DISCUSSION PAPER SERIES

IZA DP No. 9879

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Melisa Bubonya
Deborah A. Cobb-Clark
Mark Wooden

April 2016

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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Melisa Bubonya
Melbourne Institute, University of Melbourne

Deborah A. Cobb-Clark
University of Sydney, ARC Life Course Centre and IZA

Mark Wooden
Melbourne Institute, University of Melbourne and IZA

Discussion Paper No. 9879
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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 9879
April 2016

ABSTRACT

Mental Health and Productivity at Work: Does What You Do Matter?*

Much of the economic cost of mental illness stems from workers' reduced productivity. We analyze the links between mental health and two alternative workplace productivity measures – absenteeism and presenteeism (i.e., lower productivity while attending work) – explicitly allowing these relationships to be moderated by the nature of the job itself. We find that absence rates are approximately five percent higher among workers who report being in poor mental health. Moreover, job conditions are related to both presenteeism and absenteeism even after accounting for workers' self-reported mental health status. Job conditions are relatively more important in understanding diminished productivity at work if workers are in good rather than poor mental health. The effects of job complexity and stress on absenteeism do not depend on workers' mental health, while job security and control moderate the effect of mental illness on absence days.

JEL Classification: I12, J22, J24

Keywords: mental health, presenteeism, absenteeism, work productivity

Corresponding author:

Deborah A. Cobb-Clark
School of Economics
University of Sydney
Merewether Building, cnr City Road/Butlin Avenue
NSW 2006 Sydney
Australia
E-mail: deborah.cobb-clark@sydney.edu.au

* This paper uses confidentialized unit record file data from the HILDA Survey. The HILDA Survey Project was initiated and is funded by the Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research. The findings and views reported in this paper, however, are those of the authors and should not be attributed to either the DSS or the Melbourne Institute. The authors are grateful for financial support from an Australian Research Council Discovery Grant (DP140102614).

1. Introduction

Mental illness is pervasive and costly. It is estimated that, at any given time, one in five working-age adults has a mental health problem with the lifetime prevalence rate reaching up to 50 percent (OECD 2012). In England the economic cost of mental illness in the 2009-10 financial year has been estimated to equal £105.2 billion (Centre for Mental Health 2010), while in the United States estimates for the period 2001 to 2003 indicate that serious mental illness is associated with an annual loss in earnings totaling $193.2 billion (Kessler et al. 2008). The economic cost includes both the direct (e.g., health care costs, disability payments, and provision of support services) and indirect costs (imposed on care givers, family members, and communities) of mental illness. It also includes the opportunity cost of the output foregone, with the mentally ill not only less likely to participate in the labor market, but also have higher unemployment rates and diminished productivity when they do (e.g., Kessler and Frank 1997; Lim et al. 2000; Marcotte and Wilcox-Gök 2001; OECD 2012; Frijters et al. 2014).

Public policy often focuses on limiting direct health care expenditure, restricting access to disability support, and creating employment incentives as the primary means to contain the escalating costs of mental illness. Yet most individuals with mental disorders are in work (OECD 2012). Consequently, much of the economic cost of mental illness occurs because workers – most of whom do not access social assistance – are simply less productive when they have mental health issues. In the United States, for example, approximately half of the overall cost of depression is attributable to the reduced productivity of workers (Kessler and Frank 1997; NIMH 2000; Marcotte and Wilcox-Gok 2001; Greenberg et al. 2003). Relatedly, work incapacity due to mental health disorders has been reported to account for 5.9 percent of work days lost in Germany and 14 percent of certified sickness absences in the UK (ILO 2000). Not surprisingly, the Organisation for Economic Co-operation and Development

(OECD 2012) has prioritized mental health as a new and pressing labor market challenge. More specifically, there is an urgent need to identify ways that employment policies and employer practices can be redesigned to support the inclusion and productivity of those experiencing mental illness.

Our objective is to analyze the relationship between mental health and two alternative measures of workplace productivity: i) absenteeism; and ii) presenteeism (i.e., diminished performance at work). Absenteeism has long been regarded as an important measure of productivity (see Johns 2010; OECD 2012). Interest in presenteeism, on the other hand, is relatively new and stems from the growing recognition that there are large productivity losses associated with attending work while ill. In fact, the overall productivity loss associated with presenteeism is estimated to be greater than that associated with absenteeism in the case of chronic diseases (Collins et al. 2005) and mental health (Lim et al. 2000; Hemp 2004; Hilton et al. 2008). Joint consideration of both forms of productivity loss is important in light of the conceptual links between them and the potential for employers to raise productivity along either dimension (see Johns 2010).

In contrast to much of the previous literature, we take advantage of large-scale, nationally representative panel data in our analysis. Much of the previous evidence is derived from samples that are not representative of the broader population (often drawn from employers or from patients of health service providers) or restricted to coverage of specific occupation or industry groups. In addition, we exploit standard panel data techniques – fixed effects in the case of presenteeism and correlated random effects in the case of absenteeism – to control for unobserved heterogeneity. The estimation strategy minimizes the potential for reverse causality and omitted variable bias. Thus, we move beyond existing cross-sectional estimates of associations to establish a more causal interpretation of the effects of poor mental health on attendance at work.

We also make an important contribution by explicitly examining the way that the relationship between poor mental health and workplace productivity varies with the nature of the job itself. A small literature suggests that mental health-related productivity loss varies across occupations (see Kessler and Frank 1997; Darr and Johns 2008; Johns 2010). We extend this to consider how absenteeism and presenteeism associated with mental illness varies across four important job dimensions, including the degree of: i) control; ii) security; iii) stress; and iv) complexity. This sheds light on the institutional arrangements that might allow some workers to maintain their productivity in the face of mental health problems.

Finally, there is evidence that women generally experience more internalizing problems, mental health conditions and general health issues than men (see Nolen-Hoeksema 2001; Patton and Johns 2007; Rosenfield and Mouzon 2012) and that women are absent from work more often (Côté and Haccoun 1991; VandenHeuvel and Wooden 1995; Patton and Johns 2007). At the same time, very little is known about gender differences in presenteeism (Johns 2010), or whether men's and women's attendance at work responds to their mental health issues in the same way. Our findings make an important contribution in highlighting that the nature of work influences the extent to which mental illness results in work-related productivity losses and that these patterns are not gender neutral.

We find that absence rates are approximately five percent higher among workers who report being in poor mental health. Moreover, job conditions influence both presenteeism and absenteeism even after accounting for workers' self-reported mental health status. Job conditions are relatively more important in understanding diminished productivity at work if workers are in good rather than poor mental health. The effects of job complexity and stress on absenteeism do not depend on workers' mental health, while job security and control moderate the effect of mental illness on absence days.

In Section 2, we briefly review the vast literature on absenteeism and presenteeism paying particular attention to the role of mental health and job characteristics. Details of our data, estimation sample, and key measures are presented in Section 3, while Section 4 outlines our conceptual framework and estimation strategy. The results of our analysis of the relationship between mental illness and attendance at work are discussed in Section 5, while our conclusions and suggestions for future research are described in Section 6.

2. The Previous Literature

There are well established literatures in both management and economics investigating the causes and consequences of absenteeism (see Johns 1997; Harrison and Martocchio 1998). Absenteeism – defined as the failure to report for scheduled work (Johns 2010) – is costly to employers in terms of lost productivity. It is also associated with other counter-productive behaviors such as lateness, reduced personal productivity and turnover (Johns 2002). In general, the most important determinants of absenteeism (in terms of frequency and duration) are those that influence workplace atmosphere (i.e., working conditions, job content, and workplace relationships) and personal well-being (and more specifically health status), as well as individual characteristics and circumstances (such as age, gender, marital status, education and lifestyle behaviors) (see Beemsterboer et al. 2009). Not surprisingly, people with mental health problems have consistently been found to have relatively high propensities to be absent from work (Duijts et al. 2007; Burton et al. 2008; Darr and Johns 2008; Lerner and Henke 2008).

Presenteeism is a related concept, which has at various times been defined in the literature either as: i) the act of attending work while ill (see Johns 2010); or ii) “decreased on-the-job performance due to the presence of health problems” (Schultz and Edington 2007: 548). The former conceptualizes presenteeism as the inverse of absenteeism – i.e., conditional on being ill, employees must choose between being absent from or present at work. In contrast, the latter focuses on the potential productivity consequences of going to work while ill. Given the important distinction in these alternative definitions, it is not surprising that there is little consensus on the best approach to measuring presenteeism. While some researchers simply measure the amount of time employees attend work while feeling ill (e.g., Aronsson and Gustafsson 2005; Gosselin et al. 2013; Arnold forthcoming), others attempt to measure the associated productivity loss by asking employees directly about any reduced work performance (Stewart et al. 2003), the degree of lost efficiency (Sanderson et al. 2007; Hilton et al. 2008), or any work limitations stemming from going to work while they were sick (Adler et al. 2006). Unfortunately, the lack of consistent measurement makes it difficult to compare results across studies. However, there is evidence that presenteeism is linked to health status, work-related factors, personal circumstances and attitudes (Schultz and Edington 2007; Hansen and Anderson 2008; Johns 2010). Importantly, depression, anxiety and emotional disorders, and overall mental health have been cited as some of the strongest correlates of presenteeism (Collins et al. 2005; Burton et al. 2008; Lerner and Henke 2008).

Researchers are increasingly recognizing that absenteeism and presenteeism result from the same decision process (Kristensen 1991; Aronsson and Gustafsson 2005), and are therefore beginning to model them jointly. Workers who fall ill or experience a personal crisis, for example, must then make a decision to either go to work or to remain at home. Workplace policies and practices that affect one choice will also affect the other. At first glance, it seems intuitive that those factors which limit the opportunity to be absent from work (e.g., attendance policies, teamwork, job insecurity, etc.) will also be associated with greater presenteeism (Theorell et al. 2003; Koopmanschap et al. 2005), a proposition which has been dubbed the "substitution hypothesis" (Caverley et al. 2007). Others, however, have argued that there are potential complementarities in the relationship between absenteeism and presenteeism. Johns (2010), for example, proposes a dynamic framework in which the choice of an ill worker to be absent from or present at work has feedback effects on the severity and longevity of the health event itself. This, in turn, has consequences for subsequent attendance behavior. Workers choosing to go to work when they are ill may relapse, leading to greater, rather than fewer, absences. Similarly, Arnold and de Pinto (2015) also allow health status to be endogenous. In their model, workers are more likely to view the health shocks they experience as a sickness if their productivity is relatively low or they have a high disutility from work. Thus, work-related factors that increase absenteeism may also increase presenteeism by altering workers' individual-specific definition of sickness. Consistent with these theoretical perspectives, empirical evidence suggests that, conditional on health status and a degree of work incapacity, presenteeism is not simply an alternative to absenteeism (Leineweber et al. 2012).

The relationship between presenteeism and absenteeism becomes even more complex when we recognize that firms cannot observe workers' disutility from work. They must, therefore, set wage contracts and employment policies to elicit the desired attendance behavior. Chatterji and Tilly (2002), for example, use a principle agent framework to demonstrate that firms have an incentive to pay more than the statutory sick pay to prevent workers from coming to work while they are sick. Similarly, Brown and Sessions (2004) show that firms can strike a balance between presenteeism (attending work while sick) and shirking (staying home while well) by setting appropriate standards for what constitute an authorized absence. Finally, Hirsch et al. (2015) argue that heterogeneity in workers' underlying health status can result in presenteeism and absenteeism co-existing.

These theoretical frameworks provide a starting point for identifying the potential determinants of workers' work attendance. In particular, understanding how work conditions influence employees' decisions to work or not work while sick is fundamental to identifying the work environments that are more susceptible to high rates of absenteeism and presenteeism. Moreover, employers need to be able to manage productivity more effectively in the face of employee health issues. Researchers have relied on various conceptual frameworks of psychosocial job characteristics to gauge which characteristics are likely to be important. For example, Karasek's (1979) job demands-control model suggests job demands, job control and, more recently, social support, can predict job strain and work-related outcomes (Johnson and Hall 1988). In contrast, the effort-reward imbalance model emphasizes the way the rewards from work interact with the need for effort in producing work-related outcomes (Siegrist 1996).

A number of empirical studies have analyzed the relationship between psychosocial job characteristics and absenteeism. High demands (Gimeno et al. 2004; Vahtera et al. 2000), low control (Melchior et al. 2003; Gimeno et al. 2004; Vahtera et al. 2000; Rugulies et al. 2007; Roelen et al. 2009), their interaction (Dwyer and Ganster 1991; Melchior et al. 2003; Gimeno et al. 2004; Vahtera et al. 2000; Virtanen et al. 2007), and lack of social support (Melchior et al. 2003; Vahtera et al. 2000; Eriksen et al. 2007; Roelen et al. 2009) have all been found to be associated with relatively high rates of absence. Recently, factors such as discrimination, physical abuse, job insecurity, work-life imbalance, working-time arrangements, role conflicts and poor psychosocial job quality, have also been linked to absence behavior (D'Souza et al. 2006; Rugulies et al. 2007; Niedhammer et al. 2013; Lesuffleur et al. 2014; Arnold and de Pinto 2015; Milner et al. 2015).

Not surprisingly, the work factors that influence absences are also correlated with presenteeism (see Johns 2010 for review). Workload (Aronsson and Gustafsson 2005; Biron et al. 2006; Deery et al. 2014; Arnold forthcoming), autonomy (Aronsson and Gustafsson 2005; Biron et al. 2006; Leineweber et al. 2011; Arnold forthcoming), social support (Hansen and Andersen 2008; Leineweber et al. 2011; Gosselin et al. 2013; Arnold forthcoming), job insecurity / temporary employment (Biron et al. 2006; Caverley et al. 2007), tenure (Arnold 2015), working-time arrangements (Böckerman and Laukkanen 2010a, 2010b; Arnold and de Pinto 2015) and adjustment latitude (Johansson and Lundberg 2004) have all been linked to presenteeism.

Unfortunately, the existing literature on presenteeism and absenteeism offers little guidance on the role that employment conditions play in shaping the work attendance of employees with mental illness. Most studies are based on very specific populations (clinical, workplace, industry sectors), use cross-sectional or prospective follow-up data, or rely on small samples (see Milner et al. 2015 for a recent exception). As such, findings are largely correlational, not generalizable to general working populations, and may be biased due to the potential for omitted variables and reverse causality. Moreover, there are no studies that explicitly consider the role of job characteristics in moderating the effects of mental illness on both presenteeism and absenteeism despite the conceptual links between the two. D'Souza et al. (2006) provide evidence that the cross-sectional association found between measures of work demands and absence is substantially reduced once mental health is controlled for, suggesting that mental illness may moderate the effect of job stress on absenteeism. However, they do not investigate presenteeism at all, which leaves open many questions about the ways that employment conditions interact with mental illness to produce productivity losses.

We fill this void in the literature by using nationally representative panel data to investigate the interaction between job characteristics and mental well-being on both absenteeism and presenteeism.

3. Data

3.1 Estimation Samples

This analysis uses data from the first 14 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a panel survey that has been collecting data on an annual basis since 2001 from members of a nationally representative sample of Australian households (see Watson and Wooden 2012).

We create separate estimation samples for our two outcomes of interest; namely presenteeism and absenteeism. In the construction of the sample used to analyze presenteeism, we select individuals who are aged between 15 and 64 and employed and working for an employer for wages or salary (i.e., are employees). The estimation sample spans 13 years, covering waves 1 to 13 (years 2001-2013). Observations from wave 14 are also used, but only in the construction of a control for attrition bias. This provides an initial sample comprising 95,646 observations from 18,505 persons. An additional 10.4 percent of observations are dropped due to non-completion of the Self-Completion Questionnaire (SCQ), the instrument from which both the outcome variable and critical explanatory variables (describing mental health and job characteristics) are derived. Finally, after dropping a further 8.6 percent of observations with incomplete data for our control variables, we are left with an estimation sample of 78,305 observations (16,513 persons).

For the absenteeism analysis, in a similar manner to above, we restrict the sample to employees aged between 15 and 64. Information on sick leave days, however, was not collected in waves 1 to 4, and hence this analysis is restricted to observations from waves 5 to 13 (2005-2013). In total, this provides an initial sample of 61,108 observations from 13,571 persons. Again, observations are lost due to SCQ non-completion (10.1%) and missing information on control variables (6.4%), providing a final estimation sample of 51,455 observations from 12,560 persons.[1]

3.2 Productivity and Mental Health Measures

Our indicator of presenteeism is derived from the Short Form (SF-36) Health Survey (see Ware et al. 2000), administered every year in the HILDA Survey as part of the SCQ. More specifically, individuals are asked whether, as a result of any emotional problems, they have experienced any of the following in the past four weeks: "cutting down the amount of time you spent on work or other activities"; "accomplished less than you would like"; and "didn't do work or other activities as carefully as usual". Yes or no responses are recoded. Using these questions we construct a binary indicator taking the value of 1 if a respondent answered "Yes" to any of the questions in that year, and 0 otherwise.[2]

Waghorn and Chant (2006) utilize the same SF-36 questions to quantify respondents' work performance. Moreover, our measure is in line with other short-response indicators of presenteeism that aim to assess reduced work performance and work cutback (Kessler and Frank 1997; Kessler et al. 1999; Stewart et al. 2003). Although more detailed questionnaires regarding presenteeism exist (e.g., the Work Limitations Questionnaire), they are currently only used in small-scale studies due to time and space constraints.

For the analysis of absenteeism the outcome variable is a self-reported measure of the number of paid sick leave days taken in the previous 12 months. The average number of paid sick leave days for men and women are 3.2 and 3.5, respectively. While quite low, these figures were not entirely unexpected given the presence of many casual employees, who do not have paid sick leave entitlements but in return are usually required to be paid a wage premium (approximately 20 percent over the period covered by our data). By international

[1] Variable definitions can be found in Appendix Table A1, while Appendix Tables A2 and A3 provide descriptive statistics for each sample.
[2] Spearman rank correlation coefficients suggest that very little information is gained from using these three presenteeism questions to create either a factor score or a measure that sums the scored responses to each item.

standards, the incidence of casual employment in Australia is relatively high, with different sources suggesting that, over the last decade or so, casual employees have accounted for about one in every five Australian workers (Shomos et al. 2013). Indeed, employees without paid sick leave entitlements represent around 26 percent of all observations in our two samples.

Our indicator of mental health is derived from the Mental Health Inventory (MHI-5), a sub-scale of the SF-36, that has been shown to be an effective screening instrument for persons with mental health problems in large populations (Rumpf et al. 2001; Hoeymans et al. 2004). The MHI-5 comprises five items (scored on a 6-point scale) that assess the frequency of anxiety and mood disturbance symptoms over the 4-week period preceding the interview. Responses on each item are summed and then re-scaled so that scores range from 0 to 100, with lower scores representing poorer mental well-being. For this analysis we create a dichotomous variable that distinguishes persons with poor mental health from others, with those in the bottom quintile of the distribution of MHI-5 scores (a score ≤ 60) classified as having "poor mental health".

Use of a dichotomized variable to separate individuals into high and low risk groups is widespread practice. There is, however, far less agreement about the appropriate threshold. A threshold of 52 is frequently used in the case of MHI-5 (e.g., Holmes 1998; Strand et al. 2003; Bültmann et al. 2004; Vukušić Rukavina et al. 2012), but thresholds as high as 72 have also been adopted (e.g., Hoeymans et al. 2004). In general, choice of a relatively low threshold (such as 52) would be warranted if the focus is on identifying persons with severe depressive symptoms. But given our focus on a sample of employed persons, where average levels of mental health are expected to be superior to that in the general population, we opted for the slightly higher threshold of 60 points. This is supported by Yamazaki et al. (2005)

who conclude, on the basis of their analysis of Japanese population data, that a threshold of 60 identifies those with either severe or moderate depressive symptoms.

The unconditional relationships between mental health status and reduced work productivity in the form of presenteeism and absenteeism are summarized in Tables 1 and 2 respectively. Men in good mental health have a 9.4 percent chance (odds equal to 1 in 10) of reporting presenteeism, while men with poor mental health a 50.3 percent chance (equal odds) of presenteeism (see Table 1). Irrespective of their mental health, women are more likely than men to report experiencing reduced productivity at work. Like men, however, women's odds of experiencing presenteeism are approximately ten times higher if they are in poor mental health (odds equal 1.4 to 1) than if they are not (odds equal to 1.4 in 10).

Approximately 60 percent of men and women report at least one absence day irrespective of their mental health status (see Table 2). However, among these workers, those with poor mental health report having slightly more than one additional absence day on average. Table 2 also shows that: i) the incidence of any absence days is, not surprisingly, substantially higher for those working 230 days or more per year (i.e., full-time, full-year workers); ii) women take more sick leave days than men, but only if they work 230 days or more per year; and iii) those in poor mental health take approximately one more absence day (conditional on any absence) than those in good mental health.

[Tables 1 and 2 about here]

3.3 Measures of Job Characteristics

All employed respondents are also asked to complete a short battery of questions in the SCQ that assess various characteristics of a respondent's current (main) job. Responses are available every wave and are scored on a 7-point Likert scale.[3] Previous research using the HILDA Survey data provides support for a four-factor model, based on the number of factors

[3] The battery used in waves 1 through 4 comprised 12 items. In wave 5 the list of items was expanded to 21. We, however, restrict our analysis to those items available in all survey waves.

with an eigen value exceeding one (Leach et al. 2010). These factors describe: job security; job control; job stress and job complexity. Further, there is evidence that item loadings are time-invariant.

For the presenteeism sample, we use a confirmatory factor analysis on waves 1 to 13 using 11 of the 12 original items and uncover the same underlying latent factors previously identified in Leach et al. (2010).[4] Similarly, for the absenteeism sample, we perform a factor analysis using the 11 items across waves 5 to 13 and obtain very similar results. Factor scores are created for each identified job characteristic, where scores are increasing in the degree of control, security, stress and complexity. These scores are standardized to have a mean of 0 and standard deviation of 1.

3.4 Covariates

Our selection of time-varying covariates is guided by previous research on absenteeism and presenteeism (Böckerman and Laukkanen 2010a, 2010b; Johns 2010; Arnold forthcoming). Specifically, our estimation models include controls for: age (and its square); household composition (the number of children and adults); relationship status; educational attainment; the presence of a long-term health condition and disability other than mental illness (differentiated by the extent to which the condition limits work); physical health (the physical functioning sub-scale of the SF36); smoking status; the log of real annual equivalized household income; and location (the regional unemployment rate, a remoteness indicator, and the SEIFA [Socio-Economic Indexes for Areas] measures of relative advantage versus disadvantage of the areas in which respondents reside). In addition to these standard demographic controls, we also include the following employment-related variables: the proportion of the last 12 months spent in employment; the number of days usually worked in a week; whether respondent works full-time (35 hours or more per week); employment

[4] Following Leach et al. (2010), we omitted the item "I get paid fairly for the things I do on my job", which did not load well on to any factor. The factor loadings are reported in Appendix Table A4.

contract type (whether employed on a permanent, fixed-term, casual, or other basis); length of tenure with the current employer (and its square); firm size (five categories); shift work; union membership; sector (private or public); occupation (eight categories); and industry (19 categories).

Given the conceptual links between presenteeism and absenteeism, we include a very similar set of covariates in the analyses of each. However, covariates in the presenteeism analysis are measured at the time of the current interview, whereas covariates in the absenteeism model are measured at the previous interview (that is, roughly 12 months earlier). Finally, we also include a variable indicating whether the sample member was a non-respondent at the next survey wave. This provides a crude control for the effects of any attrition bias (Verbeek and Nijman 1992).

4. Estimation Strategy

4.1 Conceptual Framework

We are interested in the work-related productivity loss stemming from employees' mental illness; i.e., in work absence (absenteeism) and diminished on-the-job productivity (presenteeism). Given this, we begin with a conceptual framework in which workers who fall ill must make a decision to either go to work or remain at home. This decision is made on the basis of the costs and benefits of the alternative choices in front of them. Thus, the choices that workers make will be shaped in part by workplace policies (e.g., with respect to sick leave entitlements, sick pay, etc.), practices (e.g., required documentation, notification, etc.), and culture (e.g., supportive vs. not). Workers' decisions about attending work will be also influenced by their individual preferences and personal circumstances. On the one hand, a higher disutility of work results in increased absence. On the other hand, workers may also be intrinsically motivated to attend work out of concerns that they risk being perceived as "shirking" or "letting the team down" if they remain at home. For this reason, workers who are unwell may choose to go to work – particularly if they are in vulnerable employment situations – despite being entitled to sick leave.

In the process of making a decision, workers form expectations about both their level of on-the-job productivity in the event they go to work and their firms' productivity losses in the event they do not. Not all mental illness results in on-the-job productivity loss, of course, implying that it is possible that neither absenteeism nor presenteeism will occur. Moreover, workers may be naïve and underestimate the extent to which their mental illness affects their work performance. However, those who do anticipate that their on-the-job productivity is likely to be low – perhaps due to the severity of their illness or the nature of their job – are more likely to remain at home. Those who anticipate that their absence would result in large productivity losses for their employer may be more likely to report for work despite being ill.

This conceptual framework leads us to two important observations. First, the productivity loss associated with mental illness will depend on a vast range of factors including: i) the severity of the illness; ii) workers' leave entitlements; iii) workers' employment vulnerability; iv) workers' disutility of, or intrinsic motivation for, work; v) firm practices; and vi) the nature of the job. Not all of these will be observed in our data. Consequently, they will comprise part of the estimation error.

Second, while clearly related, absenteeism and presenteeism are not merely the opposite sides of the same coin. Like other researchers, we unfortunately do not observe each episode of mental illness experienced nor the corresponding attendance decision made. Instead, we observe self-reported mental health in the four weeks preceding the interview. Our dichotomous measure of the degree of on-the-job productivity loss is observed over the same timeframe, while absences are reported over the preceding 12 months. Consequently, although presenteeism and absenteeism are conceptually related, we will be unable to estimate them simultaneously. Instead, we estimate separate models for each and shed light on the relationship between them by explicitly comparing the effects of those factors common to both.

4.2 Estimation Model: Presenteeism

Given the discrete nature of our presenteeism measure, we analyze the relationship between mental health status, job characteristics and diminished performance at work using a conditional fixed-effects logit model. Specifically, we assume that the underlying propensity of experiencing diminished on-the-job productivity as a result of emotional issues is given by the following:

$$Y_{it}^{*} = f(MH_{it}, JC_{it}, X_{it}, m_i, \varepsilon_{it}) \tag{1}$$

where: Y_{it}^{*} is the continuous latent propensity that individual i experiences presenteeism in period t; MH_{it} is our indicator of poor mental health; JC_{it} is a vector of job characteristics (i.e., control, security, stress and complexity); and X_{it} is a vector of time-varying controls for demographic and human capital characteristics, employment characteristics, income, and local labor market conditions, all of which are likely to influence the costs and benefits of going to work while mentally ill. Finally, m_i captures time-invariant, unobserved individual-specific differences in individuals and ε_{it} is a stochastic error term which we assume is independently, logistically distributed.

We do not observe Y_{it}^{*} directly. Rather, we observe:

$$Y_{it} = \begin{cases} 1 & if\ Y_{it}^{*} > 0 \\ 0 & otherwise \end{cases}. \tag{2}$$

The log-odds of individuals experiencing presenteeism (i.e., that Y_{it}=1) is then given by the following:

$$\log\left(\frac{\Pr(Y_{it} = 1)}{1 - \Pr(Y_{it} = 1)}\right) = \gamma^{MH} MH_{it} + JC_{it}\gamma^{JC} + X_{it}\gamma^{X} + m_i \tag{3}$$

where $\gamma = [\gamma^{MH}, \gamma^{JC}, \gamma^{X}]$ denotes the vector of parameters to be estimated. We account for individual-specific fixed effects (m_i) using conditional maximum likelihood.

There are two parameters of interest. The first (γ^{MH}) captures the effect of self-reported mental health status on the extent to which productivity at work is reduced due to "emotional problems". We expect $\widehat{\gamma^{MH}}$ to be positive. However, given that mental health issues do not always result in self-assessed productivity loss, the strength of this relationship is an empirical question. The second (γ^{JC}) captures the effect of job characteristics on reduced on-the-job productivity, holding constant workers' mental health status.

In addition to this baseline model, we also estimate an extended model in which poor mental health and job characteristics interact to influence the degree of on-the-job productivity loss. Specifically,

$$\log\left(\frac{\Pr(Y_{it}=1)}{1-\Pr(Y_{it}=1)}\right) = \gamma^{MH} MH_{it} + JC_{it}\gamma^{JC} + \gamma^{k}(JC_{it}^{k} \times MH_{it}) + X_{it}\gamma^{X} + m_i \qquad (4)$$

where JC_{it} is the vector of job characteristics (control, security, stress and complexity) as before and JC_{it}^{k} $k = 1 \ldots 4$ is a single element of that vector. Thus, we focus on the interaction of mental health with each job characteristic in isolation which facilitates the interpretation of our results. In particular, γ^{k} captures the disparity in the link between job characteristics and diminished on-the-job productivity among workers who do and do not report a mental health problem.

4.3 *Estimation Model: Absenteeism*

Our measure of absenteeism (A_{it}) – the number of days absent in the past year – is a count variable characterized by overdispersion; i.e., the conditional variance is greater than the conditional mean. Given this, we follow standard practice and estimate a random effects negative binomial model (Hausman et al. 1984; Cameron and Trivedi 2015). Specifically,

$$\Pr(A_{it} = a_{it} | x_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + a_{it})}{\Gamma(\lambda_{it})\Gamma(a_{it}+1)} \left(\frac{1}{1+\delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i}\right)^{a_{it}} \qquad (5)$$

where

$$\lambda_{it} = e^{x_{it}\beta} \tag{6}$$

and δ_i is a time-invariant, individual-specific effect, while x_{it} is a vector of controls (including a constant) measured at the previous interview including self-reported poor mental health status (MH_{it-1}), job characteristics (JC_{it-1}), and the demographic, human capital, and employment conditions (X_{it-1}) previously noted.

As specified, equation (6) implicitly assumes that employees have equal exposure to the risk of absence; however, this is not the case in our sample since employees have different exposures to work (i.e., the number of days worked during the year). We account for differential exposure across employees and time by multiplying the conditional mean of absences (given in equation 6) by annual work days (ξ_{it}) as follows:[5]

$$\xi_{it}\lambda_{it} = \xi_{it}e^{x_{it}\beta}$$

$$\xi_{it}\lambda_{it} = e^{x_{it}\beta+\log(\xi_{it})}. \tag{7}$$

In our model, dispersion (i.e., variance relative to the mean) is equal to $(1+\delta_i)$ which is constant for individual *i*. In effect, the dispersion parameter, δ_i, captures time-invariant, individual-specific unobserved heterogeneity. We account for this by specifying a random effects model in which the individual-specific effects are allowed to depend on the means of all time-varying variables in a Mundlak (1978) fashion in order to increase the likelihood that the conditional independence assumption holds (see Cameron and Trivedi 2015).[6] Our conditionally correlated random effects specification effectively models δ_i as:

[5] The exposure variable is derived by multiplying the number of weeks potentially worked in a year (46 weeks for employees who report receiving paid annual leave and 52 weeks for those that do not) by both the proportion of the previous 12 months in paid employment and the number of usual work days per week. The six week difference reflects 4 weeks of paid annual leave, which all Australian employees covered by industrial awards are entitled to, plus 2 weeks of paid public holidays. The proportion of previous 12 months spent in employment and the usual work days per week variables are thus not included in the vector of employment controls for the analysis of absenteeism.

[6] We chose not to estimate the conditional fixed-effects negative binomial model since it is not strictly speaking a fixed-effect method (Allison & Waterman 2002). The correlated random-effects method we adopt has been proposed as a suitable alternative (see Allison 2005; Cameron & Trivedi 2015).

$$\delta_i = e^{(\bar{x}_i \pi + \mu_i)} \tag{8}$$

where μ_i captures unobserved heterogeneity that is uncorrelated with the regressors and π is a vector of parameters to be estimated.

We are interested in modelling the conditional mean of exposure-weighted absences, $E(\xi_{it} \curlywedge_{it})$, rather than absences themselves. Our fully specified model is therefore:

$$\log(\curlywedge_{it}) = \beta_0 + \beta^{MH} MH_{it-1} + JC_{it-1}\beta^{JC} + X_{it-1}\beta^X + \bar{X}_i \pi + \mu_i + \varepsilon_{it} + \log(\xi_{it})$$

$$\log\left(\frac{\curlywedge_{it}}{\xi_{it}}\right) = \beta_0 + \beta^{MH} MH_{it-1} + JC_{it-1}\beta^{JC} + X_{it-1}\beta^X + \bar{X}_i \pi + \mu_i + \varepsilon_{it} \tag{9}$$

where $\left(\frac{\curlywedge_{it}}{\xi_{it}}\right)$ is the absence rate, ε_{it} is an i.i.d. error term that follows a gamma distribution, and β and π refer to vectors of parameters to be estimated.

As with our analysis of presenteeism, we investigate the link between job characteristics and absence rates for workers with and without mental health issues by re-estimating extended versions of equation (9) that sequentially include an interaction term between a specific job characteristic and poor mental health.

5. Results

5.1 Presenteeism

Estimates of the relationship between job characteristics, mental health, and presenteeism are presented in Table 3 separately by gender. Four alternative specifications of equation (3) are considered, each increasing in controls.[7] To facilitate interpretation, our results are presented in the form of odds ratios (OR); i.e., the change in the odds of presenteeism associated with a one-unit change in the relevant independent variable. For example, in our preferred specification with full controls and conditional fixed effects (see column 4), we estimate that the odds that men in poor mental health report diminished

[7] An expanded set of results are presented in Appendix Table A5.

productivity at work is 6.18 times higher than those of otherwise similar men in good mental health. Similarly, women with poor mental health have odds of presenteeism that are 6.92 times higher than women in good mental health. The large disparity in the odds of presenteeism associated with mental health status is not surprising given that respondents are explicitly asked about reductions in work effort and productivity that stem from experiencing "emotional problems".

[Table 3 about here]

Importantly, employment circumstances also influence the odds of presenteeism even after accounting for workers' self-reported mental health status. Each standard deviation increase in job control, for example, is associated with an 8.3 (5.2) percent reduction in the odds of men (women) experiencing diminished productivity at work. Similarly, the odds of workers' reporting diminished on-the-job productivity are lower in jobs that are more secure (by 10.8 (men) or 8.8 (women) percent) and more complex (by 7.5 (men) or 4.3 (women) percent). In contrast, job stress and presenteeism appear to go hand-in-hand. Each standard deviation increase in job stress is associated with odds of presenteeism that are 33.1 percent higher for women and 41.5 percent higher for men. Taken together, these results indicate that workers' job conditions have a large and meaningful effect on their chances of being less productive at work as a result of their emotional problems. The link between job characteristics and presenteeism is particularly strong for men and exists despite accounting for workers' mental health status.

We turn now to consider whether there is an interaction between employment conditions and mental illness in driving the odds of presenteeism. Specifically, does self-reported mental illness intensify (or mitigate) the relationship between workers' job conditions and the chances that they will be less productive at work? We address this question by estimating the relationship specified in equation (4). In effect, we interact our indicator of mental illness with our job characteristics and include these interaction terms (one at a time) as additional controls in two specifications: without and with conditional fixed effects (see Table 4).[8]

[Table 4 about here]

As before, we present results in terms of odds ratios implying that the interaction term effectively captures the ratio of odds ratios; i.e., the change in the odds of presenteeism associated with a one standard-deviation change in each job characteristic for those with a mental illness relative to those in good mental health. Consider first the interaction between job control and mental illness in the odds of presenteeism (see Panel A Table 4). Each standard deviation increase in men's job control is associated with a 12.0 percent reduction in the odds of presenteeism for those in good mental health (OR = 0.880), but no reduction in the odds of presenteeism for those with a mental illness (OR = 1.002). The ratio of these two odds ratios is statistically significant and equals 1.139, indicating that increased job control is associated with odds of presenteeism that are significantly higher (by 13.9 percent) for mentally ill men. In short, while increased job control is associated with lower chances that men will experience presenteeism, this is true only for men in good mental health. We find parallel results for women, though the differential impact of job control for women in poor versus good mental health is not statistically significantly.

The interaction effects of increased job security and job complexity are strikingly similar. Higher levels of job security and job complexity serve to reduce the odds of presenteeism much more for those in good mental health than for those reporting a mental illness. As job security increases, for example, women's odds of presenteeism fall by 11.7 percent if they are in good mental health, but by only 2.9 percent if they are not. This disparity is both statistically significant and economically meaningful. Similarly, increased

[8] All models contain a full set of controls including the measures of all other job characteristics. The corresponding specifications without the interaction term are presented in columns 3 and 4 of Table 3.

job complexity is linked to a 9.6 percent reduction in the odds of presenteeism among men in good mental health, but only a 3.0 percent reduction among those who are not. Although this interaction effect is not statistically significant once we account for conditional fixed effects, it remains sizeable.

Unlike job control, security and complexity, job stress is associated with increased odds of presenteeism – particularly for workers in good mental health. The effect of a one standard deviation increase in job stress on the odds of presenteeism is 7.1 percent smaller if men are mentally ill, and 11.4 percent smaller if women are mentally ill than if they are in good mental health.

Taken together, our results provide clear evidence that job conditions are relatively more important in explaining the variation in diminished work productivity as a result of emotional problems if workers are in good mental health overall. Worker reported presenteeism is less sensitive to the nature of employment if workers' self-reported mental health is consistent with moderate to severe depressive symptoms.

5.2 Absenteeism

The key results of our model of absenteeism are presented in Table 5 in the form of incidence rate ratios; i.e., the change in absence days as a fraction of annual days worked associated with a one-unit change in each independent variable.[9] We estimate, for example, that the absence rate of men (women) who report being in poor mental health is 4.9 (5.3) percent higher than otherwise similar men (women) in good mental health (see column 4). These disparities take unobserved, individual-specific heterogeneity into account and are less than half the size of those that result when correlated random effects are omitted from the model (see column 3). Thus, estimates of the relationship between absenteeism and mental

[9] Incidence rate ratios are calculated by taking the exponent of the estimated coefficients. An expanded set of results are presented in Appendix Table A6.

illness are likely to be vastly overstated in models which do not account for unobserved heterogeneity.

[Table 5 about here]

Absence rates are also related to the degree of control, security, stress, and complexity inherent in workers' jobs, but in ways that often differ for men and women. While absenteeism is unrelated to women's job control, each standard deviation increase in men' job control is associated with absence rates that are 4.4 percent lower. At the same time, increased job stress is associated with increased absence rates (2.7 percent) for women, but not men. Job security is linked to increased rates of absence from work for both male (2.8 percent) and female (3.4 percent) employees, while absence rates do not vary significantly with the complexity of jobs.

Does the relationship between absenteeism and employment conditions vary with workers' mental health status? We address this question using our extended model of absenteeism which includes an interaction between workers' job conditions and our indicator for mental illness. Results are presented in Table 6. In general, we find that the effect of job characteristics on absence rates does not vary significantly by workers' mental health status whether or not we account for correlated random effects. The estimated effect of a one standard deviation increase in job complexity is virtually identical – and in fact nearly zero – whether or not men and women have a mental illness. Results are similar when we consider the relationship between job stress and workers' absence rate.

[Table 6 about here]

At the same time, there is evidence of important interactions between workers' mental health status and their job security and control – which while not always statistically significant – are, in some cases, nonetheless large enough to be potentially economically meaningful. The effect of increased job security on absence rates is nearly twice as high (5.1

vs. 2.8 percent) for women in poor versus good mental health. Similarly, increased job control is associated with a larger drop in absenteeism if men report a mental health issue (6.2 percent) than if they do not (4 percent). Finally, while job control is associated with significantly lower (2.8 percent) absence rates among female workers in good mental health, it is associated with significantly higher absence rates (3.8 percent) if women report that they have poor mental health. This disparity in the effects of job control on women's absence rates is both large (6.8 percent) and statistically significant.

Thus, whether or not job characteristics moderate the link between mental illness absence rates and job conditions depends on workers' gender and the specific job condition we have in mind. The effect of mental illness on men's and women's absenteeism appears to be independent of the complexity and stress level of their jobs. Women's absence rates increase much more in response to greater job control and security if they have a mental illness than if they do not. Men are also more sensitive to increased job control if they have a mental illness, however, greater job control is linked to lower not higher absenteeism.

6. Conclusions

The toll that mental illness takes on worker productivity results in substantial economic costs for firms, employees, and society more generally. The potential for reducing these costs rests in large part on employers developing employment policies and workplace cultures that support their mentally ill workers in not only attending work, but in also being productive while they are there. Unfortunately, there is a great deal we do not yet understand about the way that the employment context itself influences the link between mental illness and worker productivity.

Our analysis points to absence rates that are approximately five percent higher among workers who report being in poor mental health, while the odds that workers in poor mental health report diminished productivity at work as a result of "emotional issues" is approximately six times higher than those of otherwise similar workers in good mental health. Importantly, the nature of the work environment – as reflected in the level of control workers have over their jobs, job security, work stress, and complexity of jobs – are relatively more important in understanding diminished productivity at work (presenteeism) if workers are in good rather than poor mental health. In contrast, workers' absenteeism is more sensitive to increased job control if they have a mental illness, while women with a mental illness are also more responsive to job security. The effects of job complexity and stress on absenteeism do not depend on workers' mental health. Consistent with the substitution hypothesis (see Caverley et al. 2007), we also find that increased job security is associated with lower presenteeism (except for women with poor mental health), but higher absence rates (except for men with poor mental health). In contrast, increased job control, stress, and complexity have parallel effects on both presenteeism and absenteeism.

These results lead us to several important conclusions. The magic bullet, to the extent that there is one, lies in the reduction of job stress. Initiatives to limit and help workers manage job stress seem to us to be the most promising avenue for improving the productivity of all workers irrespective of their mental health state or gender. In other cases, the complex interaction between job characteristics, mental health, and worker productivity makes such overarching generalizations impossible. Increased job control, for example, appears to be helpful in reducing absences for women with good mental health, but seems more likely to increase the absence days of women in poor mental health. Thus, some sorting of workers across jobs may be optimal. Finally, the fact that presenteeism rates among mentally-ill workers are relatively insensitive to the work environment suggests that developing institutional arrangements to enhance the productivity of those experiencing mental illness may prove challenging.

Going forward, two areas of research would be particularly valuable. First, we need to know more about the extent to which mental illness diminishes productivity at work and the mechanisms through which this occurs. This would be instrumental in furthering our understanding of the potential for employment policy and practices to minimize presenteeism. Second, we need to know more about the dynamics of the relationship between mental illness and worker productivity in order to understand the tradeoffs between presenteeism and absenteeism. In particular, would policies that incentivize mentally-ill workers to remain at home improve overall productivity by reducing presenteeism?

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Table 1: Probability and Odds of Presenteeism, by Mental Health and Gender

	Presenteeism	
Mental health status	***Probability***	***Odds Ratio***
A: Men		
Good Mental Health (MHI-5 >60)	(3,000/ 31,867) = 9.41%	0.1039
Poor Mental Health (MHI-5 ≤ 60)	(3,218/ 6,394) = 50.33%	1.0132
B: Women		
Good Mental Health (MHI-5 >60)	(3,915/31,904) = 12.27%	0.1399
Poor Mental Health (MHI-5 ≤ 60)	(4,691/8,140) = 57.66%	1.3601

Notes: The probability of experiencing presenteeism is the ratio of self-reports of presenteeism (A) to the total sample size (N). The odds of presenteeism (i.e. the ratio of "success" to "failure") are calculated as: A ("success") to N-A=B ("failures") resulting in odds ratio of A/B.

Table 2: Incidence and Mean Level (Days) of Absenteeism, by Mental Health and Gender

	Full sample		*Worked < 230 days per year*		*Worked >= 230 days per year*	
Mental health status	***% with at least 1 absence day***	***Mean absence days | absence days ≥1***	***% with at least 1 absence day***	***Mean absence days | absence days ≥1***	***% with at least 1 absence day***	***Mean absence days | absence days ≥1***
A: Men						
Good Mental Health (MHI-5 > 60)	57.79	5.35 (7.66)	42.33	5.37 (7.00)	63.06	5.34 (7.80)
Poor Mental Health (MHI-5 ≤ 60)	59.80	6.55 (10.42)	43.36	6.80 (10.97)	65.92	6.49 (10.29)
B: Women						
Good Mental Health (MHI-5 > 60)	59.80	5.70 (7.08)	47.24	5.39 (7.19)	71.74	5.90 (7.01)
Poor Mental Health (MHI-5 ≤ 60)	57.73	6.93 (10.04)	44.08	6.49 (10.31)	72.88	7.23 (9.84)

Notes: Standard deviations in parentheses.

Table 3: The Relationship between Presenteeism, Poor Mental Health and Job Conditions by Gender (Logit Odds Ratios)

	(1)	*(2)*	*(3)*	*(4)*
A: Men				
Poor mental health	9.750***	8.658***	6.537***	6.180***
	[9.165-10.371]	[8.118-9.233]	[6.111-6.994]	[5.524-6.913]
Control (increasing in)	-	-	0.960**	0.917***
			[0.927-0.994]	[0.865-0.973]
Security	-	-	0.868***	0.892***
			[0.841-0.897]	[0.847-0.939]
Stress	-	-	1.501***	1.415***
			[1.451-1.552]	[1.340-1.495]
Complexity	-	-	0.981	0.925**
			[0.946-1.017]	[0.871-0.983]
Controls		Yes	Yes	Yes
Conditional Fixed Effects				Yes
N (observations)	38261	38261	38261	17000
N (individuals)	8026	8026	8026	2328
B: Women				
Poor mental health	9.724***	8.593***	7.249***	6.917***
	[9.201-10.276]	[8.113-9.102]	[6.832-7.690]	[6.279-7.620]
Control (increasing in)	-	-	0.994	0.948**
			[0.965-1.023]	[0.902-0.996]
Security	-	-	0.899***	0.912***
			[0.874-0.926]	[0.871-0.955]
Stress	-	-	1.398***	1.331***
			[1.358-1.439]	[1.270-1.395]
Complexity	-	-	0.984	0.957*
			[0.954-1.016]	[0.910-1.007]
Controls	Yes	Yes	Yes	Yes
Conditional fixed effects				Yes
N (observations)	40044	40044	40044	20897
N (individuals)	8487	8487	8487	2995

Notes: Specifications (1) – (3) are pooled logit models, while (4) is the fully specified conditional fixed effects logit model. Odds ratios (OR) are reported with corresponding 95% confidence intervals reported in parentheses. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 4: Interactions between Poor Mental Health and Job Conditions in Presenteeism by Gender (Logit Odds Ratios)

	Men		*Women*	
	Logit (1)	***CFE-Logit (2)***	***Logit (3)***	***CFE-Logit (4)***
A: Control				
Effect of increase in control for those with:				
Poor mental health	1.004	1.002	1.024	0.992
	[0.950-1.061]	[0.916-1.097]	[0.977-1.073]	[0.920-1.070]
Good mental health	0.936***	0.880***	0.977	0.927***
	[0.896-0.976]	[0.823-0.941]	[0.943-1.013]	[0.876-0.981]
Interaction term (ratio of ORs)	1.073**	1.139**	1.047	1.070
	[1.004-1.147]	[1.030-1.260]	[0.990-1.109]	[0.983-1.165]
B: Security				
Effect of increase in security for those with:				
Poor mental health	0.933***	0.910**	0.977	0.971
	[0.886-0.982]	[0.839-0.986]	[0.934-1.022]	[0.905-1.042]
Good mental health	0.833***	0.883***	0.855***	0.883***
	[0.800-0.866]	[0.832-0.937]	[0.825-0.886]	[0.837-0.932]
Interaction term (ratio of ORs)	1.120***	1.030	1.142***	1.100**
	[1.052-1.193]	[0.939-1.130]	[1.081-1.207]	[1.014-1.193]
C: Stress				
Effect of increase in stress for those with:				
Poor mental health	1.368***	1.349***	1.293***	1.235***
	[1.300-1.439]	[1.243-1.464]	[1.240-1.349]	[1.156-1.319]
Good mental health	1.591***	1.452***	1.475***	1.394***
	[1.526-1.658]	[1.363-1.547]	[1.423-1.529]	[1.320-1.473]
Interaction term (ratio of ORs)	0.860***	0.929	0.877***	0.886***
	[0.807-0.916]	[0.846-1.020]	[0.832-0.924]	[0.821-0.956]
D: Complexity				
Effect of increase in complexity for those with:				
Poor mental health	1.031	0.970	1.020	0.951
	[0.975-1.089]	[0.886-1.062]	[0.974-1.069]	[0.882-1.026]
Good mental health	0.953**	0.904***	0.963*	0.960
	[0.913-0.995]	[0.845-0.968]	[0.928-1.000]	[0.907-1.016]
Interaction term (ratio of ORs)	1.081**	1.072	1.059**	0.991
	[1.012-1.155]	[0.971-1.184]	[1.002-1.119]	[0.913-1.075]
N (observations)	38261	17000	40044	20897
N (individuals)	8026	2328	8487	2995

Notes: Each regression controls for the main effects of other job characteristics and the standard demographic and employment covariates outlined in the data section. Odds ratios (OR) are reported with corresponding 95% confidence intervals reported in parentheses. The delta-method has been used to obtain confidence intervals for the effect of each job characteristic for those with poor mental health. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 5: The Relationship between Absenteeism, Poor Mental Health, and Job Conditions by Gender (Negative Binomial Incidence Rate Ratios)

	(1)	*(2)*	*(3)*	*(4)*
A: Men				
Poor Mental Health	1.276***	1.167***	1.133***	1.049*
	[1.210-1.345]	[1.110-1.228]	[1.075-1.195]	[0.997-1.103]
Control (increasing in)			0.922***	0.956***
			[0.903-0.942]	[0.934-0.979]
Security			0.981*	1.028**
			[0.961-1.001]	[1.006-1.050]
Stress			1.003	1.005
			[0.982-1.025]	[0.983-1.027]
Complexity			1.018	0.984
			[0.995-1.040]	[0.961-1.009]
Controls		Yes	Yes	Yes
Correlated Random Effects				Yes
N (observations)	25070	25070	25070	25070
N (individuals)	6101	6101	6101	6101
LR test for individual effects (χ^2)				3263.04
B: Women				
Poor Mental Health	1.175***	1.209***	1.172***	1.053**
	[1.121-1.231]	[1.158-1.263]	[1.120-1.226]	[1.007-1.101]
Control (increasing in)			0.956***	0.986
			[0.939-0.973]	[0.966-1.007]
Security			1.003	1.034***
			[0.984-1.021]	[1.013-1.055]
Stress			1.058***	1.027***
			[1.039-1.077]	[1.007-1.047]
Complexity			1.017*	1.007
			[0.997-1.037]	[0.985-1.030]
Controls		Yes	Yes	Yes
Correlated Random Effects				Yes
N (observations)	26385	26385	26385	26385
N (individuals)	6459	6459	6459	6459
LR test for individual effects (χ^2)				2742.56

Notes: Specifications (1) – (3) are pooled negative binomial models, while (4) is the fully specified correlated random effects negative binomial model. For absenteeism models covariates are measured at the previous interview (roughly 12 months prior). We do not control for the main effects of either the proportion of the previous 12 months in employment or the number of days usually worked per week given these are used in the construction of the exposure measure, but we do include a control identifying job changers. Incidence rate ratios (IRR) are reported with corresponding 95% confidence intervals reported in parentheses. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 6: Interactions between Poor Mental Health and Job Conditions in Absenteeism by Gender (Negative Binomial Incidence Rate Ratios)

	Men		*Women*	
	NEG BIN (1)	***NB-CRE (2)***	***NEG BIN (3)***	***NB-CRE (4)***
A: Control				
Effect of increase in control for those with:				
Poor mental health	0.907***	0.938***	1.060***	1.038**
	[0.865-0.950]	[0.900-0.977]	[1.022-1.101]	[1.003-1.074]
Good mental health	0.925***	0.960***	0.931***	0.972**
	[0.904-0.947]	[0.936-0.984]	[0.913-0.950]	[0.951-0.994]
Interaction term (ratio of IRRs)	0.980	0.977	1.139***	1.068***
	[0.931-1.031]	[0.937-1.018]	[1.093-1.187]	[1.031-1.105]
LR test for individual effects (χ^2)		3264.02		2742.37
B: Security				
Effect of increase in security for those with:				
Poor mental health	1.043*	1.028	1.024	1.051***
	[0.998-1.090]	[0.990-1.067]	[0.988-1.061]	[1.017-1.087]
Good mental health	0.966***	1.028**	0.996	1.028**
	[0.945-0.988]	[1.004-1.051]	[0.975-1.017]	[1.006-1.051]
Interaction term (ratio of IRRs)	1.079***	1.000	1.028	1.022
	[1.028-1.133]	[0.962-1.040]	[0.988-1.070]	[0.988-1.059]
LR test for individual effects (χ^2)		3259.24		2740.69
C: Stress				
Effect of increase in stress for those with:				
Poor mental health	1.004	1.011	1.070***	1.024
	[0.962-1.048]	[0.975-1.049]	[1.036-1.106]	[0.993-1.055]
Good mental health	1.003	1.003	1.054***	1.028***
	[0.980-1.027]	[0.979-1.027]	[1.032-1.076]	[1.007-1.050]
Interaction term (ratio of IRRs)	1.001	1.009	1.016	0.996
	[0.955-1.050]	[0.971-1.048]	[0.979-1.054]	[0.965-1.028]
LR test for individual effects (χ^2)		3263.16		2742.62
D: Complexity				
Effect of increase in complexity for those with:				
Poor mental health	1.026	0.980	1.023	1.019
	[0.978-1.076]	[0.940-1.021]	[0.984-1.063]	[0.983-1.055]
Good mental health	1.016	0.985	1.016	1.004
	[0.992-1.041]	[0.960-1.011]	[0.994-1.038]	[0.981-1.028]
Interaction term (ratio of IRRs)	1.010	0.994	1.007	1.014
	[0.959-1.063]	[0.954-1.037]	[0.966-1.050]	[0.979-1.051]
LR test for individual effects (χ^2)		3263.09		2741.88
N (observations)	25070	25070	26385	26385
N (individuals)	6101	6101	6459	6459

Notes: Each regression controls for the main effects of other job characteristics and the standard demographic and employment covariates outlined in the data section. For absenteeism models covariates are measured at the previous interview (roughly 12 months prior). We do not control for the main effects of either the proportion of the previous 12 months in employment or the number of days usually worked per week given these are used in the construction of the exposure measure, but we do include a control identifying job changers. Incidence rate ratios (IRR) are reported with corresponding 95% confidence intervals reported in parentheses. The delta-method has been used to obtain confidence intervals for the effect of each job characteristic for those with poor mental health. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Appendix

Table A1: Variable Definitions

Variable name	*Definition*
Outcomes / Variables of Interest	
Absenteeism	Number of days of paid sick leave taken in last 12 months.
Presenteeism	Equals 1 if respondent indicated that that in the past four weeks they had experienced any of the following as a result of any emotional problems, and 0 otherwise. (i) “Cutting down the amount of time you spent on work or other activities”; (ii) “Accomplished less than you would like”; (iii) “Didn’t do work or other activities as carefully as usual”.
Poor Mental Health	Equals 1 if respondent’s MHI-5 score is less than or equal to 60.
Job Control	An index of 3 items scored on a 7 point scale, standardized to have a mean 0 and standard deviation 1. Increasing in the level of control.
Job Security	An index of 3 items scored on a 7 point scale, standardized to have a mean 0 and standard deviation 1. Increasing in the level of security.
Job Stress	An index of 2 items scored on a 7 point scale, standardized to have a mean 0 and standard deviation 1. Increasing in the level of stress.
Job Complexity	An index of 3 items scored on a 7 point scale, standardized to have a mean 0 and standard deviation 1. Increasing in the level of complexity.
Exposure	
Exposure	Indicator of the number of days a respondent was potentially working in the past 12 months. Our exposure variable is derived by multiplying the number of weeks potentially worked in a year (46 weeks for employees who report receiving paid annual leave and 52 weeks for those that do not) by both the proportion of the previous 12 months in paid employment” and the number of usual work days per week. The six week difference reflects 4 weeks of paid annual leave, which all Australian employees covered by industrial awards are entitled to, plus 2 weeks of paid public holidays.
Demographic controls	
Age	Age (in years) at 30th June in year prior to interview.
# Children	Number of own children aged less than 15 years living with respondent.
# Adults	Number of persons aged 15 years or more living in the household.
Marital status	Married: Equals 1 if respondent is legally married. De-facto: Equals 1 if respondent is in a de-facto relationship. Single: Equals 1 if respondent is single which includes being separated, divorced, widowed or never married/de-facto (reference category).
Education	Postgrad: Equals 1 if respondent’s highest education level is a masters, doctorate, graduate diploma or graduate certificate. Undergrad: Equals 1 if respondent’s highest education level is a bachelor’s degree, degree with honours, advanced diploma or diploma. Cert: Equals 1 if respondent’s highest education level Certificate III or IV. Year12: Equals 1 if respondent’s highest education level is high school completion. Year11: Equals 1 if respondent did not finish high school (reference category).
Disability	No disability: Equals 1 if respondent has no long-term health condition. (Includes people who only report a mental health condition) (reference category) . Mild: Equals 1 if respondent has a long-term health condition that does not limit work. (Persons who only reported having a mental illness are excluded.) Moderate: Equals 1 if respondent has a restrictive long-term health condition that prevents any work being undertaken/limits the amount of work. (Persons who only reported having a mental illness are excluded.)
Physical health (SF-36)	Physical functioning sub-scale of the SF-36 Health Survey. Scores are standardized to range from 0 to 100.
Smoker	Equals 1 if respondent is currently a smoker (smokes on a daily, weekly or less basis).
Ln household	Log of real equivalized disposable household income for the previous financial year

disposable income	($000 at 2010 prices) with missing values imputed and non-positive incomes set to $1. The equivalence scale used is the OECD modified scale (which assigns a weight of 1 to the first adult in the household, 0.5 for each other adult, and 0.3 for each child).
Non-positive income	Equals 1 if real disposable household income for the financial year is non-positive.
Regional unemployment	The official unemployment rate in the major statistical region for October of the interview year, and sourced from ABS, Labour Force, Australia, Detailed - Electronic Delivery (ABS cat. no. 6291.0.55.001), Table 02: Labour force status by State, Capital city / Balance of state and Sex.
Regional Indicators	Inner Regional: Equals 1 if respondent lives in inner regional Australia (as defined in the Australian Standard Geographical Classification [ASGC]). Outer Regional: Equals 1 if respondent lives in outer regional Australia. Remote: Equals 1 if respondent lives in remote or very remote location in Australia. Major Urban: Equals 1 if respondent lives in a major urban Australia (reference category).
SEIFA index	Decile of index of relative socio-economic advantage/disadvantage for regions, where 1 represents highest relative disadvantage and 10 highest relative advantage (ABS 2001). It takes into account variables such as the proportion of families with high incomes, people with a tertiary education, and people employed in a skilled occupation.
NR at t+1	Equals 1 if the respondent did not respond at the next survey wave.

Employment Controls

Usual work days per week	Number of days respondent usually works in a week.
% of previous 12 months in employment	Proportion of last 12 months since interview respondent spent in employment. Derived from the calendar, which collects activity in the early, middle and late part of each month, for the period 12 months before the interview till the month of the interview. Jobs include any job, full or part-time. If a third of a month overlaps between employment, unemployment or not in the labour force, then a half or a third is allocated to each as appropriate.
Full-time employment	Equals 1 if respondent is employed full-time.
Employment contract	Fixed-term: Equals 1 if respondent has a fixed-term employment contract. Casual: Equals 1 if respondent has a casual employment contract. Permanent: Equals 1 if respondent has a permanent employment contract (reference category). Other: Equals 1 if respondent has an ‘other’ type of employment contract.
Tenure	Number of years the respondent has worked for their current employer.
Firm size	<20 Employees: Equals 1 if the number of employees belonging to a firm Australia wide is less than 20. 20-99 Employees: Equals 1 if the number of employees belonging to a firm Australia wide is from 20 to 99. 100-499 Employees: Equals 1 if the number of employees belonging to a firm Australia wide is from 100 to 499. 500> Employees: Equals 1 if the number of employees belonging to a firm Australia wide is 500 or greater (reference category). Missing: Equals 1 if firm size is missing.
Union	Equals 1 if respondent has a union membership or employee association.
Regular work schedule	Equals 1 if respondent’s current work schedule is a regular daytime schedule.
Private sector	Equals 1 if respondent works in the Private sector (for profit organisation).
Job changer	Equals 1 if a respondent changed job within the 12 month period we observe absence days, derived from the question about tenure with current employer. Only used in absenteeism analysis.
Occupation	Categorical occupation dummies derived from the respondent’s current occupation. The classifications come from the Australian and New Zealand Standard Classification of Occupations (ANZSCO), First Edition, 2006 (ABS Cat. No. 1220.0) [1 digit]. Managers (reference category); Professionals; Technicians and trade workers; Community and personal service workers; Clerical and administrative workers; Sales workers; Machinery operators and drivers; Labourers.

Industry	Categorical industry dummies derived from the respondent's current employment industry. The classifications come from the Australian and New Zealand Standard Industrial Classification (ANZSIC), Second Edition, 2006 (ABS Cat. No. 1292.0) [1 digit]. Industries include: Agriculture, Forestry and Fishing (reference category); Mining; Manufacturing; Electricity, Gas, Water and Waste Services; Construction; Wholesale Trade; Retail Trade; Accommodation and Food Services; Transport, Postal and Warehousing; Information Media and Telecommunications; Financial and Insurance Services; Rental, Hiring and Real Estate Services; Professional, Scientific and Technical Services; Administrative and Support Service; Public Administration and Safety; Education and Training; Health Care and Social Assistance; Arts and Recreation Services; Other Services.

Table A2: Summary Statistics – Presenteeism Sample by Mental Health and Gender

	Men				*Women*			
	Poor MH		*Good MH*		*Poor MH*		*Good MH*	
Variable	***Mean***	***SD***	***Mean***	***SD***	***Mean***	***SD***	***Mean***	***SD***
Presenteeism	0.50	(0.50)	0.09	(0.29)	0.58	(0.49)	0.12	(0.33)
Job Control	-0.16	(0.97)	0.13	(0.97)	-0.24	(1.01)	-0.05	(1.01)
Job Security	-0.48	(1.04)	0.02	(0.97)	-0.26	(1.05)	0.15	(0.96)
Job Stress	0.59	(1.06)	-0.07	(0.91)	0.37	(1.16)	-0.14	(0.96)
Job Complexity	-0.12	(0.99)	0.08	(0.97)	-0.17	(1.05)	-0.01	(1.01)
Age	36.69	(12.14)	37.51	(12.84)	36.15	(12.82)	37.73	(12.98)
# Children	0.71	(1.06)	0.78	(1.10)	0.80	(1.09)	0.83	(1.09)
# Adults	2.35	(1.05)	2.42	(1.03)	2.39	(1.07)	2.41	(1.05)
Marital status: Married	0.42	(0.49)	0.32	(0.47)	0.45	(0.50)	0.36	(0.48)
Marital status: De-facto	0.42	(0.49)	0.51	(0.50)	0.37	(0.48)	0.47	(0.50)
Marital status: Single (ref)	0.16	(0.36)	0.17	(0.38)	0.17	(0.38)	0.17	(0.37)
Education: Postgrad	0.08	(0.28)	0.11	(0.31)	0.10	(0.30)	0.13	(0.34)
Education: Undergrad	0.22	(0.41)	0.24	(0.42)	0.25	(0.44)	0.29	(0.46)
Education: Cert	0.26	(0.44)	0.27	(0.44)	0.17	(0.38)	0.15	(0.35)
Education: Year12	0.17	(0.37)	0.17	(0.38)	0.20	(0.40)	0.19	(0.39)
Education: Year11 (ref)	0.27	(0.44)	0.21	(0.41)	0.28	(0.45)	0.25	(0.43)
Disability: None (ref)	0.77	(0.42)	0.87	(0.33)	0.75	(0.43)	0.88	(0.33)
Disability: Mild	0.10	(0.30)	0.07	(0.26)	0.10	(0.29)	0.06	(0.24)
Disability: Moderate	0.13	(0.33)	0.05	(0.22)	0.15	(0.36)	0.06	(0.24)
Physical health (SF-36)	85.60	(20.00)	92.46	(15.43)	84.25	(20.15)	91.23	(15.02)
Smoker	0.32	(0.47)	0.24	(0.42)	0.27	(0.44)	0.18	(0.38)
Ln household disposable income	10.60	(0.63)	10.69	(0.62)	10.56	(0.73)	10.68	(0.62)
Non-positive income	0.00	(0.04)	0.00	(0.04)	0.00	(0.05)	0.00	(0.04)
Regional unemployment	5.16	(1.11)	5.15	(1.12)	5.17	(1.10)	5.14	(1.12)
Region: Inner Regional	0.23	(0.42)	0.23	(0.42)	0.21	(0.41)	0.23	(0.42)
Region: Outer Regional	0.09	(0.29)	0.10	(0.29)	0.10	(0.30)	0.10	(0.29)
Region: Remote	0.02	(0.13)	0.01	(0.11)	0.01	(0.11)	0.01	(0.11)
Region: Major Urban (ref)	0.66	(0.47)	0.66	(0.47)	0.67	(0.47)	0.65	(0.48)
SEIFA index	5.56	(2.85)	5.86	(2.83)	5.66	(2.85)	5.95	(2.82)
NR at t+1	0.09	(0.28)	0.07	(0.26)	0.08	(0.28)	0.07	(0.25)
Usual workdays / week	4.84	(1.04)	4.84	(1.05)	4.23	(1.31)	4.25	(1.29)
Proportion of past year in employment	0.95	(0.16)	0.96	(0.14)	0.93	(0.19)	0.95	(0.16)
Full-time employment	0.83	(0.38)	0.85	(0.36)	0.50	(0.50)	0.53	(0.50)
Employment: Fixed-term	0.09	(0.29)	0.09	(0.29)	0.10	(0.30)	0.10	(0.30)
Employment: Causal	0.20	(0.40)	0.16	(0.37)	0.31	(0.46)	0.25	(0.43)
Employment: Permanent (ref)	0.70	(0.46)	0.74	(0.44)	0.59	(0.49)	0.65	(0.48)
Employment: Other	0.00	(0.07)	0.00	(0.06)	0.00	(0.05)	0.00	(0.05)
Tenure	6.16	(7.69)	6.73	(8.13)	4.69	(6.12)	5.98	(7.10)
Firm size: <20	0.21	(0.41)	0.20	(0.40)	0.21	(0.41)	0.20	(0.40)
Firm size: 20-99	0.17	(0.38)	0.16	(0.36)	0.15	(0.36)	0.15	(0.35)
Firm size: 100-499	0.14	(0.35)	0.13	(0.34)	0.11	(0.32)	0.11	(0.32)
Firm size: 500> (ref)	0.43	(0.49)	0.46	(0.50)	0.43	(0.50)	0.46	(0.50)
Firm size: Missing	0.05	(0.22)	0.05	(0.22)	0.09	(0.29)	0.08	(0.27)
Union	0.28	(0.45)	0.29	(0.45)	0.25	(0.43)	0.28	(0.45)
Regular work schedule	0.74	(0.44)	0.76	(0.43)	0.72	(0.45)	0.77	(0.42)
Private sector	0.75	(0.43)	0.73	(0.45)	0.63	(0.48)	0.57	(0.49)
Occupation Dummies:								
Managers (ref)	0.11	(0.31)	0.14	(0.34)	0.06	(0.24)	0.08	(0.26)
Professionals	0.19	(0.39)	0.21	(0.41)	0.23	(0.42)	0.29	(0.45)
Technicians and trade	0.20	(0.40)	0.21	(0.41)	0.05	(0.22)	0.04	(0.19)

workers								
Community and personal service workers	0.07	(0.25)	0.07	(0.26)	0.18	(0.38)	0.15	(0.36)
Clerical and administrative workers	0.09	(0.28)	0.09	(0.28)	0.23	(0.42)	0.24	(0.43)
Sales workers	0.07	(0.25)	0.07	(0.25)	0.15	(0.36)	0.14	(0.34)
Machinery operators and drivers	0.13	(0.33)	0.11	(0.31)	0.01	(0.10)	0.01	(0.10)
Labourers	0.15	(0.36)	0.11	(0.32)	0.09	(0.29)	0.06	(0.24)
Industry Dummies:								
Agriculture, Forestry and Fishing (ref)	0.03	(0.16)	0.02	(0.15)	0.01	(0.07)	0.01	(0.09)
Mining	0.02	(0.16)	0.03	(0.18)	0.00	(0.06)	0.01	(0.08)
Manufacturing	0.16	(0.36)	0.14	(0.35)	0.06	(0.24)	0.04	(0.20)
Electricity, Gas, Water and Waste Services	0.02	(0.13)	0.02	(0.14)	0.00	(0.07)	0.00	(0.07)
Construction	0.09	(0.29)	0.10	(0.30)	0.01	(0.12)	0.01	(0.11)
Wholesale Trade	0.04	(0.19)	0.05	(0.21)	0.02	(0.15)	0.02	(0.15)
Retail Trade	0.10	(0.30)	0.09	(0.28)	0.14	(0.34)	0.13	(0.33)
Accommodation and Food Services	0.06	(0.24)	0.05	(0.23)	0.10	(0.30)	0.07	(0.26)
Transport, Postal and Warehousing	0.07	(0.26)	0.07	(0.25)	0.02	(0.14)	0.02	(0.14)
Information Media and Telecommunications	0.03	(0.16)	0.03	(0.16)	0.03	(0.16)	0.02	(0.14)
Financial and Insurance Services	0.03	(0.18)	0.03	(0.18)	0.04	(0.20)	0.04	(0.20)
Rental, Hiring and Real Estate Services	0.01	(0.10)	0.01	(0.10)	0.01	(0.11)	0.02	(0.12)
Professional, Scientific and Technical Services	0.07	(0.26)	0.07	(0.25)	0.06	(0.24)	0.06	(0.24)
Administrative and Support Service	0.03	(0.17)	0.02	(0.13)	0.03	(0.18)	0.03	(0.16)
Public Administration and Safety	0.09	(0.28)	0.10	(0.30)	0.06	(0.23)	0.07	(0.25)
Education and Training	0.05	(0.22)	0.07	(0.25)	0.13	(0.34)	0.17	(0.38)
Health Care and Social Assistance	0.06	(0.23)	0.05	(0.21)	0.21	(0.41)	0.23	(0.42)
Arts and Recreation Services	0.02	(0.14)	0.02	(0.14)	0.02	(0.13)	0.02	(0.12)
Other Services	0.03	(0.17)	0.04	(0.19)	0.03	(0.17)	0.03	(0.16)
N (observations)	6394		31867		8140		31904	

Table A3: Summary Statistics – Absenteeism Sample by Gender and Mental Health

	Men				Women			
	Poor MH		*Good MH*		*Poor MH*		*Good MH*	
Variable	***Mean***	***SD***	***Mean***	***SD***	***Mean***	***SD***	***Mean***	***SD***
Absenteeism	3.92	(8.68)	3.09	(6.39)	4.00	(8.36)	3.41	(6.15)
Job Control	-0.18	(0.97)	0.11	(0.96)	-0.26	(1.01)	-0.09	(1.02)
Job Security	-0.49	(1.04)	0.02	(0.96)	-0.26	(1.06)	0.15	(0.96)
Job Stress	0.57	(1.06)	-0.10	(0.91)	0.34	(1.16)	-0.16	(0.96)
Job Complexity	-0.13	(0.99)	0.05	(0.98)	-0.21	(1.07)	-0.04	(1.03)
Exposure	220.01	(52.74)	221.79	(49.19)	190.41	(63.18)	194.65	(59.82)
Age	37.17	(12.13)	37.89	(12.94)	36.64	(12.95)	38.24	(13.08)
# Children	0.73	(1.06)	0.78	(1.09)	0.81	(1.09)	0.83	(1.09)
# Adults	2.34	(1.06)	2.41	(1.04)	2.38	(1.07)	2.40	(1.05)
Marital status: Married	0.43	(0.50)	0.52	(0.50)	0.37	(0.48)	0.48	(0.50)
Marital status: De-facto	0.16	(0.37)	0.18	(0.38)	0.17	(0.38)	0.17	(0.37)
Marital status: Single (ref)	0.40	(0.49)	0.31	(0.46)	0.46	(0.50)	0.35	(0.48)
Education: Postgrad	0.09	(0.29)	0.11	(0.32)	0.10	(0.30)	0.13	(0.34)
Education: Undergrad	0.22	(0.42)	0.24	(0.43)	0.26	(0.44)	0.30	(0.46)
Education: Cert	0.27	(0.44)	0.27	(0.44)	0.18	(0.39)	0.15	(0.36)
Education: Year12	0.17	(0.37)	0.17	(0.38)	0.19	(0.39)	0.18	(0.39)
Education: Year11 (ref)	0.26	(0.44)	0.20	(0.40)	0.26	(0.44)	0.24	(0.42)
Disability: None (ref)	0.77	(0.42)	0.87	(0.33)	0.74	(0.44)	0.87	(0.33)
Disability: Mild	0.10	(0.31)	0.07	(0.26)	0.10	(0.30)	0.06	(0.24)
Disability: Moderate	0.12	(0.33)	0.05	(0.22)	0.16	(0.36)	0.07	(0.25)
Physical health (SF-36)	86.00	(19.29)	92.65	(15.16)	84.25	(20.26)	91.18	(14.95)
Smoker	0.31	(0.46)	0.23	(0.42)	0.25	(0.44)	0.17	(0.38)
Ln household disposable income	10.64	(0.62)	10.72	(0.61)	10.59	(0.71)	10.71	(0.61)
Non-positive income	0.00	(0.04)	0.00	(0.04)	0.00	(0.05)	0.00	(0.04)
Regional unemployment	4.79	(0.94)	4.78	(0.94)	4.80	(0.93)	4.79	(0.95)
Region: Inner Regional	0.23	(0.42)	0.23	(0.42)	0.21	(0.41)	0.24	(0.42)
Region: Outer Regional	0.09	(0.29)	0.10	(0.29)	0.10	(0.30)	0.10	(0.29)
Region: Remote	0.02	(0.12)	0.01	(0.11)	0.01	(0.11)	0.01	(0.11)
Region: Major Urban (ref)	0.66	(0.47)	0.66	(0.47)	0.67	(0.47)	0.65	(0.48)
SEIFA index	5.54	(2.84)	5.89	(2.82)	5.62	(2.85)	5.96	(2.80)
NR at t+1	0.06	(0.23)	0.05	(0.22)	0.06	(0.23)	0.04	(0.21)
Full-time employment	0.84	(0.37)	0.85	(0.35)	0.50	(0.50)	0.53	(0.50)
Employment: Fixed-term	0.09	(0.29)	0.09	(0.29)	0.09	(0.29)	0.10	(0.29)
Employment: Causal	0.19	(0.39)	0.15	(0.36)	0.31	(0.46)	0.24	(0.43)
Employment: Permanent (ref)	0.72	(0.45)	0.75	(0.43)	0.60	(0.49)	0.66	(0.47)
Employment: Other	0.00	(0.06)	0.00	(0.05)	0.00	(0.05)	0.00	(0.04)
Tenure	6.34	(7.74)	6.79	(8.14)	4.83	(6.20)	6.16	(7.26)
Firm size: <20	0.20	(0.40)	0.20	(0.40)	0.21	(0.41)	0.19	(0.39)
Firm size: 20-99	0.17	(0.38)	0.16	(0.36)	0.15	(0.35)	0.14	(0.35)
Firm size: 100-499	0.14	(0.34)	0.14	(0.34)	0.11	(0.32)	0.11	(0.32)
Firm size: 500> (ref)	0.44	(0.50)	0.47	(0.50)	0.45	(0.50)	0.48	(0.50)
Firm size: Missing	0.05	(0.22)	0.05	(0.21)	0.09	(0.28)	0.08	(0.26)
Union	0.28	(0.45)	0.28	(0.45)	0.25	(0.43)	0.28	(0.45)
Regular work schedule	0.75	(0.43)	0.77	(0.42)	0.73	(0.44)	0.78	(0.41)
Private sector	0.75	(0.43)	0.72	(0.45)	0.63	(0.48)	0.56	(0.50)
Job changer	0.17	(0.38)	0.14	(0.35)	0.19	(0.39)	0.14	(0.35)
Occupation Dummies:								
Managers (ref)	0.10	(0.31)	0.14	(0.35)	0.07	(0.25)	0.08	(0.27)
Professionals	0.20	(0.40)	0.22	(0.41)	0.23	(0.42)	0.29	(0.46)
Technicians and trade workers	0.20	(0.40)	0.21	(0.41)	0.05	(0.22)	0.03	(0.18)

Community and personal service workers	0.07	(0.26)	0.07	(0.26)	0.17	(0.38)	0.15	(0.36)
Clerical and administrative workers	0.09	(0.29)	0.09	(0.28)	0.22	(0.42)	0.24	(0.43)
Sales workers	0.07	(0.25)	0.07	(0.25)	0.16	(0.36)	0.13	(0.34)
Machinery operators and drivers	0.13	(0.33)	0.10	(0.30)	0.01	(0.10)	0.01	(0.10)
Labourers	0.14	(0.35)	0.11	(0.31)	0.09	(0.29)	0.06	(0.23)
Industry Dummies:								
Agriculture, Forestry and Fishing (ref)	0.03	(0.16)	0.02	(0.14)	0.00	(0.07)	0.01	(0.09)
Mining	0.02	(0.16)	0.03	(0.18)	0.00	(0.06)	0.01	(0.08)
Manufacturing	0.15	(0.36)	0.14	(0.34)	0.05	(0.23)	0.04	(0.20)
Electricity, Gas, Water and Waste Services	0.01	(0.12)	0.02	(0.14)	0.00	(0.07)	0.00	(0.07)
Construction	0.09	(0.29)	0.10	(0.30)	0.01	(0.12)	0.01	(0.11)
Wholesale Trade	0.04	(0.19)	0.04	(0.20)	0.02	(0.15)	0.02	(0.15)
Retail Trade	0.10	(0.30)	0.09	(0.28)	0.14	(0.35)	0.13	(0.33)
Accommodation and Food Services	0.05	(0.22)	0.05	(0.22)	0.10	(0.30)	0.07	(0.26)
Transport, Postal and Warehousing	0.08	(0.27)	0.07	(0.25)	0.02	(0.14)	0.02	(0.13)
Information Media and Telecommunications	0.03	(0.16)	0.02	(0.16)	0.02	(0.16)	0.02	(0.14)
Financial and Insurance Services	0.04	(0.18)	0.04	(0.19)	0.04	(0.20)	0.05	(0.21)
Rental, Hiring and Real Estate Services	0.01	(0.10)	0.01	(0.10)	0.01	(0.12)	0.02	(0.12)
Professional, Scientific and Technical Services	0.07	(0.26)	0.07	(0.25)	0.06	(0.24)	0.06	(0.24)
Administrative and Support Service	0.03	(0.17)	0.02	(0.14)	0.04	(0.19)	0.03	(0.16)
Public Administration and Safety	0.09	(0.29)	0.10	(0.30)	0.06	(0.23)	0.07	(0.26)
Education and Training	0.05	(0.21)	0.07	(0.26)	0.14	(0.34)	0.18	(0.38)
Health Care and Social Assistance	0.06	(0.24)	0.05	(0.22)	0.22	(0.41)	0.23	(0.42)
Arts and Recreation Services	0.02	(0.14)	0.02	(0.13)	0.02	(0.12)	0.01	(0.12)
Other Services	0.03	(0.18)	0.04	(0.19)	0.03	(0.17)	0.02	(0.16)
N (observations)	4167		20903		5205		21180	

Table A4: Factor Loadings for Job Conditions by Analysis Sample

		Rotated factor loadings	
Factor	***Items***	***Presenteeism Sample***	***Absenteeism Sample***
Control	I have a lot of freedom to decide how I do my own work	0.7843	0.7953
	I have a lot of say about what happens on my job	0.7787	0.7876
	I have a lot of freedom to decide when I do my work	0.6201	0.6369
Security	I have a secure future in my job	0.6540	0.6745
	The company I work for will still be in business 5 years from now	0.4923	0.4982
	I worry about the future of my job (reverse coded)	0.5467	0.5734
Complexity	My job is complex and difficult	0.5221	0.5474
	My job often requires me to learn new skills	0.6605	0.6719
	I use many of my skills and abilities in my current job	0.5931	0.5946
Stress	My job is more stressful than I had ever imagined	0.7541	0.7560
	I fear that the amount of stress in my job will make me physically ill	0.7389	0.7392

Table A5: Complete Regression Results: Presenteeism (Table 3) by Gender

	Men		*Women*	
	LOGIT (1)	***CFE-LOGIT (2)***	***LOGIT (3)***	***CFE-LOGIT (4)***
Poor mental health	6.537***	6.180***	7.249***	6.917***
	[6.111-6.994]	[5.524-6.913]	[6.832-7.690]	[6.279-7.620]
Control	0.960**	0.917***	0.994	0.948**
	[0.927-0.994]	[0.865-0.973]	[0.965-1.023]	[0.902-0.996]
Security	0.868***	0.892***	0.899***	0.912***
	[0.841-0.897]	[0.847-0.939]	[0.874-0.926]	[0.871-0.955]
Stress	1.501***	1.415***	1.398***	1.331***
	[1.451-1.552]	[1.340-1.495]	[1.358-1.439]	[1.270-1.395]
Complexity	0.981	0.925**	0.984	0.957*
	[0.946-1.017]	[0.871-0.983]	[0.954-1.016]	[0.910-1.007]
Age	1.025**	0.988	0.968***	0.945**
	[1.004-1.047]	[0.933-1.046]	[0.950-0.986]	[0.899-0.994]
Age (square)	0.966***	0.971	1.030**	1.031
	[0.941-0.991]	[0.907-1.039]	[1.006-1.054]	[0.972-1.095]
# Children	0.984	0.942	1.002	1.023
	[0.946-1.023]	[0.861-1.031]	[0.967-1.038]	[0.934-1.121]
# Adults	0.951***	0.966	0.913***	0.953*
	[0.919-0.984]	[0.905-1.030]	[0.886-0.941]	[0.901-1.008]
Married	0.691***	0.605***	0.709***	0.670***
	[0.630-0.757]	[0.490-0.747]	[0.658-0.764]	[0.558-0.806]
De-facto	0.787***	0.665***	0.900**	0.777***
	[0.716-0.865]	[0.556-0.796]	[0.830-0.976]	[0.663-0.910]
Postgraduate	1.215***	0.560*	1.029	0.687*
	[1.050-1.406]	[0.309-1.014]	[0.913-1.160]	[0.451-1.046]
Undergraduate	1.269***	0.724	1.082*	0.824
	[1.135-1.419]	[0.465-1.130]	[0.988-1.185]	[0.605-1.123]
Certificate	1.227***	0.896	1.090*	1.002
	[1.114-1.351]	[0.620-1.295]	[0.993-1.197]	[0.771-1.302]
Year 12	1.195***	0.880	1.084*	0.877
	[1.077-1.326]	[0.634-1.221]	[0.994-1.182]	[0.699-1.102]
Mild disability	1.261***	1.066	1.377***	1.348***
	[1.131-1.405]	[0.910-1.249]	[1.244-1.524]	[1.159-1.569]
Moderate disability	1.798***	1.300***	1.848***	1.541***
	[1.613-2.004]	[1.086-1.555]	[1.680-2.034]	[1.311-1.811]
Physical health (SF-36)	0.989***	0.987***	0.990***	0.990***
	[0.987-0.991]	[0.984-0.990]	[0.989-0.992]	[0.987-0.993]
Smoker	1.397***	1.366***	1.233***	1.244***
	[1.300-1.500]	[1.150-1.624]	[1.151-1.321]	[1.058-1.464]
Ln household disposable income	0.818***	1.067	0.906***	0.981
	[0.758-0.883]	[0.930-1.224]	[0.848-0.968]	[0.875-1.101]
Non-positive income	0.134***	1.566	0.397*	1.354
	[0.044-0.408]	[0.263-9.328]	[0.155-1.019]	[0.284-6.464]
Regional unemployment	1.015	1.019	1.010	1.018
	[0.986-1.044]	[0.975-1.064]	[0.984-1.036]	[0.979-1.059]
Inner regional	1.043	1.074	0.929*	0.897
	[0.960-1.134]	[0.847-1.363]	[0.862-1.001]	[0.716-1.124]
Outer regional	1.176***	1.936***	0.917*	0.795
	[1.050-1.317]	[1.389-2.699]	[0.827-1.016]	[0.573-1.103]
Remote	1.370**	1.085	1.037	0.589*
	[1.065-1.763]	[0.571-2.064]	[0.812-1.325]	[0.320-1.084]
SEIFA index	1.024***	1.046***	1.033***	1.032**
	[1.011-1.037]	[1.012-1.081]	[1.021-1.045]	[1.003-1.061]
NR at t+1	0.992	1.016	0.974	0.904
	[0.884-1.114]	[0.832-1.242]	[0.877-1.082]	[0.755-1.083]

Usual workdays / week	0.954**	0.969	0.941***	0.949**
	[0.918-0.991]	[0.913-1.029]	[0.915-0.967]	[0.910-0.990]
Proportion of past year in employment	1.316**	1.393*	0.954	1.080
	[1.043-1.660]	[0.972-1.999]	[0.806-1.128]	[0.843-1.382]
Full-time employed	0.910	0.923	0.898***	0.902
	[0.801-1.033]	[0.757-1.126]	[0.830-0.972]	[0.797-1.020]
Fixed-term contract	0.927	0.865*	1.004	0.889
	[0.830-1.036]	[0.733-1.020]	[0.911-1.107]	[0.771-1.024]
Casual contract	1.039	1.064	1.043	0.912
	[0.932-1.159]	[0.895-1.264]	[0.961-1.133]	[0.802-1.037]
Other contract	1.139	1.225	0.971	0.462**
	[0.685-1.895]	[0.575-2.606]	[0.567-1.664]	[0.215-0.991]
Tenure	0.981***	1.013	0.996	1.033***
	[0.969-0.994]	[0.990-1.037]	[0.983-1.008]	[1.010-1.056]
Tenure (square)	1.047**	0.955	0.959*	0.889***
	[1.006-1.089]	[0.882-1.034]	[0.916-1.005]	[0.819-0.964]
Firm size: <20	0.921*	0.995	1.076*	1.279***
	[0.835-1.015]	[0.835-1.184]	[0.988-1.172]	[1.102-1.484]
Firm size: 20-99	0.935	0.846**	1.060	1.105
	[0.850-1.029]	[0.720-0.994]	[0.972-1.157]	[0.958-1.275]
Firm size: 100-499	1.011	0.990	1.078	1.069
	[0.917-1.115]	[0.845-1.161]	[0.983-1.182]	[0.924-1.236]
Firm size: Missing	1.022	0.962	0.947	1.017
	[0.885-1.180]	[0.779-1.187]	[0.850-1.054]	[0.870-1.188]
Union	1.068	1.114	1.046	1.161**
	[0.987-1.155]	[0.960-1.292]	[0.973-1.125]	[1.024-1.317]
Regular work schedule	0.913**	1.043	0.949	0.884**
	[0.842-0.990]	[0.908-1.199]	[0.884-1.019]	[0.787-0.993]
Private sector	0.849***	0.927	0.935	1.110
	[0.763-0.946]	[0.761-1.129]	[0.858-1.019]	[0.955-1.290]
Occupation / Industry dummies	Yes	Yes	Yes	Yes
N (observations)	38261	17000	40044	20897
N (individuals)	8026	2328	8487	2995

Notes: Presented are the expanded estimates from Table 3, columns (3) and (4). Columns (1) and (3) are pooled logit models, while (2) and (4) are the fully specified conditional fixed effects logit models. Full estimates are available on request. Odds ratios (OR) are reported with corresponding 95% confidence intervals reported in parentheses. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table A6: Complete Regression Results: Absenteeism (Table 5) by Gender

	Men		*Women*	
	NEG BIN (1)	***NB-CRE (2)***	***NEG BIN (3)***	***NB-CRE (4)***
Poor mental health	1.133***	1.049*	1.172***	1.053**
	[1.075-1.195]	[0.997-1.103]	[1.120-1.226]	[1.007-1.101]
Control	0.922***	0.956***	0.956***	0.986
	[0.903-0.942]	[0.934-0.979]	[0.939-0.973]	[0.966-1.007]
Security	0.981*	1.028**	1.003	1.034***
	[0.961-1.001]	[1.006-1.050]	[0.984-1.021]	[1.013-1.055]
Stress	1.003	1.005	1.058***	1.027***
	[0.982-1.025]	[0.983-1.027]	[1.039-1.077]	[1.007-1.047]
Complexity	1.018	0.984	1.017*	1.007
	[0.995-1.040]	[0.961-1.009]	[0.997-1.037]	[0.985-1.030]
Age	0.962***	0.961***	0.975***	1.023*
	[0.950-0.974]	[0.935-0.988]	[0.964-0.986]	[0.997-1.051]
Age (square)	1.040***	1.069***	1.021***	0.989
	[1.024-1.056]	[1.035-1.105]	[1.007-1.036]	[0.959-1.020]
# Children	0.964***	1.002	0.983	0.964*
	[0.942-0.988]	[0.966-1.039]	[0.962-1.004]	[0.926-1.004]
# Adults	0.986	0.983	0.971***	0.987
	[0.966-1.007]	[0.956-1.010]	[0.952-0.989]	[0.962-1.012]
Married	1.150***	1.112**	1.093***	1.015
	[1.088-1.216]	[1.020-1.213]	[1.046-1.143]	[0.937-1.098]
De-facto	1.092***	1.025	1.042	1.070*
	[1.031-1.156]	[0.953-1.103]	[0.990-1.097]	[0.999-1.146]
Postgraduate	0.905**	1.007	1.027	1.323**
	[0.832-0.985]	[0.770-1.318]	[0.958-1.101]	[1.062-1.647]
Undergraduate	1.008	1.211*	1.085***	1.542***
	[0.942-1.078]	[0.971-1.511]	[1.026-1.148]	[1.285-1.851]
Certificate	1.020	0.978	1.107***	1.329***
	[0.962-1.082]	[0.836-1.145]	[1.045-1.172]	[1.140-1.550]
Year 12	1.012	1.039	1.105***	1.255***
	[0.949-1.080]	[0.870-1.241]	[1.044-1.169]	[1.065-1.478]
Mild disability	1.327***	1.004	1.237***	1.030
	[1.240-1.421]	[0.945-1.066]	[1.159-1.321]	[0.970-1.094]
Moderate disability	1.403***	1.017	1.263***	1.030
	[1.298-1.516]	[0.942-1.097]	[1.182-1.349]	[0.962-1.103]
Physical health (SF-36)	0.994***	0.998***	0.995***	0.999
	[0.993-0.995]	[0.997-1.000]	[0.994-0.996]	[0.998-1.000]
Smoker	1.079***	1.058	1.081***	1.039
	[1.030-1.130]	[0.985-1.137]	[1.033-1.131]	[0.967-1.116]
Ln household disposable income	0.982	1.029	1.014	1.013
	[0.932-1.034]	[0.969-1.093]	[0.969-1.061]	[0.960-1.069]
Non-positive income	0.463*	1.818	1.159	1.341
	[0.211-1.014]	[0.811-4.074]	[0.576-2.331]	[0.633-2.838]
Regional unemployment	0.999	0.979*	0.965***	0.986
	[0.979-1.020]	[0.958-1.000]	[0.947-0.983]	[0.966-1.007]
Inner regional	0.934***	0.938	0.972	0.905*
	[0.888-0.982]	[0.847-1.039]	[0.929-1.017]	[0.816-1.003]
Outer regional	0.979	0.976	0.842***	0.993
	[0.913-1.049]	[0.831-1.146]	[0.790-0.897]	[0.850-1.161]
Remote	1.112	0.814	0.797***	0.752**
	[0.941-1.314]	[0.613-1.082]	[0.680-0.935]	[0.576-0.981]
SEIFA index	0.982***	1.001	0.987***	0.994
	[0.974-0.989]	[0.988-1.015]	[0.980-0.994]	[0.982-1.006]
NR at t+1	0.987	0.995	1.103**	1.058

	(1)	(2)	(3)	(4)
	[0.906-1.076]	[0.910-1.088]	[1.018-1.195]	[0.973-1.151]
Full-time employed	1.160***	1.105*	1.039*	1.026
	[1.075-1.253]	[0.999-1.221]	[0.998-1.082]	[0.978-1.076]
Fixed-term contract	0.785***	0.893***	0.878***	0.954*
	[0.736-0.838]	[0.838-0.952]	[0.830-0.930]	[0.904-1.008]
Casual contract	0.213***	0.279***	0.195***	0.286***
	[0.196-0.230]	[0.249-0.313]	[0.184-0.206]	[0.262-0.311]
Other contract	0.948	0.747	0.693**	0.813
	[0.667-1.346]	[0.524-1.065]	[0.485-0.989]	[0.561-1.177]
Tenure	1.015***	1.036***	1.013***	1.015***
	[1.008-1.022]	[1.026-1.045]	[1.006-1.020]	[1.006-1.024]
Tenure (square)	0.996	0.918***	0.992	0.967**
	[0.975-1.018]	[0.889-0.947]	[0.971-1.014]	[0.938-0.996]
Firm size: <20	0.644***	0.813***	0.603***	0.754***
	[0.606-0.684]	[0.750-0.881]	[0.570-0.637]	[0.698-0.815]
Firm size: 20-99	0.816***	0.891***	0.809***	0.870***
	[0.770-0.864]	[0.833-0.954]	[0.766-0.854]	[0.816-0.928]
Firm size: 100-499	0.841***	0.907***	0.883***	0.952
	[0.794-0.892]	[0.854-0.964]	[0.836-0.934]	[0.897-1.010]
Firm size: Missing	0.924	0.990	0.859***	0.921**
	[0.840-1.016]	[0.904-1.084]	[0.802-0.920]	[0.863-0.984]
Union	1.231***	1.059*	1.107***	1.064**
	[1.175-1.290]	[1.000-1.121]	[1.061-1.155]	[1.010-1.121]
Regular work schedule	1.167***	1.126***	1.070***	1.109***
	[1.107-1.229]	[1.057-1.199]	[1.020-1.122]	[1.044-1.179]
Private sector	0.776***	0.919**	0.777***	0.946
	[0.727-0.829]	[0.848-0.997]	[0.737-0.819]	[0.885-1.011]
Job changer	1.006	0.824***	1.071**	0.854***
	[0.949-1.067]	[0.782-0.868]	[1.014-1.130]	[0.813-0.898]
Occupation / Industry dummies	Yes	Yes	Yes	Yes
N (observations)	25070	25070	26385	26385
N (individuals)	6101	6101	6459	6459
LR test for individual effects (χ^2)		3263.04		2742.56

Notes: Presented are the full estimates from Table 4, columns (3) and (4). Columns (1) and (3) are pooled negative binomial models, while (2) and (4) are the fully specified correlated random effects negative binomial models. Full estimates are available on request. For absenteeism models covariates are measured at the previous interview (roughly 12 months prior). We do not control for the main effects of either the proportion of the previous 12 months in employment or the number of days usually worked per week given these are used in the construction of the exposure measure, but we do include a control identifying job changers. Incidence rate ratios (IRR) are reported with corresponding 95% confidence intervals reported in parentheses. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.