shift	-0.226 (1.81)	0.647 (1.80)	0.580 (1.77)	0.870 (1.42)	0.775 (1.41)	0.737 (1.41)
on_call_wk	-0.583 (1.44)	-0.519 (1.44)	-0.055 (1.38)	0.856 (1.01)	0.832 (1.01)	0.789 (1.03)
irregular_wk	0.034 (0.68)	-0.008 (0.68)	0.160 (0.70)	-0.268 (0.50)	-0.256 (0.50)	-0.244 (0.50)
over_employed	-2.329 (0.41)***	-2.608 (0.41)***	-2.877 (0.41)***	-0.927 (0.28)***	-0.922 (0.28)***	-1.020 (0.30)***
under_employed	-4.594 (0.71)***	-4.149 (0.71)***	-2.329 (0.68)***	-0.903 (0.44)**	-0.967 (0.44)**	-0.640 (0.45)
reg_evening_over	-4.636 (2.60)*	-4.091 (2.54)	-3.609 (2.59)	-1.972 (2.18)	-1.941 (2.17)	-1.462 (2.10)
reg_evening_under	5.814 (2.61)**	5.648 (2.59)**	5.740 (2.60)**	1.163 (1.88)	1.086 (1.88)	1.334 (1.89)
reg_night_over	-0.642 (3.22)	-0.292 (3.22)	-0.556 (3.25)	0.635 (2.06)	0.734 (2.06)	0.702 (2.10)
reg_night_under	-2.740 (3.36)	-2.884 (3.31)	-2.668 (3.37)	-0.611 (1.85)	-0.653 (1.87)	-0.583 (1.86)
rot_shift_over	1.071 (1.41)	1.212 (1.40)	1.176 (1.35)	0.686 (1.07)	0.708 (1.07)	0.979 (1.06)
rot_shift_under	2.152 (1.91)	1.967 (1.91)	1.536 (1.80)	0.205 (1.22)	0.312 (1.22)	0.325 (1.22)
split_shift_over	4.231 (2.55)*	4.199 (2.52)*	5.193 (2.58)**	2.229 (1.66)	2.298 (1.65)	2.616 (1.71)
split_shift_under	-2.545 (3.90)	-2.800 (3.87)	-2.848 (3.78)	0.337 (2.21)	0.492 (2.20)	0.142 (2.20)
on_call_over	-2.713 (2.48)	-2.899 (2.46)	-2.467 (2.26)	-1.015 (1.69)	-1.013 (1.69)	-1.159 (1.69)
on_call_under	1.515 (2.68)	1.414 (2.66)	1.159 (2.58)	0.400 (1.88)	0.378 (1.88)	0.245 (1.89)
irregular_over	0.651 (1.22)	0.613 (1.23)	1.319 (1.14)	0.326 (0.85)	0.302 (0.85)	0.100 (0.84)
irregular_under	-2.873 (1.49)*	-3.007 (1.49)**	-2.377 (1.49)	-1.134 (1.11)	-1.085 (1.11)	-1.094 (1.09)
unemployed	-11.972 (1.83)***	-13.152 (1.90)***	-7.794 (1.88)***	-3.609 (1.29)***	-3.393 (1.35)**	-2.574 (1.42)*
nilf	-4.135 (0.77)***	-5.314 (0.93)***	-2.154 (1.06)**	-1.231 (0.48)**	-0.990 (0.61)	-0.496 (0.78)
professionals		-0.385 (0.68)	0.018 (0.66)		0.547 (0.54)	0.756 (0.55)
tech_trade_wk		-3.585 (1.19)***	-2.826 (1.16)**		0.218 (0.92)	0.370 (0.91)
community_wk		-2.130 (0.86)**	-1.335 (0.83)		0.308 (0.68)	0.401 (0.68)
clerical_admin_wk		-1.161 (0.71)	-0.975 (0.67)		-0.419 (0.52)	-0.270 (0.52)
sales_wk		-1.870 (0.94)**	-0.942 (0.88)		0.013 (0.72)	0.030 (0.71)
machinery_wk		-2.109 (1.65)	-1.074 (1.54)		0.117 (1.56)	0.067 (1.48)
labourers		-2.793 (1.07)***	-2.440 (1.05)**		1.571 (0.78)**	1.558 (0.78)**
age_25to34			-0.084 (0.57)			0.688 (0.51)
age_50to64			1.519 (0.57)***			-0.325 (0.48)
hhpers			-0.493 (0.25)**			-0.399 (0.23)*
aboriginal_torres			-5.831 (2.81)**			-
overseasborn_english			1.423 (0.77)*			-
overseasborn_other			-0.928 (0.78)			-
arrived_less_than_10yrs			0.579 (1.81)			-

Detailed results: pooled OLS and fixed effects - females

Females

Mental Health	**Pooled OLS**			**Fixed Effects**		
	(1)	(2)	(3)	(1)	(2)	(3)
children_age_0to4			1.039 (0.59)*			1.306 (0.45)***
children_age_5to14			-0.461 (0.58)			0.803 (0.45)*
children_age_15to24			-0.242 (0.49)			-0.340 (0.34)
separated			-4.149 (1.11)***			-3.661 (1.03)***
divorced			-1.275 (0.88)			-0.123 (0.95)
widowed			-0.448 (1.92)			-1.714 (2.46)
never_married			-2.320 (0.90)***			-0.864 (0.90)
university			-1.136 (0.70)			-1.209 (3.04)
tertiary			-1.487 (0.64)**			-1.064 (1.30)
year12			-0.318 (0.81)			0.374 (2.07)
hlth_cond			-4.390 (0.64)***			-1.370 (0.45)***
limit_hlth_cond			-6.274 (0.92)***			-2.577 (0.63)***
lnincome			1.415 (0.40)***			0.498 (0.28)*
homeowner			1.366 (0.58)**			0.017 (0.48)
hours_worked			0.012 (0.02)			0.025 (0.01)*
tenure_curr_occupation			0.022 (0.03)			-0.023 (0.02)
tenure_curr_employer			0.112 (0.03)***			-0.047 (0.03)*
more1job			2.053 (0.57)***			0.357 (0.42)
employer			0.309 (1.08)			1.520 (1.02)
own_acct_wk			-0.877 (0.91)			1.077 (0.66)
contr_family_mbr			0.507 (1.69)			0.408 (1.30)
casual			-0.510 (0.56)			0.498 (0.40)
Time dummies	No	No	Yes	No	No	Yes
State and section of state dummies	No	No	Yes	No	No	Yes
_cons	76.601 (0.30)***	77.781 (0.61)***	61.554 (4.45)***	75.267 (0.14)***	75.062 (0.41)***	70.163 (3.55)***
N	17607	17607	17607	17607	17607	17607
R-squared	0.018	0.020	0.094	0.003	0.004	0.017
Adjusted R-squared	0.016	0.019	0.090	0.002	0.002	0.013
Root MSE	16.18	16.16	15.56	-	-	-

Heteroskedasticity-robust and clustered standard errors in parentheses

* p-value<0.10 ** p-value<0.05 *** p-value<0.01

Detailed results: linear DPD - males

Males

Linear Dynamic Panel Data				
Mental Health	**Base specification**		**Endogeneity specified**	
	one-step	two-step	one-step	two-step
L.mental_hlth	0.096 (0.02)***	0.083 (0.02)***	0.097 (0.02)***	0.081 (0.02)***
regular_evening_wk	-0.736 (1.76)	-1.092 (1.74)	-0.774 (1.76)	-1.216 (1.77)
regular_night_wk	0.040 (1.37)	0.103 (1.36)	0.201 (1.37)	0.596 (1.33)
rotating_shift	-0.702 (0.82)	-0.741 (0.82)	-0.653 (0.82)	-0.500 (0.82)
split_shift	3.880 (1.81)**	3.615 (1.80)**	3.922 (1.81)**	3.807 (1.73)**
on_call_wk	-0.755 (1.25)	-0.518 (1.21)	-0.787 (1.25)	0.141 (1.19)
irregular_wk	0.080 (0.67)	0.059 (0.67)	0.038 (0.67)	-0.094 (0.67)
over_employed	-1.135 (0.33)***	-1.048 (0.33)***	-1.305 (0.33)***	-1.184 (0.33)***
under_employed	0.385 (0.60)	0.275 (0.60)	0.408 (0.60)	0.331 (0.59)
reg_evening_over	2.498 (1.90)	2.552 (1.86)	2.684 (1.91)	2.814 (1.93)
reg_evening_under	-0.564 (2.83)	-0.507 (2.89)	-0.483 (2.83)	0.019 (2.86)
reg_night_over	1.435 (2.18)	0.783 (2.15)	1.441 (2.17)	1.933 (2.04)
reg_night_under	-1.022 (2.21)	-1.078 (2.22)	-0.887 (2.23)	-1.439 (2.20)
rot_shift_over	-0.093 (1.15)	-0.356 (1.14)	-0.116 (1.15)	0.028 (1.16)
rot_shift_under	-1.298 (1.67)	-1.406 (1.70)	-1.268 (1.67)	-0.870 (1.75)
split_shift_over	-7.277 (3.14)**	-6.400 (3.08)**	-7.357 (3.14)**	-6.402 (2.96)**
split_shift_under	-5.806 (4.53)	-6.273 (3.95)	-6.149 (4.57)	-6.403 (4.80)
on_call_over	1.629 (1.64)	1.484 (1.59)	1.669 (1.64)	0.757 (1.52)
on_call_under	0.663 (2.63)	0.354 (2.54)	0.769 (2.62)	0.424 (2.51)
irregular_over	-0.500 (0.87)	-0.507 (0.87)	-0.470 (0.87)	-0.176 (0.88)
irregular_under	-0.945 (1.44)	-0.641 (1.45)	-0.906 (1.44)	-0.774 (1.46)
unemployed	-2.585 (1.54)*	-2.495 (1.54)	-2.514 (1.54)	-2.258 (1.54)
nilf	-2.310 (1.33)*	-1.977 (1.33)	-2.282 (1.33)*	-2.186 (1.29)*
professionals	-0.508 (0.52)	-0.417 (0.52)	-0.506 (0.52)	-0.577 (0.52)
tech_trade_wk	0.634 (0.62)	0.634 (0.62)	0.628 (0.62)	0.783 (0.63)
community_wk	-0.674 (1.13)	-0.372 (1.14)	-0.716 (1.13)	0.169 (1.13)
clerical_admin_wk	-0.312 (0.55)	-0.212 (0.55)	-0.351 (0.55)	-0.333 (0.55)
sales_wk	-0.716 (0.85)	-0.745 (0.86)	-0.725 (0.86)	-0.766 (0.88)
machinery_wk	-0.855 (0.86)	-0.541 (0.85)	-0.860 (0.86)	-0.737 (0.85)
labourers	1.085 (0.77)	1.076 (0.78)	1.055 (0.77)	0.984 (0.79)
age_25to34	-1.694 (0.79)**	-1.670 (0.78)**	-1.727 (0.78)**	-1.771 (0.77)**
age_50to64	0.229 (0.72)	0.099 (0.71)	0.310 (0.72)	0.119 (0.71)
hhpers	-0.146 (0.32)	-0.209 (0.33)	-0.133 (0.32)	-0.152 (0.33)
children_age_0to4	0.099 (0.65)	0.123 (0.66)	0.081 (0.65)	0.015 (0.65)
children_age_5to14	-0.394 (0.58)	-0.280 (0.59)	-0.322 (0.58)	-0.176 (0.58)
children_age_15to24	-0.475 (0.50)	-0.411 (0.50)	-0.421 (0.50)	-0.446 (0.51)

Detailed results: linear DPD - males

Males

Linear Dynamic Panel Data				
Mental Health	**Base specification**		**Endogeneity specified**	
	one-step	two-step	one-step	two-step
separated	-3.927 (1.46)***	-3.836 (1.50)**	-3.893 (1.46)***	-3.510 (1.48)**
divorced	-4.107 (1.66)**	-4.048 (1.72)**	-3.946 (1.66)**	-3.596 (1.73)**
widowed	-1.046 (2.55)	-0.522 (2.51)	-0.813 (2.55)	-0.429 (2.56)
never_married	-0.814 (1.39)	-1.236 (1.40)	-0.680 (1.39)	-0.954 (1.39)
university	-0.441 (3.09)	-0.158 (3.17)	-0.563 (3.08)	-0.588 (3.25)
tertiary	1.464 (1.78)	1.844 (1.79)	1.533 (1.79)	1.701 (1.84)
year12	0.005 (2.50)	0.223 (2.61)	-0.046 (2.51)	0.171 (2.64)
hlth_cond	-0.613 (0.43)	-0.716 (0.44)	-0.524 (0.42)	-0.392 (0.41)
limit_hlth_cond	-1.917 (0.64)***	-1.941 (0.65)***	-1.913 (0.62)***	-1.767 (0.62)***
lnincome	-0.129 (0.30)	-0.081 (0.31)	-0.108 (0.30)	-0.019 (0.31)
homeowner	0.576 (0.66)	0.522 (0.67)	0.587 (0.66)	0.415 (0.68)
hours_worked	0.019 (0.02)	0.021 (0.02)	0.020 (0.02)	0.015 (0.02)
tenure_curr_occupation	-0.013 (0.02)	-0.017 (0.02)	-0.012 (0.02)	-0.013 (0.02)
tenure_curr_employer	-0.064 (0.02)***	-0.056 (0.02)**	-0.062 (0.02)**	-0.060 (0.02)**
more1job	1.286 (0.61)**	1.145 (0.60)*	1.365 (0.61)**	1.175 (0.59)**
employer	0.391 (0.90)	0.822 (0.90)	0.414 (0.90)	0.634 (0.88)
own_acct_wk	0.754 (0.65)	0.718 (0.64)	0.779 (0.65)	0.748 (0.64)
contr_family_mbr	0.850 (3.56)	0.184 (3.82)	0.848 (3.55)	0.251 (3.65)
casual	0.356 (0.64)	0.453 (0.64)	0.393 (0.64)	0.507 (0.65)
Time dummies	Yes	Yes	Yes	Yes
State and section of state dummies	Yes	Yes	Yes	Yes
_cons	69.209 (4.43)***	69.832 (4.52)***	68.747 (4.42)***	70.006 (4.46)***
N (no. of groups)	11860 (2553)	11860 (2553)	11860 (2553)	11860 (2553)
No. of instruments	92	92	155	155
Wald Chi2	152.68	137.57	159.16	136.56
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.37	0.54	0.35	0.60
Sargan test	0.01	0.19	0.10	0.65

Heteroskedasticity-robust standard errors in parentheses

* p-value<0.10 ** p-value<0.05 *** p-value<0.01

p-values reported for serial correlation and Sargan tests

One-step and two-step estimates reported

Endogeneity refers to *over_employed, hlth_cond, limit_hlth_cond* instrumented along *L.mental_hlth*

Detailed results: linear DPD - females

Females

Linear Dynamic Panel Data				
Mental Health	**Base specification**		**Endogeneity specified**	
	one-step	two-step	one-step	two-step
L.mental_hlth	0.101 (0.02)***	0.103 (0.02)***	0.096 (0.02)***	0.093 (0.02)***
regular_evening_wk	-0.543 (1.71)	-0.225 (1.73)	-0.604 (1.70)	-0.583 (1.76)
regular_night_wk	2.999 (1.52)**	3.272 (1.54)**	3.047 (1.51)**	2.653 (1.56)*
rotating_shift	0.473 (0.93)	0.782 (0.93)	0.523 (0.92)	0.574 (0.93)
split_shift	-1.045 (1.75)	-0.683 (1.75)	-1.007 (1.74)	-0.641 (1.67)
on_call_wk	0.503 (1.63)	0.939 (1.63)	0.577 (1.62)	1.181 (1.57)
irregular_wk	-0.353 (0.73)	-0.202 (0.73)	-0.340 (0.72)	-0.123 (0.72)
over_employed	-1.096 (0.39)***	-0.987 (0.39)**	-1.066 (0.38)***	-1.090 (0.38)***
under_employed	-0.344 (0.63)	-0.373 (0.63)	-0.355 (0.63)	-0.514 (0.61)
reg_evening_over	-7.510 (2.44)***	-7.790 (2.50)***	-7.412 (2.44)***	-7.091 (2.54)***
reg_evening_under	2.860 (1.95)	2.786 (1.97)	3.013 (1.94)	3.353 (1.98)*
reg_night_over	3.037 (3.03)	2.881 (3.16)	2.832 (3.02)	3.406 (3.25)
reg_night_under	-5.105 (2.83)*	-5.172 (2.86)*	-5.106 (2.83)*	-5.325 (3.07)*
rot_shift_over	0.037 (1.30)	-0.146 (1.31)	-0.017 (1.29)	0.119 (1.31)
rot_shift_under	-0.742 (1.89)	-0.537 (1.91)	-0.782 (1.88)	0.059 (1.91)
split_shift_over	3.224 (2.64)	2.835 (2.70)	3.255 (2.63)	2.717 (2.50)
split_shift_under	1.336 (2.98)	0.557 (2.92)	1.231 (2.97)	0.725 (2.72)
on_call_over	-1.362 (2.52)	-1.719 (2.50)	-1.412 (2.51)	-1.610 (2.46)
on_call_under	-1.270 (2.78)	-1.426 (2.86)	-1.393 (2.77)	-1.887 (2.76)
irregular_over	0.017 (1.20)	-0.129 (1.20)	0.045 (1.20)	0.028 (1.18)
irregular_under	-0.110 (1.48)	-0.173 (1.49)	-0.135 (1.48)	-0.382 (1.51)
unemployed	-1.249 (1.86)	-0.289 (1.86)	-1.187 (1.85)	-0.184 (1.83)
nilf	0.510 (1.11)	0.684 (1.12)	0.515 (1.10)	0.936 (1.09)
professionals	1.861 (0.71)***	1.689 (0.71)**	1.861 (0.71)***	1.939 (0.71)***
tech_trade_wk	0.903 (1.26)	1.153 (1.25)	0.883 (1.25)	1.108 (1.26)
community_wk	0.937 (0.90)	0.900 (0.91)	0.896 (0.90)	0.892 (0.91)
clerical_admin_wk	-0.019 (0.71)	0.258 (0.71)	-0.009 (0.71)	0.407 (0.70)
sales_wk	0.261 (1.04)	0.589 (1.05)	0.174 (1.04)	0.590 (1.06)
machinery_wk	1.160 (2.18)	1.439 (2.15)	1.184 (2.17)	1.187 (2.05)
labourers	1.329 (1.00)	1.612 (1.00)	1.278 (1.00)	1.818 (0.99)*
age_25to34	0.601 (0.83)	0.685 (0.82)	0.549 (0.82)	0.690 (0.83)
age_50to64	-0.689 (0.76)	-0.701 (0.75)	-0.698 (0.76)	-0.699 (0.73)
hhpers	-0.380 (0.33)	-0.434 (0.33)	-0.405 (0.33)	-0.341 (0.32)
children_age_0to4	0.288 (0.78)	0.271 (0.79)	0.279 (0.77)	0.293 (0.78)
children_age_5to14	1.897 (0.68)***	1.819 (0.69)***	1.910 (0.68)***	1.981 (0.69)***
children_age_15to24	0.830 (0.54)	0.702 (0.54)	0.850 (0.53)	0.716 (0.53)

Detailed results: linear DPD - females

Females

Linear Dynamic Panel Data				
Mental Health	**Base specification**		**Endogeneity specified**	
	one-step	two-step	one-step	two-step
separated	-6.014 (1.46)***	-5.811 (1.45)***	-5.991 (1.46)***	-5.356 (1.49)***
divorced	-0.370 (1.33)	-0.422 (1.33)	-0.367 (1.33)	-0.915 (1.29)
widowed	1.016 (3.10)	0.266 (2.97)	0.959 (3.06)	-0.654 (2.74)
never_married	-0.609 (1.37)	-0.742 (1.37)	-0.635 (1.36)	-0.964 (1.38)
university	2.795 (3.90)	1.205 (3.98)	2.982 (3.88)	1.376 (3.99)
tertiary	1.611 (1.65)	1.722 (1.67)	1.644 (1.66)	1.496 (1.75)
year12	4.920 (2.65)*	4.367 (2.67)	4.696 (2.65)*	4.182 (2.78)
hlth_cond	-0.704 (0.58)	-0.782 (0.58)	-0.742 (0.56)	-0.592 (0.56)
limit_hlth_cond	-2.297 (0.81)***	-2.202 (0.81)***	-2.283 (0.79)***	-2.107 (0.79)***
lnincome	-0.051 (0.38)	-0.182 (0.37)	-0.026 (0.38)	-0.320 (0.37)
homeowner	-0.411 (0.72)	-0.315 (0.72)	-0.379 (0.71)	-0.457 (0.72)
hours_worked	0.041 (0.02)*	0.044 (0.02)**	0.042 (0.02)*	0.046 (0.02)**
tenure_curr_occupation	-0.025 (0.02)	-0.017 (0.02)	-0.026 (0.02)	-0.024 (0.02)
tenure_curr_employer	-0.040 (0.04)	-0.028 (0.04)	-0.040 (0.04)	-0.030 (0.04)
more1job	-0.175 (0.59)	-0.061 (0.58)	-0.179 (0.58)	-0.125 (0.58)
employer	3.219 (1.39)**	2.902 (1.42)**	3.147 (1.38)**	2.907 (1.41)**
own_acct_wk	0.333 (0.91)	-0.030 (0.91)	0.270 (0.91)	0.039 (0.92)
contr_family_mbr	2.450 (1.69)	2.243 (1.66)	2.326 (1.69)	2.273 (1.67)
casual	0.998 (0.63)	0.885 (0.63)	0.938 (0.63)	0.878 (0.63)
Time dummies	Yes	Yes	Yes	Yes
State and section of state dummies	Yes	Yes	Yes	Yes
_cons	65.123 (4.91)***	66.539 (4.90)***	65.361 (4.89)***	68.281 (4.80)***
N (no. of groups)	11190 (2348)	11190 (2348)	11190 (2348)	11190 (2348)
No. of instruments	92	92	155	155
Wald Chi2	197.36	185.59	195.59	173.15
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.05	0.05	0.06	0.10
Sargan test	0.04	0.24	0.34	0.60

Heteroskedasticity-robust standard errors in parentheses

* p-value<0.10 ** p-value<0.05 *** p-value<0.01

p-values reported for serial correlation and Sargan tests

One-step and two-step estimates reported

Endogeneity refers to *over_employed, hlth_cond, limit_hlth_cond* instrumented along *L.mental_hlth*

Appendix 2D: Tests of joint statistical significance

Pooled OLS and fixed effects - males

Males						
	Pooled OLS			Fixed Effects		
F-tests	(1)	(2)	(3)	(1)	(2)	(3)
Non-standard work	1.63	1.50	0.99	0.26	0.25	0.29
Working hours' mismatch	34.88 ***	34.89 ***	34.20 ***	10.25 ***	10.09 ***	9.13 ***
Interaction terms	1.28	1.15	0.86	0.45	0.47	0.51
All focus variables	6.31 ***	6.30 ***	5.75 ***	2.13 ***	2.11 ***	2.03 ***
F-statistics reported						
Statistical significance * p<0.10 ** p<0.05 *** p<0.01						

Pooled OLS and fixed effects - females

Females						
	Pooled OLS			Fixed Effects		
F-tests	(1)	(2)	(3)	(1)	(2)	(3)
Non-standard work	0.98	0.93	0.69	0.59	0.48	0.47
Working hours' mismatch	33.63 ***	33.30 ***	29.68 ***	6.73 ***	6.94 ***	6.69 ***
Interaction terms	1.97 **	1.96 **	1.90 **	0.51	0.51	0.57
All focus variables	5.73 ***	5.69 ***	4.78 ***	1.58 **	1.54 *	1.52 *
F-statistics reported						
Statistical significance * p<0.10 ** p<0.05 *** p<0.01						

Linear DPD

	Males			Females		
	Linear DPD					
Wald tests	(1)	(2)	(3)	(1)	(2)	(3)
Non-standard work	6.76	7.18	7.08	5.99	5.58	6.56
Working hours' mismatch	10.46 ***	10.22 ***	12.24 ***	6.35 **	6.78 **	8.03 **
Interaction terms	12.93	12.94	12.30	21.57 **	22.04 **	20.87 **
All focus variables	29.32 *	29.24 *	30.68 *	40.07 ***	40.27 ***	42.38 ***
Chi-squared statistics reported						
Statistical significance * p<0.10 ** p<0.05 *** p<0.01						

Appendix 2E: Sargan tests of overidentifying restrictions

Specification (3) only

Comparison between base tests and tests with endogenous variables

Males				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, under_employed	Yes over_employed, under_employed
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.37	0.54	0.39	0.58
Sargan test	0.01	0.19	0.02	0.07
Females				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, under_employed	Yes over_employed, under_employed
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.05	0.05	0.06	0.06
Sargan test	0.04	0.24	0.09	0.23

p-values reported

Males				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond, unemployed	Yes over_employed, hlth_cond, limit_hlth_cond, unemployed
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.37	0.54	0.36	0.59
Sargan test	0.01	0.19	0.05	0.60
Females				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond, unemployed	Yes over_employed, hlth_cond, limit_hlth_cond, unemployed
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.05	0.05	0.07	0.09
Sargan test	0.04	0.24	0.34	0.66

p-values reported

Males				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond	Yes over_employed, hlth_cond, limit_hlth_cond
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.37	0.54	0.35	0.60
Sargan test	0.01	0.19	0.10	0.65
Females				
	One-step	Two-step	One-step	Two-step
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond	Yes over_employed, hlth_cond, limit_hlth_cond
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.05	0.05	0.06	0.10
Sargan test	0.04	0.24	0.34	0.60

p-values reported

Comparison between base tests and tests with endogenous variables and restricted number of lags used

Males				
	One-step	Two-step	One-step *	Two-step *
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond	Yes over_employed, hlth_cond, limit_hlth_cond
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.37	0.54	0.29	0.47
Sargan test	0.01	0.19	0.26	0.80
Females				
	One-step	Two-step	One-step *	Two-step *
Endogenous variables specified	No	No	Yes over_employed, hlth_cond, limit_hlth_cond	Yes over_employed, hlth_cond, limit_hlth_cond
Serial correlation test m(1)	0.00	0.00	0.00	0.00
Serial correlation test m(2)	0.05	0.05	0.05	0.07
Sargan test	0.04	0.24	0.26	0.60

p-values reported

* Restricted to 2 lags of the dependent variable to instrument the first-differenced lag of mental health

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