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The Bilateral Relationship between Depressive Symptoms and Employment Status

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NON-TECHNICAL SUMMARY

Mental health and employment outcomes are inherently intertwined. People with poor mental health have lower levels of economic activity, lower earnings, and less stable employment. On the other hand, employment difficulties can undermine mental health; many who struggle to find meaningful work or who lose their jobs will experience poorer mental well-being as a result. But are mental health issues a cause or consequence of poor labor market outcomes?

Using nationally representative data, we estimate how transitions into and out of depressive episodes affect subsequent employment outcomes, including participation, employment and unemployment. Further, we address the potential for the reverse relationship to exist by estimating how changes in employment status affect the chances of developing severe depressive symptoms. We aim to shed light on the interplay between depression and the labor market, which is particularly important because the appropriate policy responses depend on whether depressive issues are a consequence or a determinant of poor labor market outcomes.

We find that severe depressive symptoms lead to economic inactivity by reducing labor force participation and employment, and increasing the likelihood of unemployment. We also find that severe depressive symptoms are partially a consequence of economic inactivity. Interestingly, our results show larger effects for men than women, indicating that men's mental health is more closely tied to their employment outcomes than is women's. Further, men seem to be more responsive to the shock of a bad event -- either the onset of a depressive episode or the onset of unemployment. In contrast, women appear to be more affected by prolonged depressive symptoms.

The results imply that reducing the economic costs of mental illness is a challenge that is best tackled from both sides: improving mental health by promoting economic activity, minimizing employment disruptions and shortening unemployment spells, and reducing the barriers to employment and providing positive work environments for those with mental health issues. The results also call for a gendered approach to these policies.

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Abstract

This paper analyzes the bilateral relationship between depressive symptoms and employment status. We find that severe depressive symptoms are partially a consequence of economic inactivity. The incidence of depressive symptoms is higher if individuals have been out of a job for an extended period. Men's mental health falls as they exit the labor force, while women's worsens only after they have been out of the labor force for a period of time. Entering unemployment is also associated with a substantial deterioration in mental health, particularly for men. We also find that severe depressive symptoms, in turn, lead to economic inactivity. Individuals are less likely to be labor force participants or employed if they experience severe depressive symptoms. Men's probability of being unemployed rises dramatically with the onset of depressive symptoms; women's unemployment is increased by protracted depressive symptoms.

Keywords: mental health; unemployment; labor market status; HILDA survey; depressive symptoms; depression; Australia

1. Introduction

Mental and economic well-being are inherently related. Mental health is, after all, a key factor of production (Layard 2013); people with poor mental health have lower levels of economic activity, lower earnings, less stable employment, and less financial security. There is also little doubt that labor market difficulties can, in turn, undermine mental health; many who struggle to find meaningful work or who lose their jobs will experience diminished mental well-being as a result. Disentangling the complex relationship between employment and mental health is methodologically challenging. Yet policy makers must begin to address the interplay between mental health and employment if labor markets are to function well (OECD 2015, 3). The policy implications of mental health problems differ if they are consequences rather than determinants of adverse labor market events (see Olesen et al. 2013).

Depressive disorders are among the most common forms of mental illness. The World Health Organization estimates that worldwide more than 300 million people suffered from depression in 2015 (WHO 2017). Common mental disorders, including depression, do not preclude employment; in fact the vast majority of individuals experiencing a common mental disorder work (OECD 2012). However, those who are mentally ill have higher unemployment rates and lower labor force participation rates; they also have diminished productivity when they do work. Half of the overall cost of depression in the United States has been attributed to the reduced productivity of workers (ILO 2000; Greenberg et al. 2003; Greenberg et al. 2015). Productivity losses are compounded by the fact that approximately half of all depressive disorders go undiagnosed and untreated (WHO 2003; OECD 2014). Along with this, the high prevalence of common mental disorders means that they raise society's overall disability burden more than severe mental disorders (Kessler et al. 2005a, 2005b; ILO 2000; OECD 2012).[1]

Our goal is to shed light on the nature of the bilateral relationship between depressive symptoms and employment status, including participation, employment, and unemployment. We do this by using 14 years of population representative data to estimate sequential dynamic fixed-effects models that allow for a bilateral relationship between mental health and employment status, while controlling for time-invariant unobserved heterogeneity. This represents an important contribution to the literature which, to date, has focused on estimating unidirectional effects; either of mental health on employment outcomes or of employment

[1] One in 10 adult Americans experiences a depressive disorder each year (ILO 2000), while common mental disorders including depression affect up to 20 percent of working-age adults across the OECD (OECD 2014).

outcomes on mental health. Standard labor supply models, however, imply that health and employment outcomes are jointly determined (see Hamilton et al. 1997; Currie and Madrian 1999), making it critical to account for structural as well as statistical endogeneity in our estimation procedures (Hamilton et al. 1997; Chatterji et al. 2011). Our strategy is to estimate models in which the timing of events allows us to avoid the simultaneity problem and identify the bilateral relationship between depressive symptoms and employment transitions without the need for exclusion restrictions.

Despite the importance of the topic, only a handful of other studies investigate the bilateral relationship between depression and employment outcomes. Dooley et al. (1994) investigate the reciprocal associations between unemployment and diagnosed clinical depression among individuals recruited in an epidemiological study of behavioral disorders at five sites in the United States in the 1980s. Jefferies et al. (2011) conduct similar analyses using a prospective cohort study of respondents drawn from primary care practices in Latin American and Europe. In more recent work, Olesen et al. (2013) estimate the reciprocal correlations between unemployment and depressive symptoms using population level data from Australia. Related research also sheds light on the relationship between depression and other employment experiences. Andreeva et al. (2015), for example, uses data from a large organization in Sweden to assess whether there is a reciprocal relationship between exposure to downsizing and depressive symptoms, while Dawson et al. (2015) use a baseline approach to estimate the associations between psychological distress and transitions between temporary and permanent employment. Only two studies attempt to provide causal estimates. Hamilton et al. (1997) use simultaneous equations methods to examine the effect of psychiatric symptoms on men's and women's employment, and Steele et al. (2013) estimate correlated random-effects models of the joint relationship between men's employment transitions and their levels of distress and anxiety.

We advance this literature by employing a fixed-effects specification to eliminate the potential for unobserved time-invariant heterogeneity – irrespective of the form it takes – to bias our results. Eliminating this likely source of statistical endogeneity helps us to provide estimates with a more causal interpretation and is a necessary first step in identifying appropriate policy responses. We adopt a broad perspective on economic well-being by examining several key labor market transitions, not just those into and out of unemployment. Another innovation is that we take advantage of data drawn from job calendars rather than point-in-time work status, allowing us to construct transition measures that more fully capture individuals' employment experiences. This is important as the point-in-time incidence of unemployment (or nonparticipation) may miss those individuals who are briefly unemployed (or nonparticipants) between interview dates leading the detrimental effect of mental health problems on employment outcomes to potentially be underestimated (see Steele et al. 2013). We also make a major contribution in using nationally representative data to provide evidence on the dynamic relationship between mental health problems and employment status for women as well as for men. There is considerable evidence that men and women differ not only in their employment behavior and mental health, but also in their mental health responses to their own employment shocks as well as to those of others around them (see Novo et al. 2001; Paul and Moser 2009; Marcus 2013; Bubonya et al. 2014; Norström et al. 2014). Given this, there is every reason to believe that the dynamic relationship between mental and economic well-being will be gendered as well.

We find that severe depressive symptoms are partially a consequence of economic inactivity. The incidence of depressive symptoms is higher if individuals have been out of a job for an extended period. Men's mental health falls as they exit the labor force, while women's worsens only after they have been out of the labor force for a period of time. Entering unemployment is also associated with a substantial deterioration in mental health, particularly for men. We also find that severe depressive symptoms, in turn, lead to economic inactivity. Individuals are less likely to be labor force participants or employed if they experience severe depressive symptoms. Men's probability of being unemployed rises dramatically with the onset of depressive symptoms; women's unemployment is increased by protracted depressive symptoms.

The rest of the paper proceeds as follows. Section 2 provides an overview of the relevant literature relating mental health and labor market outcomes. In Section 3, we discuss our estimation approach, including our conceptual framework and identification strategy, while the data are described in Section 4. Our results are presented in Section 5 and we test the sensitivity of these results in Section 6. Finally, our conclusions and suggestions for future research are discussed in Section 7.

2. Previous Literature

There is considerable evidence that mental health problems limit labor market success.[2] Those with mental health issues, including depression and anxiety, may experience reduced productivity (lower concentration, cognitive capacity and motivation, higher absence), lower earnings, and employer discrimination (see Ettner et al. 1997; Currie and Madrian 1999). Each can lower labor market attachment and reduce employment options. Empirical evidence from representative samples indicates, for example, that poor mental health is associated with participation (Chatterji et al. 2011; Banerjee et al. 2017) and employment rates (Ettner et al. 1997; Alexandre and French 2001; Chatterji et al. 2007; Ojeda et al. 2010; Frijters et al. 2014; Banerjee et al. 2017) that are between 10 and 30 percentage points lower.[3] These disparities are large and economically meaningful. While some studies report larger effects for women (Chatterji et al. 2007; Frijters et al. 2014), others find similar (Ojeda et al. 2010; Chatterji et al. 2011) or even larger effects for men (Banerjee et al. 2017).

Interestingly, the evidence on the effect of mental health on earnings and hours worked is also mixed. Some researchers find that mental health problems reduce the number of hours and weeks worked in a year (Ettner et al. 1997; Alexandre and French 2001; Banerjee et al. 2017), while others find no effect (Chatterji et al. 2007; Chatterji et al. 2011; Peng et al. 2013). Further, mental health problems, which interfere with work capacity and productivity, may lower earrings. Marcotte et al. (2000) provide evidence that mental illnesses are associated with lower incomes, while Ettner et al. (1997) find the same for earnings though their result is sensitive to estimation method and specification. More recent evidence does not find an effect of mental health on earnings (Chatterji et al. 2011; Peng et al. 2013).

Researchers investigating the labor market consequences of poor mental health have frequently relied on instrumental variable (IV) methods to isolate exogenous variation in mental health. A range of IVs have been employed including: i) early onset of mental health issues (Ettner et al. 1997; Chatterji et al. 2007; Chatterji et al. 2011; Banerjee et al. 2017); ii) parental mental health (Ettner et al. 1997; Chatterji et al. 2011); iii) social support (Alexandre and French 2001; Ojeda et al. 2010); iv) religiosity (Alexandre and French 2001; Ojeda et al.

[2] For reviews of the literature regarding the role of health in the labor market more generally see Currie and Madrian (1999), Chirikos (1993), and Barnay (2016).

[3] There is limited evidence on the impact of mental health on unemployment. Butterworth et al. (2012) provide a recent exception by demonstrating that poor mental health increases the risk of future unemployment. There is also a small literature assessing whether psychological problems in adolescence predict young-adult unemployment (see Egan et al. 2016).

2010); and v) adverse life events (e.g. death of a friend) (Frijters et al. 2014). Many of these IVs are difficult to defend theoretically, raising concerns about whether the exclusion restrictions necessary to achieve causal identification actually hold (e.g. Ettner et al. 1997; Chatterji et al. 2007; Ojeda et al. 2010; Banerjee et al. 2017).

It is also clear that labor market outcomes have the potential to affect mental health. There is ample evidence, for example, that unemployed individuals have worse mental health (Björklund and Eriksson 1998; Paul and Moser 2009), leading researchers to largely focus on analyzing whether job loss itself reduces mental health.[4] Job loss has been hypothesized to worsen mental health through a variety of channels including increased stress and anxiety, reduced income, constrained health investments, and the loss of the psychological (e.g. sense of control, sense of purpose, externally generated goals) and social benefits of employment (e.g. social relationships, time structure) (see Ezzy 1993; McKee-Ryan et al. 2005 for reviews). Recent meta-analyses of the relationship between unemployment and mental distress conclude that effect sizes are small to medium and are moderated by gender, age, occupation and macroeconomic climate (i.e. recessions, local unemployment rates, welfare systems) (McKee-Ryan et al. 2005; Paul and Moser 2009; Norström et al. 2014).

Much of the literature on the mental health consequences of labor market outcomes identifies associations rather than causal effects. Increasingly, however, a variety of econometric approaches are being used to identify effects that are more plausibly causal. Some researchers, for example, control for unobserved heterogeneity using individual-specific random- or fixed-effects models (Dockery 2006; Green 2011), while others attempt to rule out reverse causality by examining transitions into unemployment (Flint et al. 2013; Milner et al. 2014). In particular, several studies estimate the mental health consequences of unemployment that results from plant closure and mass-layoffs, which some researchers argue are exogenous shocks (Paul and Moser 2009; Chadi and Hetschko 2016), though this has been a matter of debate (Bubonya et al. 2014). The results have been mixed despite a similar research methodology being adopted.[5] Unemployment stemming from plant closure was found to have a negative effect on mental health in Greece with larger effects for men than women (Drydakis 2015), either no (Schmitz 2011) or negative effects (Marcus 2013) in Germany, and no effect

[4] There is less evidence on the effects of employment patterns on mental health. See Virtanen et al. (2005) for a review of the literature on temporary employment and health and Stansfeld and Candy (2006) for a review of the literature on the psychosocial dimensions of the work environment and mental health.

[5] Results are also mixed in studies that rely on administrative data for prescriptions and hospital admissions to identify mental illness (Kuhn et al. 2009; Eliason and Storrie 2010; Browning and Heinesen 2012).

on the mental health of older Americans (Salm 2009).[6]

Unfortunately, this extensive literature tells us very little about the nature of the bilateral relationship between mental health and labor market outcomes. Empirical evidence from epidemiological studies indicates that unemployment is often associated with a heightened risk of depressive mood disorders subsequently; there is less empirical support for an association between depression and future unemployment (Dooley et al. 1994; Jefferis et al. 2011; Olesen et al. 2013; Andreeva et al. 2015).[7] Most economic studies, however, begin with a maintained assumption about the direction of causality – i.e. either from mental health to labor market outcomes or the reverse – and then adopt the best available empirical strategy to minimize the threats to causal inference. "The debate around the direction of causality between health and employment status requires re-examination through a longitudinal analysis that captures changes in mental health and employment transitions, as only then will we be able to comprehend whether a change in mental health precedes or follows a change in employment." (Dawson et al. 2015, 51).

It is only recently that economists have begun to jointly model the relationship between mental health and labor market outcomes in an attempt to establish the direction of causality. Hamilton et al. (1997) appears to be the first to analyze the reciprocal relationship between mental health and employment, thus accounting for structural endogeneity. The authors exploit a small (N = 447) sample of working-age individuals in Montreal to estimate a simultaneous equations model of the link between psychiatric symptoms and the propensity of being employed, with the model being identified through exclusion restrictions. The results indicate that improved mental health is associated with increased employability and being employed is associated with fewer psychiatric symptoms.

Subsequent research has turned to more representative samples. Dawson et al. (2015) and Steele et al. (2013) both draw on 18 waves of panel data for working-aged individuals captured in the British Household Panel Study. Dawson et al. consider transitions between permanent employment and different types of temporary arrangements including seasonal, casual, temporary, or fixed-term contracts. They find that psychological distress and anxiety precedes

[6] Rather than focusing on plant closures, Gathergood (2013) exploits another source of exogenous variation, the industry-age-year unemployment rate, to instrument for unemployment propensities. He finds a negative impact of unemployment on mental health in Britain, with larger effects for men than women.

[7] In particular, Dooley et al. (1994) find no support for an effect of depression on subsequent unemployment, while Jefferis et al. (2011) and Olesen et al. (2013) find evidence of a reciprocal relationship that is substantially stronger from unemployment to depression rather than the reverse. Andreeva et al. (2015) find that depressive symptoms are associated with a higher likelihood of being unemployed in the future for women, but not men.

a transition into temporary employment, but that mental health is not significantly lower for those who previously experienced temporary employment. Using the same data, Steele et al. (2013) link transitions in men's employment status to changes in their mental health using a correlated random-effects specification. They find that moving from employment to unemployment increases psychological distress and anxiety. At the same time, the onset of mental health issues is associated with an increase in economic inactivity and a small increase in the probability of being unemployed.

We add to this literature by estimating the bilateral relationship between employment status and depressive symptoms using sequential dynamic fixed-effects specifications that account for time-invariant unobserved heterogeneity irrespective of the form it takes. Our consideration of several alternative labor market transitions allows us to provide a broad perspective on the relationship between mental and economic well-being. Finally, we conduct all estimation separately for both men and women in order to shed light on the gendered nature of the relationship between mental health and labor market outcomes.

3. Estimation Strategy

The objective of this paper is to estimate the dynamic relationship between episodes of depressive symptoms and transitions in employment status. Our estimation strategy recognizes that there are strong conceptual links between people's mental health and employment status. Mental well-being is a form of human capability; it directly affects people's labor market productivity and can thereby increase economic well-being (Hamilton et al. 1997; Currie and Madrian 1999; Layard 2013). Mental health, like physical health, can also be thought of as a consumption good that directly raises utility and well-being (Grossman 1972). This implies that, as with other normal goods, income changes will lead to changes in mental health-related behaviors. Employment may also have environmental impacts on mental well-being which can either improve (e.g. through positive social interactions and networks, greater self-esteem) or tax mental health (e.g. as a result of job stress, poor working conditions) (see Hamilton et al. 1997; Cai and Kalb 2006).

These conceptual links make identifying the nature of the relationship between mental health and employment challenging. Yet isolating the separate effects of each on the other is important for setting policies which improve mental health and for determining whether poor mental health is indeed a significant barrier to employment. As usual, the biggest threat to causality is the endogeneity of mental health and employment outcomes. The inter-relationship between the two implies that we need to be concerned about both structural (reverse causality, simultaneity) and statistical endogeneity (unobserved heterogeneity, justification bias) (see Cai 2010; Chatterji et al. 2011).

Previous research has relied on two main strategies to tackle structural endogeneity. The first is to estimate a simultaneous equations model and impose exclusion restrictions to identify the model. Effectively, one must find valid instruments for employment outcomes in a reduced-form model of mental health as well as for health outcomes in a reduced-form model of employment outcomes. The maintained assumptions necessary to achieve identification are often difficult to justify on theoretical grounds. A second approach avoids the need for exclusion restrictions by jointly estimating models in which the sequence (or timing) of events eliminates the risk of reverse causality. Given the discrete nature of most data sources, this typically involves modelling transitions into and out of various labor market and mental health states (e.g. García-Gómez and López-Nicolás 2006; Haan and Myck 2009; Olesen et al. 2013; Steele et al. 2013).[8] A key weakness, however, of the timing approach is that it abstracts from the possibility of concurrent reciprocal effects.

We adopt this latter timing approach and account for the bilateral relationship between mental health and employment by estimating sequential models of the dynamic transitions between mental health and employment states. We use fixed-effects specifications to control for time-invariant unobserved heterogeneity. This is an advance over previous studies that account for statistical endogeneity using propensity score matching which fail to account for unobserved confounders (García-Gómez and López-Nicolás 2006) or random effects models that require observed and unobserved factors to be independent (Haan and Myck 2009; Cai 2010). The inclusion of a rich set of controls minimizes the potential for concurrent reciprocal events to bias our results. The timing approach further eliminates concerns about justification bias, as it is not sensible to expect individuals to report mental health issues in one period to justify their employment status (e.g., job loss) in the next. Our model is most similar to Haan and Myck (2009) who investigate the dual causality in the non-employment and general health of German men using a sequential model.

Our estimation equations consider three labor market (LM) outcomes—employment, labor

[8] Continuous time approaches, for example bivariate duration models, would require detailed information about the precise timing of events (see Van den Berg 2001; Abbring et al. 2005; Lalive et al. 2008).

force participation and unemployment (conditional on labor force participation)—and the presence of depressive symptoms. We begin by investigating the effects of mental health transitions on each of our labor market outcomes by estimating linear probability models of the form:

$$LM_{it} = \beta_0 + MH\_trans_{it-1}\beta_{MH} + X_{it-1}\beta + \delta_t + u_i + \varepsilon_{it} \quad (1)$$

where LM_{it} is a binary indicator of individual *i*'s employment, participation, or unemployment status over period *t*-1 to *t*; MH_trans_{t-1} is a vector of mental health transitions (chronic depressive symptoms, exiting a depressive episode, entering a depressive episode, stable good mental health) between *t*-2 and *t*-1; and X_{it-1} is a vector of demographic, financial, and geographic controls measured at *t*-1 and an attrition indicator measured at *t*. We incorporate wave (year) fixed-effects (δ_t) to control for Australia-wide economic and institutional conditions and individual-level fixed effects (u_i) to account for unobserved, time-invariant personal characteristics. Finally, ε_{it} is a stochastic time- and individual-varying error term. All remaining terms are parameters to be estimated.

We analyze the effects of labor market transitions on the incidence of depressive symptoms by estimating linear probability models separately for each set of labor market transitions, using the following:

$$MH_{it} = \gamma_0 + LM\_trans_{it-1}\gamma_{LM} + X_{it}\gamma + \theta_t + \pi_i + \eta_{it} \quad (2)$$

where MH_{it} is a binary indicator of whether individual *i* has depressive symptoms at time *t*. Further, LM_trans_{it-1} is a vector characterizing the four labor market transitions that are possible between the periods (a) *t*-2 and *t*-1 and (b) *t*-1 and the month prior to the current interview (*t*-4w), the period over which mental health is measured. These transitions vary depending on the labor market outcome under consideration. For example, individuals' employment histories between *t*-2 and *t*-4w can be characterized by one of four possible scenarios: continuously employed, continuously non-employed, entry to employment and exit from employment. We derive transitions for participation and unemployment states similarly. In addition, X_{it} is a vector of other observed controls identical to those listed above; however, these are measured at time *t*. As our measure of mental health refers to the four weeks prior to the current interview, we include contemporaneous controls in our model of depressive symptoms in order to minimize the potential for mismatch in the timing of employment information to influence our results.[9] Finally, θ_t is a vector of wave fixed-effects, π_i is an individual-specific fixed effect and η_{it} is a stochastic error term.

4. Data

The data for our empirical analyses come from the Household, Income and Labor Dynamics in Australia (HILDA) survey, a nationally representative panel survey that interviewed 7,682 Australian households with 19,914 people in 2001 and has subsequently re-interviewed the people from those households annually (see Watson and Wooden 2012). At each interview, survey subjects complete multiple instruments, including a Household Form, Household Questionnaire, Person Questionnaire (PQ), and Self-Completion Questionnaire (SCQ), which ask about their economic and subjective well-being, income, employment, health, family circumstances, and other outcomes. Our empirical analyses use data from waves 1 to 14, or roughly 2001 to 2014.[10]

4.1 Mental Health

In each wave, the HILDA SCQ administers the Short Form (SF-36) Health Survey (Ware et al. 2000). We use five items from the SF-36 to construct the abbreviated Mental Health Inventory (MHI-5) scale. The MHI-5 screens for mental health issues, more specifically anxiety and mood disorders, and has proven effective in large populations (Yamazaki et al. 2005; Cuijpers et al. 2009) and primary care settings (Rumpf et al. 2001). In particular, the items ask how often during the past four weeks respondents have:

i. "Been a nervous person,"

ii. "Felt so down in the dumps nothing could cheer [them] up,"

iii. "Felt calm and peaceful,"

iv. "Felt down," and

v. "Been a happy person."

Answers to each item are recorded on a 1-6 scale, ranging from "all of the time" to "none of

[9] We also re-estimated all models using controls lagged one period. Results are available upon request. We found slightly larger effects of labor market transitions on poor mental health for men, while results for women are unchanged.
[10] We extracted the HILDA data with PanelWhiz; see Hahn and Haisken-DeNew (2013) for more information.

the time." We follow Ware et al. (2000) by: reverse coding items iii and v so that all items correspond to better mental health; summing the raw scores across all items; subtracting five; and dividing by 25 to form a 0-100 scale. For individuals with missing values on two or fewer items, we impute values by averaging their remaining valid responses. To measure the presence of depressive symptoms, we follow the common practice of using a binary indicator for a MHI-5 score of 52 or lower, which is best interpreted as identifying people with severe depressive symptoms (see, e.g., Yamazaki et al. 2005; Strand et al. 2009) or a recent major depressive episode (Holmes 1998). In sensitivity analyses, we also examine an indicator of moderate or severe depressive symptoms that adopts a 60-point threshold.[11]

When we model mental health as an outcome, we use the binary measure for the presence of depressive symptoms reported at the time of the interview, t. When we model mental health as an explanatory variable, we use the binary indicators from the two waves preceding the interview, $t-2$ and $t-1$, to construct a set of transition measures. We classify those with no depressive symptoms at $t-2$ and $t-1$ as having stable good mental health and use them as our reference group. We classify individuals whose mental health indicates no depressive symptoms at $t-2$ but the presence of depressive symptoms at $t-1$ as entering a depressive episode, those with depressive symptoms at $t-2$ but not at $t-1$ as exiting a depressive episode, and those with depressive symptoms at both $t-2$ and $t-1$ as experiencing a chronic depressive episode. We note that these classifications are imprecise because mental health is only reported over the four weeks before each SCQ and not continuously between interviews; thus, individuals can experience other mental health transitions that we do not observe.

4.2 Labor Market Transitions

We also create a series of measures that characterize individuals' labor market histories. Respondents to each HILDA PQ completed employment calendars that capture whether they were working, unemployed, or out of the labor force in each 10-day period over the preceding year. Using this information, we construct separate binary variables that indicate whether the respondent i) participated in the labor force; ii) was employed; and iii) was unemployed, at any time (i.e., at least one third of a month) between the previous and current waves, $t-1$ and t. Our

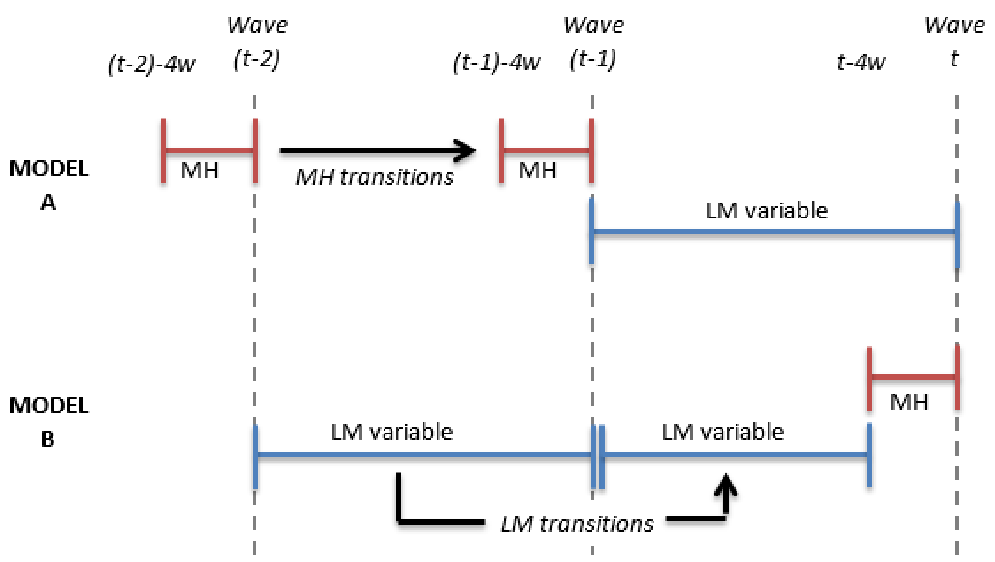
[11] Results using this alternative measure of poor mental health are substantively the same, though there are some differences worth noting. Employment exit is significantly related to a higher probability of men experiencing a depressive episode when we use a 60-point threshold. Poor mental health no longer impacts on women's employment and participation propensities when we move to a less severe definition, though exiting from unemployment reduces the incidence of a depressive episode. Results are available on request.

calendar-based measures allow us to identify short episodes of employment, participation or unemployment which are missed by point-in-time measures of employment status, thus reducing estimation bias.

Along with estimating the effect of changes in mental health on employment status, we are also interested in the link between employment transitions and mental health status. Consequently, we create two binary variables identifying whether respondents were employed i) at any time between the previous two waves, $t-2$ and $t-1$, and ii) at any time between the previous wave and the four weeks (month) before the current interview, $t-1$ and $t-4$w.[12] We exclude these four weeks to avoid any simultaneous overlap with our mental health indicator. The relationship between the periodicities of the underlying health and employment measures is shown in Figure 1. For each combination of the employment indicators, we then construct indicators for people who were i) employed at least 10 days in both waves (reference category); ii) who were not employed between $t-2$ and $t-1$ but subsequently employed between $t-1$ and $t-4$w (entered employment); iii) who were employed between $t-2$ and $t-1$ but not employed between $t-1$ and $t-4$w (exited employment); and iv) who were not employed between $t-2$ and $t-1$ or between $t-1$ and $t-4$w (chronically not-employed). We construct similar transition variables for labor force participation and unemployment.

Figure 1: Modelling the timing of transitions and outcomes.

A. Timing of poor mental health transitions (chronic; exit; entry; stable) and its impact on labor market outcomes (employment; participation; unemployment).
B. Timing of labor market transitions (chronic; exit; entry; stable) and its impact on mental health.



[12] We investigated the sensitivity of our results to seam bias by re-estimating all models using labor market transitions between t-2 and t-8weeks. Results (available upon request) are virtually identical.

4.3 Explanatory Variables

Our multivariate analyses include a detailed set of explanatory and conditioning variables which are motivated by our conceptual framework and supported by prior research (see for example, Roy and Schurer 2013; Bubonya et al. 2016). We condition all of our analyses on gender. We also include demographic controls for the numbers of adults and children in the household, relationship status, highest level of education achieved, long-term health conditions/disability, the extent to which the disability limits work (excluding individuals who identify only mental illness as their disability), the SF-36 physical functioning scale, smoking behavior, and residence in a remote area.

In addition, we include a set of financial controls for whether the household owns (or pays a mortgage on) a home, home equity, the logarithm of real equivalized disposable income of other household members, a flag for non-positive disposable income, the log of the respondent's real equivalized non-labor income, and a flag for non-positive non-labor income. It is likely that total personal disposable income (including earnings) impacts mental well-being; consequently when modelling mental health, we estimate models that do and do not include total disposable income.

Given the four-week periodicity of our mental health measure and the annual periodicity of our employment measures, we control for contemporaneous covariates (time t) in our models of mental health and lagged covariates (time $t-1$) in our models of employment status. Our models also include wave (year) dummies and a dichotomous variable indicating if the individual is a non-respondent at the next wave as a control for selective attrition (see Verbeek and Nijman 1992). We provide more detailed descriptions of all our analysis variables in Appendix Table A1.

4.4 Analysis Sample

The universe for our analysis sample consists of working-age individuals aged 18 to 64 years who are not full-time students, full-time retired, or completely disabled (22,629 individuals, 138,123 person-year observations). Because our estimation relies on lagged explanatory variables and requires data from the SCQ, we restrict the sample to individuals who were interviewed and completed SCQs in three consecutive waves: $t-2$, $t-1$, and t, which results in a loss of 58,488 person-year observations. We omit individuals who were part of the wave 11 top-up sample because they had insufficient information to contribute to the analysis, dropping another 7.9 percent of the initial sample. We further exclude observations with missing information on any explanatory variables, leaving a sample of 65,198 person-year observations from 11,447 individuals for most of our analyses. Our analyses of unemployment use a more restrictive sample that only includes 49,319 person-year observations for 9,666 individuals who were in the labor force in $t-2$, $t-1$, and t.

4.5 The Overall Relationship between Depressive Symptoms and Employment Status

Mean employment-to-population, participation, and unemployment rates both in aggregate and conditional on mental health history (stable good mental health, chronic depressive episodes, exit from a depressive episode, entry into a depressive episode) are provided in Table 1. Statistics for men are shown in the top panel, while the statistics for women are given in the bottom panel.

Across the study period, 95.3 percent of working-age men who are not enrolled in school, retired, or disabled participate in the labor force, and 93.8 percent are employed. Women have a participation rate of 85.8 percent and an employment-to-population rate of 83.3 percent. Men have an unemployment rate of 5.7 percent, while women have a rate that is somewhat lower at 5.0 percent.

Unsurprisingly, men and women with consistently good mental health have higher employment-to-population and participation rates and lower unemployment rates. Among men with no recent depressive episodes, employment and labor force participation are nearly universal, while the unemployment rate is only 4.8 percent. Women with no recent depressive episodes have rates of employment (86 percent) and participation (87.9 percent) that are only slightly lower than those of men. Interestingly, these women have an unemployment rate (4.0 percent) that is somewhat lower than that of their male counterparts. There is a large employment penalty associated with experiencing chronic depressive episodes; 19.7 percentage points (pp) for men and 22.2 pp for women. Further, those with chronic depressive symptoms are less likely to participate in the labor force (15.9 pp men; 17.4 pp women) and are approximately three times more likely to experience unemployment when they do. Still, consistent with patterns in the OECD generally (OECD 2012), employment is the norm for those experiencing severe depression.

Table 1. Current labor market outcomes conditional on previous mental health transitions, by gender.

	Percent of working age population		Percent of labor force unemployed
	Employed	Participating	
A: Men			
Average	93.8	95.3	5.7
Stable MH (ref)	95.6	96.6	4.8
Chronic depressive episodes	75.9	80.7	13.6
Exit depressive episode	88.0	91.6	9.4
Enter depressive episode	88.3	91.5	11.8
Observations	30789	30789	26132
B: Women			
Average	83.3	85.8	5.0
Stable MH (ref)	86.0	87.9	4.0
Chronic depressive episodes	63.8	70.5	14.9
Exit depressive episode	77.1	80.8	7.5
Enter depressive episode	76.8	80.8	8.1
Observations	34409	34409	23187

Notes: The employment and participation analysis use the same estimation sample. Here the employment rate refers to the employment to population ratio. Similarly, the participation rate refers to participation conditional on the working age population. The unemployment rate, however, is conditional on labor force participation and hence uses a sample of labor force participants. All transitions are significantly different from the reference group using a t-test, further chi-squared tests also reveal significant differences between all of the transition categories.

Table 2 presents prevalence rates of mental health problems overall and conditional on recent labor market history. Approximately one in ten (10.6 percent) working-age men who are not enrolled in school, retired, or disabled report being in a depressive episode. Consistent with previous evidence of gender differentials in mental illness (ILO 2000; Rosenfield and Mouzon, 2013), slightly more women (13.4 percent) than men report experiencing severe depressive symptoms.

The vast majority of men and most women in the population have a recent history of continuous labor force participation and employment. The incidence of severe depressive symptoms is substantially lower for these individuals. In contrast, those who have do not have stable employment – either because they are chronically unemployed or because they do not have a recent history of labor force participation – are two to three times as likely to report experiencing a depressive episode.

Table 2. Current mental health outcome conditional on previous labor market transitions, by gender.

	Percent experiencing a depressive episode	
	Men	**Women**
A: Employment		
Stable employment (ref)	9.2	10.9
Chronic non-employed	33.3	25.2
Exit from employment	22.8	19.6
Entry to employment	20.0	19.4
B: Participation		
Stable participation (ref)	9.5	11.4
Chronic non-participation	33.5	24.7
Exit from participation	25.1	19.7
Entry to participation	22.7	20.4
Average for working-age population	10.6	13.4
Observations	30789	34409
C: Unemployment		
Never unemployed (ref)	8.2	9.7
Chronic unemployment	23.6	23.0
Exit from unemployment	13.0	16.8
Entry to unemployment	16.6	18.9
Average for labor force	9.0	10.5
Observations	26132	23187

Notes: The employment and participation analysis use the same estimation sample. All transitions are significantly different from the reference group using a t-test, further chi-squared tests also reveal significant differences between all of the transition categories.

5. Results

We begin our multivariate empirical analysis by examining results from two-way (individual and wave) longitudinal fixed-effect linear probability regression models of individuals' annual employment outcomes. All the models are estimated separately for men and women and include the lagged mental health transition measures and all the other control measures (except own disposable income) listed in Appendix Table A1 as explanatory variables. Initial Breusch-Pagan specification tests indicated that controls for time-invariant unobserved variables were appropriate for all the models, and Hausman-Wu tests rejected the null hypothesis that the unobserved variables were independent of the observed controls. Accordingly, we only report results from fixed-effect specifications. We report estimates from linear probability models to simplify the interpretation of results; estimates from fixed-effect logit specifications, which are not reported but available upon request, are similar.

Table 3 presents selected estimated regression coefficients and robust standard errors for men's and women's annual employment outcomes in the first two columns, labor force participation outcomes in the next two columns, and unemployment outcomes in the last two columns. For men, occurrences of depressive symptoms in either of the preceding two years are estimated to lower employment in the current year by modest but statistically distinguishable amounts. Chronic depressive episodes are estimated to reduce the probability of working by 2.2 pp relative to being in stable good mental health; entering into a depressive episode is estimated to reduce employment by 1.2 pp; and exiting from a depressive episode is associated with employment probabilities that are 2.0 pp lower. Given that the men's employment-to-population ratio is 93.8 percent overall, our estimates imply that there is a 2.3 percent disparity in employment-to-population ratios for those who are continuously well versus those who are chronically unwell. This employment gap is approximately one tenth the size of the unconditional disparity in employment (see Table 1) demonstrating the importance of adjusting for other characteristics through statistical controls. Our fixed-effect estimates indicate that chronic depressive episodes lower women's probability of employment by 2.9 pp (3.5 percent) relative to being in stable good mental health; the development of severe depressive symptoms lowers the probability by (a statistically insignificant) 0.5 pp (0.6 percent); while recovery is associated with an employment probability that is 1.5 pp (1.8 percent) lower. These conditional disparities in women's employment rates across mental health status are also much smaller than those that do not account for differences in women's characteristics (see Table 1). Our effect sizes are similar in magnitude to corresponding estimates that relate self-assessed general health to employment (García-Gómez and López-Nicolás 2006).

Mental health issues have somewhat smaller associations with men's and women's labor force participation (Table 3 columns 3 and 4). Chronic depressive episodes and exits from depressive episodes are each significantly associated with lower participation rates for both men and women, though the differentials are small (in the range of one to three percent). Developing symptoms of severe depression is also weakly associated with lower labor force participation for men and women, though our estimates cannot be statistically distinguished from zero. In comparison, Cai (2010) finds that the change from fair to poor self-assessed general health is associated with a 2.4 pp (2.7 percent) fall in participation among men and a 3.7 pp (5.0 percent) decline in participation for women.

Table 3. Selected results from OLS-FE models of various labor market outcomes, by gender.

	Employment		Participation		Unemployment	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Stable MH (ref)						
Chronic depressive episodes	-0.022*	-0.029**	-0.017*	-0.022**	0.007	0.047***
	(0.011)	(0.012)	(0.010)	(0.011)	(0.014)	(0.013)
Exit depressive episode	-0.020***	-0.015**	-0.011**	-0.018**	-0.001	0.003
	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)
Enter depressive episode	-0.012**	-0.005	-0.007	-0.005	0.022***	0.006
	(0.006)	(0.007)	(0.006)	(0.007)	(0.009)	(0.007)
Within R^2	0.021	0.023	0.021	0.020	0.004	0.007
Observations	30789	34409	30789	34409	26132	23187

Notes: Estimated coefficients presented and robust standard errors in parenthesis. All models control for demographic, financial and regional variables, measured at t-1 (i.e. the previous interview). Models also include wave dummies and a control for attrition. A full set of regression results can be found in Appendix Table A4. *, **, *** indicates significance at the 10%, 5 % and 1% levels respectively.

Mental health problems are also associated with higher unemployment rates (Table 3 columns 5 and 6). Men who develop severe depressive symptoms have a probability of experiencing unemployment in the subsequent year that is 2.2 pp (38.6 percent) higher. In contrast, men who experience chronic depressive symptoms have the same probability of ever being unemployed as do men who are consistently in good mental health. This suggests that the onset of mental health problems may result in temporary unemployment from which men recover relatively quickly. Steele et al. (2013) also finds that employed men with poor mental health in any given year are not substantially more likely to be unemployed in the following year. In comparison, it is ongoing mental health issues that are most directly related to women's unemployment experiences. Women with chronic depressive symptoms have unemployment rates that are 4.7 pp higher than women with stable good mental health. While this represents a near doubling (94.0 percent increase) of the risk of unemployment, it still means that the overwhelming majority of women with chronic depressive episodes work, as the underlying risk of unemployment is low. In all other cases, transitions in mental health appear to have weak, statistically insignificant links to men's and women's chances of being unemployed.

We turn now to consider the effect of transitions in employment status on mental health. Table 4 reports estimates from two-way fixed-effect linear probability models that regress changes in labor market status between waves $t-2$ and $t-1$ on the incidence of severe depressive symptoms in wave t. As with our models of employment outcomes, initial specification tests for our mental health model supported the use of individual-specific fixed-effects. Estimation results were not sensitive to alternative binary logit specifications. The top panel of Table 4 presents estimates from models with transitions in employment as the principal explanatory variables; the middle panel reports estimates from models exploiting transitions in labor force participation; and the bottom panel shows the link between transitions in unemployment and mental health status. In each case, we report estimates from models that do and do not include the individual's log equivalized disposable income as an explanatory measure. As we will subsequently discuss, controlling for income has next to no effect on estimates of the other covariates. The models also include all the other controls listed in Appendix Table A1.

We find evidence that individuals' employment histories are linked to their current mental health status. Although our estimates are occasionally imprecise and only marginally significant, they are often economically meaningful, particularly for men. Chronic non-employment, for example, is associated with worse mental health outcomes for both men and women. Working-age men who are not employed over the past two years have an incidence of severe depressive symptoms that is 3.1 pp (29.2 percent) higher than men who are continuously employed. And while this disparity is substantially smaller for women (13.4 percent), it is nonetheless large enough to be important. Men who exit or enter employment have an incidence of depressive symptoms that is approximately 10 to 20 percent higher than continuously employed men, an effect that cannot be distinguished from zero. In contrast, women who exit or enter employment have an incidence of depressive symptoms that is statistically equivalent to that of women who remain continuously employed. Interestingly, these patterns remain unchanged regardless of whether disposable income is included or excluded from the model, suggesting that income is not an important mechanism for transmitting the effects of employment to mental health.

The results in the middle panel of Table 4 focus on participation patterns rather than employment histories. Men who exit the labor force are 3.6 pp (34.0 percent) more likely to report severe depressive symptoms subsequently. Similarly, chronic non-participation and entry into the labor force are associated with rates of depressive symptoms that are approximately 10 to 20 percent higher; though these effects are imprecisely estimated and not statistically distinguishable from zero. Women's mental health is most directly linked to their long-term pattern of economic activity. Those who do not participate in the labor force over the previous two years are 23.9 percent (3.2 pp) more likely to report experiencing a depressive episode than are women who participate continuously. Labor force entry is associated with somewhat smaller mental health penalty relative to continuous participation, though the effect is statistically indistinguishable from zero. Once again, the inclusion of controls for personal income does not alter the results.

Table 4. Selected results from OLS-FE models of poor mental health, by gender.

	Men		Women	
	With income	**Without income**	**With Income**	**Without income**
A: Employment				
Stable employment (ref)				
Chronic non-employed	0.031*	0.033*	0.016	0.018*
	(0.019)	(0.019)	(0.011)	(0.010)
Exit from employment	0.020	0.021	0.003	0.005
	(0.015)	(0.015)	(0.010)	(0.010)
Entry to employment	0.011	0.012	-0.002	-0.000
	(0.017)	(0.017)	(0.011)	(0.011)
Within R^2	0.013	0.013	0.012	0.011
N	30789	30789	34409	34409
B: Participation				
Stable participation (ref)				
Chronic non-participation	0.012	0.014	0.032***	0.034***
	(0.020)	(0.020)	(0.011)	(0.011)
Exit from participation	0.036**	0.037**	0.006	0.008
	(0.016)	(0.016)	(0.010)	(0.010)
Entry to participation	0.019	0.020	0.016	0.018
	(0.023)	(0.023)	(0.012)	(0.011)
Within R^2	0.013	0.013	0.012	0.012
N	30789	30789	34409	34409
C: Unemployment				
Never unemployed (ref)				
Chronic unemployment	0.029	0.031	0.009	0.011
	(0.019)	(0.019)	(0.020)	(0.020)
Exit from unemployment	0.013	0.014	-0.007	-0.007
	(0.014)	(0.010)	(0.012)	(0.012)
Entry to unemployment	0.032**	0.032**	0.021	0.021
	(0.014)	(0.014)	(0.016)	(0.016)
Within R^2	0.010	0.010	0.010	0.010
N	26132	26132	23187	23187

Notes: Estimated coefficients presented and robust standard errors in parenthesis. All models control for demographic, financial and regional variables, measured at time t (i.e. the current interview). Models also include wave dummies and a control for attrition. A full set of regression results can be found in Appendix Table A5. *, **, *** indicates significance at the 10%, 5 % and 1% levels respectively.

Finally, we consider the link between individuals' current mental health and their unemployment histories (bottom panel Table 4). Men who begin a spell of unemployment are 35.6 percent (3.2 pp) more likely to experience severe depressive symptoms subsequently. Chronic unemployment is estimated to have a similar sized relationship to depressive symptoms, but our estimate is imprecise and cannot be distinguished from zero. Men who exit unemployment have rates of depressive symptoms that are similar to those of men who are continuously employed, suggesting that men's mental health may rebound relatively quickly from episodes of unemployment. The relationship between unemployment and mental health problems is somewhat weaker for women. Those women entering unemployment have a 20 percent (2.1 pp) higher probability of experiencing severe depressive symptoms, though this difference is statistically insignificant. Women who exit unemployment or who are chronically unemployed have virtually the same incidence of a depressive episode as women who are continuously employed.

Overall, these results are consistent with a bilateral relationship between depressive episodes and employment status. The incidence of economic inactivity – i.e. non-employment, non-participation, unemployment – is higher for those with a history of depressive symptoms; individuals are also more likely to experience depressive symptoms if they do not have a history of continuous employment.

6. Sensitivity Analysis

A key innovation of this paper is its use of employment calendar information to capture employment histories, rather than relying on point-in-time measures. Analyzing employment status at the interview date, which is most common in the literature, may fail to capture employment transitions that occur between interviews. For example, someone who suffers a mental health shock at t-1 might experience a period of unemployment within the following 12 months but be reemployed at time t. Our calendar-based measure, in contrast, captures any unemployment event within those 12 months. We test the sensitivity of our results to this measurement issue by replacing our calendar-based measures of labor market outcomes and transitions with their annual point-in-time counterparts and re-estimating all of our models.

Appendix Table A6 presents the resulting estimated effects of mental health transitions on labor market outcomes. We find that the estimates from our models of employment and participation are largely unchanged, although some effects are slightly stronger. Important differences emerge, however, when we contrast these point-in-time unemployment results to our previous estimates. Using the point-in-time measure, we find no effect of severe depressive symptoms on subsequent unemployment. This is in sharp contrast to results based on our job calendar measure which captures any periods of unemployment over the year (Table 3); in this case we find a significant effect of depressive symptoms in increasing the probability of unemployment. As expected, the point-in-time measure results in an underestimate of the overall relationship between mental health and unemployment.

In Appendix Table A7 we present parallel results for the effects of transitions in annual labor market status on mental health. The estimates are imprecise and are roughly half the size of our main estimates (Table 4). Interestingly, beginning a spell of unemployment is associated with a probability of women experiencing depressive symptoms that is 2.3 pp (22 percent) lower than similar women in stable employment.

7. Conclusions

At any point in time, one in five working-age individuals in the OECD is thought to suffer from a mental health problem making mental health issues responsible for up to half of all long-term sickness and disability among the working age population (OECD 2015, 3). Depression is particularly insidious because it often goes undiagnosed and untreated (WHO 2003; OECD 2014). Moreover, depressive mood disorders are extremely common, generating enormous economic costs (ILO 2000) and making a major contribution to the global burden of disease (WHO 2017). Reducing the economic and health costs of depressive mood disorders requires that we understand – and address – the interaction between mental and economic well-being. If episodes of depression largely respond to labor market outcomes then initiatives to promote economic activity, minimize employment disruptions, and shorten unemployment spells could have significant public health benefits. If, on the other hand, depressive symptoms drive employment outcomes then efforts are needed to reduce the barriers to employment and provide positive work environments for those with mental health issues.

We address this issue by using 14 years of population representative data to estimate a series of sequential dynamic fixed-effects models that allow us to shed light on the nature of the bilateral relationship between depressive symptoms and employment outcomes. We find evidence that depressive symptoms are both a cause and a consequence of economic inactivity. Perhaps unsurprisingly, the best mental health outcomes are associated with continuous participation and employment; continuous participation and employment, in turn, are more common amongst those in good mental health. This link between economic activity and mental health is particularly important for men and we find no evidence to suggest that it is income-related. There is also a close tie between mental health and unemployment. The onset of severe depressive symptoms results in increased unemployment for men, while it is women with chronic depressive symptoms who are more likely to experience unemployment. At the same time, mental health also deteriorates as a consequence of unemployment.

These results lead us to a number of important conclusions. First, there is value in adopting a broad-brush approach to examining the nature of the relationship between economic and mental well-being as we have done here. Very few studies account for the bilateral relationship between mental health and labor market outcomes. Those that do have focused narrowly on a single labor market outcome (Hamilton et al. 1997; Olsen et al. 2013; Dawson et al. 2015) or analyzed only men (Steele et al. 2013). Yet differences in estimation methods, samples, and institutional contexts make it virtually impossible to compare results across studies and leave us with a limited understanding of the bilateral relationship between mental health and employment status overall.

Second, it is clear to us that the relationship between depressive symptoms and employment status is gendered. Men's mental health is more closely tied to their employment outcomes than is women's. In virtually all cases, the magnitude of our estimates is larger for men. Moreover, men seem to be more responsive to the shock of a bad event -- either the onset of a depressive episode or the onset of unemployment. They then they appear to recover to a great extent, though perhaps not completely. In contrast, women appear to be more affected by chronic depressive symptoms. We can only speculate about the source of these differences, though at first blush they appear to be consistent with traditional social norms which often assign men a larger responsibility for financially supporting the family (Bernard 1981; Thompson and Walker 1989). Interestingly, however, we find no evidence that income is the pathway linking employment outcomes to mental health, highlighting the need to pay greater attention to the psychological and social benefits of economic activity in sustaining mental well-being. Our results also reinforce the need for gender-based mental health and employment strategies.

Third, the large reduction in the association between depressive episodes and employment status that occurs when we account for people's observed and unobserved characteristics highlights the importance of accounting for selection effects. The twenty percentage point gap in employment rates faced by those with chronic depressive symptoms (Table 1) is one tenth the size after we account for selection (Table 3). Thus, there is little evidence that the majority of those with depressive mood disorders face substantially greater barriers in accessing employment than do similar individuals who are mentally well. A more pressing issue may be ensuring that workplaces and employment practices are flexible enough to allow workers experiencing the symptoms of depression to maintain their productivity while at work (OECD 2012).

Finally, the bilateral relationship between economic activity and symptoms of depression implies that reducing the economic costs of mental illness is a challenge that is best tackled from both sides; improving mental health by increasing employment rates and reducing the barriers to employment for those with mental health issues. It is common in many countries, however, for the mental health and employment sectors to operate independently, with medical personnel giving scant attention to employment outcomes and employment services staff having little expertise in mental health issues (OECD 2015, 10). Our results support the OECD's recent call for closer integration of the two.

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Appendix

Table A1: Variable definitions.

Variable name	*Definition*
Outcomes	
Mental health (MHI-5)	Sub-scale of the SF-36 Health Survey that measures mental health. Respondents are asked 5 questions (scored on a 6pt scale) about their mental wellbeing over the preceding 4 weeks: (i) Been a nervous person; (ii) Felt so down in the dumps nothing could cheer you up; (iii) Felt calm and peaceful; (iv) Felt down; and (v) Been a happy person. Following Ware et al (2000) questions are reversed to be increasing in mental health. For persons missing 2 items or less, missings are imputed by taking the average score across valid items. Scores on each item are then summed and transformed to derive a 0-100 scale, with lower scores indicating poorer mental health. From this score we create a binary indicator to identify persons with severe depressive symptoms, which equals one if a respondents have a MHI-5 score less than or equal to 52 at the current interview (*t*).
Participation	Equals 1 if respondent participated in the labor force for at least one third of a month between their last interview (*t-1*) and their current interview (*t*), derived using calendar variables.
Employment	Equals 1 if respondent held a job for at least one third of a month between their last interview (*t-1*) and their current interview (*t*), derived using calendar variables.
Unemployment	Equals 1 if respondent was unemployed for at least one third of a month between their last interview (*t-1*) and their current interview (*t*), derived using calendar variables.
Transitions	
Mental Health	We construct one wave (*t-1*) and two wave (*t-2*) lags of the poor mental health indicator (which equals 1 if respondent has a mHI-5 score less than or equal to 52). For each possible combination of these lagged indicators [*t-2*, *t-1*] we derive distinct binary transition variables: a. Stable good MH (ref): [0,0] – No depressive symptoms at (*t-2*) or (*t-1*) b. Chronic depressive episodes: [1,1] – Severe depressive symptoms at both (*t-2*) or (*t-1*) c. Exit depressive episode: [1,0] – Severe depressive symptoms present at (*t-2*) but not at (*t-1*). a. Enter depressive episode: [0,1] – No depressive symptoms at (*t-2*) but a severe depressive symptoms identified at (*t-1*).
Participation Transitions	We create two binary variables identifying if the respondent had participated in the labor force: i) at any time during the previous wave between (*t-2*) and (*t-1*) and, ii) at any time during the current wave, excluding the 4 week period preceding the current interview (i.e. between *t-1* and *t-4w*). For each possible combination of these indicators [i), ii)] we derive distinct binary transition variables: b. Stable participation (ref): [1,1] – At least some participation over both periods (*t-2* to *t-1*) and (*t-1* to *t-4w*). c. Chronic non-participation: [0,0] – No participation in both periods. d. Exit from participation: [1,0] – At least some participation between (*t-2* to *t-1*) but none in the period (*t-1* to *t-4w*). e. Entry to participation: [0,1] – No participation between (*t-2* to *t-1*) but at least some participation in (*t-1* to *t-4w*).
Employment Transitions	We create two binary variables identifying if the respondent was employed: i) at any time during the previous wave between (*t-2*) and (*t-1*) and, ii) at any time during the current wave, excluding the 4 week period preceding the current interview (i.e.

	between *t-1* and *t-4w*). For each possible combination of these indicators [i), ii)] we derive distinct binary transition variables: a. Stable employment (ref): [1,1] – At least some employment over both periods (*t-2* to *t-1*) and (*t-1* to *t-4w*). b. Chronic non-employment: [0,0] – No employment in both periods. c. Exit from employment: [1,0] – At least some employment between (*t-2* to *t-1*) but none in the period (*t-1* to *t-4w*). d. Entry to employment: [0,1] – No employment between (*t-2* to *t-1*) but at least some employment in (*t-1* to *t-4w*).
Unemployment Transitions	We create two binary variables identifying if the respondent was unemployed: i) at any time during the previous wave between (*t-2*) and (*t-1*) and, ii) at any time during the current wave, excluding the 4 week period preceding the current interview (i.e. between *t-1* and *t-4w*). For each possible combination of these indicators [i), ii)] we derive distinct binary transition variables: a. Never unemployment (ref): [0,0] – No unemployment spells in either periods (*t-2* to *t-1*) and (*t-1* to *t-4w*). b. Chronic unemployment: [1,1] – Some unemployment in both periods. c. Exit from unemployment: [1,0] – At least some unemployment between (*t-2* to *t-1*) but none in the period (*t-1* to *t-4w*). d. Entry to unemployment: [0,1] – No unemployment between (*t-2* to *t-1*) but at least some unemployment in (*t-1* to *t-4w*).
Controls	
Number of children	Number of own children aged less than 15 years living with respondent.
Number of adults	Number of persons aged 15 years or more living in the household.
Coupled	Equals 1 if respondent is legally married or in a de-facto relationship. (reference category: Single)
Separated	Equals 1 if respondent is separated, divorced or widowed. (reference category: Single)
Postgraduate	Equals 1 if respondent's highest education level is a masters, doctorate, graduate diploma or graduate certificate. (reference category: Year 11 or below)
Undergraduate	Equals 1 if respondent's highest education level is a bachelor's degree, degree with honours, advanced diploma or diploma. (reference category: Year 11 or below)
Certificate	Equals 1 if respondent's highest education level Certificate III or IV. (reference category: Year 11 or below)
Year12	Equals 1 if respondent's highest education level is high school completion. (reference category: Year 11 or below)
Mild disability	Equals 1 if respondent has a long-term health condition that does not limit work. Persons who only reported having a mental illness are treated as having no disability. (reference category: No disability)
Moderate disability	Equals 1 if respondent has a restrictive long-term health condition limits the amount of work. Persons who only reported having a mental illness are treated as having no disability. (reference category: No disability)
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 equiv.household disposable income	Log of real equivalized disposable household income (minus the respondents personal disposable income) for the previous financial year (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.

Ln equiv. household non-labor income	Log of real equivalized non-labor income for the financial year. This is the sum of interest, rent, royalties, dividends from shares and dividends from own incorporated businesses. Missing values are imputed and non-positive incomes set to $1. The equivalence scale used is the OECD modified scale.
Non-positive non labor income	Equals 1 if real equivalized non-labor income for the financial year is non-positive.
Homeowner	Equals 1 if respondent lives in a household where a member owns, or is paying the mortgage on, the place of residence.
Home equity	Estimated resale value of residence less value of outstanding home loans ($m at 2010 prices), with missing values imputed.
Inner regional	Equals 1 if respondent lives in inner regional Australia (as defined in the Australian Standard Geographical Classification [ASGC]). (reference category: Major Urban)
Outer regional	Equals 1 if respondent lives in outer regional Australia. (reference category: Major Urban)
Remote	Equals 1 if respondent lives in remote or very remote location in Australia. (reference category: Major Urban)
Non-respondent (*t+1*)	Equals 1 if the respondent did not respond at the next survey wave.

Table A2. Means of analysis measures conditional on gender, non-employment and poor mental health.

	Men			Women		
Characteristics	**All**	**Not employed**	**Severe depressive episode**	**All**	**Not employed**	**Severe depressive episode**
Number of children	0.91	0.64***	0.77***	1.10	1.55***	1.10
Number of adults	2.30	2.20***	2.20***	2.25	2.20***	2.22**
Coupled	0.74	0.56***	0.60***	0.72	0.72	0.61***
Separated	0.08	0.16***	0.13***	0.13	0.14***	0.19***
Never-coupled	0.18	0.28***	0.27***	0.15	0.13***	0.20***
Postgraduate	0.11	0.06***	0.08***	0.13	0.06***	0.09***
Undergraduate	0.24	0.15***	0.20***	0.28	0.16***	0.21***
Certificate	0.29	0.26***	0.27**	0.16	0.13***	0.18***
Year 12	0.14	0.13*	0.14	0.16	0.18***	0.16
Year 11 or below	0.22	0.41***	0.30***	0.28	0.47***	0.36***
No disability	0.79	0.35***	0.58***	0.79	0.63***	0.56***
Mild disability	0.09	0.07**	0.11***	0.07	0.06***	0.09***
Moderate disability	0.12	0.54***	0.30***	0.14	0.29***	0.34***
Physical health (SF-36)	89.26	69.78***	77.61***	87.12	79.59***	75.90***
Smoker	0.25	0.41***	0.35***	0.20	0.27***	0.32***
Ln equiv. hh dispos inc	8.22	7.41***	7.35***	8.56	8.37***	7.82***
Non-pos hh dispos inc	0.17	0.24***	0.25***	0.17	0.18	0.23***
Ln equiv. hh nonlab inc	3.82	2.89***	2.99***	3.72	2.73***	2.83***
Non-pos nonlab inc	0.47	0.63***	0.57***	0.48	0.62***	0.59***
Homeowner	0.73	0.59***	0.63***	0.72	0.59***	0.60***
Home equity	0.28	0.23***	0.21***	0.28	0.23***	0.21***
City	0.66	0.55***	0.66	0.65	0.59***	0.63**
Inner Regional	0.22	0.29***	0.21	0.22	0.26***	0.24**
Outer Regional	0.11	0.15***	0.12**	0.11	0.13***	0.11
Remote	0.02	0.02	0.01**	0.02	0.02	0.02
Non-respondent (t+1)	0.04	0.05	0.05***	0.04	0.04	0.04***
Observations	30789	1918	3270	34409	5759	4614

Notes: Authors' calculations using data from the HILDA employment and participation analysis sample. Asterisks indicate statistically significant differences in means between not employed and employed people, and people with poor mental health and good mental health. *, **, *** indicates significance at the 10%, 5 % and 1% levels respectively.

Table A3. Means of analysis measures conditional on gender, for unemployment sample.

Characteristics	**Men**	**Women**
Number of children	0.96	0.96
Number of adults	2.31	2.29
Coupled	0.77	0.72
Separated	0.07	0.13
Never-coupled	0.16	0.15
Postgraduate	0.12	0.14
Undergraduate	0.25	0.31
Certificate	0.30	0.16
Year 12	0.13	0.15
Year 11 or below	0.20	0.24
No disability	0.83	0.83
Mild disability	0.09	0.07
Moderate disability	0.09	0.10
Physical health (SF-36)	90.83	88.92
Smoker	0.23	0.18
Ln equiv. hh dispos inc	8.29	8.55
Non-pos hh dispos inc	0.16	0.18
Ln equiv. hh nonlab inc	3.88	3.98
Non-pos nonlab inc	0.46	0.44
Homeowner	0.75	0.76
Home equity	0.29	0.30
City	0.67	0.66
Inner Regional	0.21	0.22
Outer Regional	0.10	0.10
Remote	0.02	0.02
Non-respondent (t+1)	0.04	0.04
Observations	26132	23187

Table A4. Full results from OLS-FE models of various labor market outcomes, by gender.

	Employment		Participation		Unemployment	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Stable MH (ref)						
Chronic depressive episodes	-0.022*	-0.029**	-0.017*	-0.022**	0.007	0.047***
	(0.011)	(0.012)	(0.010)	(0.011)	(0.014)	(0.013)
Exit depressive episode	-0.020***	-0.015**	-0.011**	-0.018**	-0.001	0.003
	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)
Enter depressive episode	-0.012**	-0.005	-0.007	-0.005	0.022***	0.006
	(0.006)	(0.007)	(0.006)	(0.007)	(0.009)	(0.007)
Number of children	0.001	-0.049***	0.002	-0.044***	-0.007**	0.004
	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)	(0.004)
Number of adults	0.008***	0.038***	0.008***	0.035***	0.005*	-0.000
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Coupled	0.020***	-0.025*	0.015***	-0.025**	-0.022**	-0.016
	(0.007)	(0.013)	(0.005)	(0.012)	(0.011)	(0.014)
Separated	0.026**	0.017	0.013	0.020	-0.022	-0.018
	(0.013)	(0.019)	(0.010)	(0.018)	(0.018)	(0.017)
Postgraduate	0.066**	0.053*	0.041*	0.029	0.017	-0.022
	(0.026)	(0.028)	(0.022)	(0.025)	(0.035)	(0.033)
Undergraduate	0.052**	0.072***	0.030	0.036*	0.007	-0.034
	(0.025)	(0.024)	(0.023)	(0.021)	(0.033)	(0.031)
Certificate	0.014	0.071***	0.000	0.032*	-0.008	0.005
	(0.015)	(0.022)	(0.015)	(0.018)	(0.026)	(0.024)
Year 12	0.022	0.014	0.011	0.005	-0.005	0.045
	(0.021)	(0.025)	(0.019)	(0.021)	(0.033)	(0.030)
Mild disability	-0.004	0.002	0.000	0.004	0.003	0.004
	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.006)
Moderate disability	-0.046***	-0.041***	-0.040***	-0.030***	0.014*	0.005
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Physical health (SF-36)	0.001***	0.001***	0.001***	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Smoker	0.001	0.005	-0.000	0.013	0.001	-0.007
	(0.006)	(0.010)	(0.005)	(0.009)	(0.008)	(0.008)
Ln equiv. hh dispos inc	0.002	-0.008**	0.004**	-0.005	-0.001	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Non-pos hh dispos inc	0.045**	-0.039	0.062***	-0.007	-0.009	-0.014
	(0.018)	(0.033)	(0.017)	(0.034)	(0.020)	(0.025)
Ln equiv. hh nonlab inc	-0.000	-0.003**	-0.001	-0.002	0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Non-pos nonlab inc	0.001	-0.018*	-0.004	-0.012	0.008	0.003
	(0.007)	(0.011)	(0.006)	(0.010)	(0.009)	(0.008)
Homeowner	0.007	0.013	-0.000	0.009	-0.002	-0.015*
	(0.004)	(0.009)	(0.004)	(0.009)	(0.007)	(0.008)
Home equity	-0.015***	-0.037***	-0.010*	-0.036***	0.004	0.010
	(0.005)	(0.010)	(0.005)	(0.009)	(0.005)	(0.006)
Inner regional	-0.019*	-0.041**	-0.014*	-0.042**	0.019	0.045***
	(0.010)	(0.017)	(0.008)	(0.017)	(0.015)	(0.017)
Outer regional	-0.034**	-0.008	-0.034**	-0.009	-0.019	0.045*
	(0.016)	(0.025)	(0.014)	(0.025)	(0.022)	(0.025)
Remote	0.000	0.068	0.000	0.066	0.051	-0.006
	(0.036)	(0.044)	(0.034)	(0.043)	(0.041)	(0.032)
Non-respondent (*t+1*)	-0.001	-0.006	-0.001	-0.007	0.002	-0.016*
	(0.006)	(0.011)	(0.005)	(0.010)	(0.010)	(0.009)
Wave (year) dummies						
2003 (ref)						
2004	-0.001	0.004	-0.004	0.006	-0.004	-0.006
	(0.004)	(0.005)	(0.003)	(0.006)	(0.005)	(0.005)
2005	-0.008*	0.019***	-0.009**	0.015**	-0.004	-0.003
	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)

2006	-0.013***	0.016**	-0.016***	0.008	-0.012**	-0.001
	(0.005)	(0.007)	(0.004)	(0.007)	(0.006)	(0.006)
2007	-0.022***	0.012	-0.024***	0.003	-0.013**	-0.007
	(0.005)	(0.008)	(0.004)	(0.008)	(0.006)	(0.007)
2008	-0.027***	0.020**	-0.027***	0.009	-0.015**	-0.018***
	(0.005)	(0.008)	(0.005)	(0.008)	(0.006)	(0.007)
2009	-0.034***	0.008	-0.029***	0.002	0.003	-0.006
	(0.005)	(0.008)	(0.005)	(0.008)	(0.007)	(0.007)
2010	-0.033***	0.006	-0.034***	0.002	-0.007	-0.006
	(0.005)	(0.009)	(0.005)	(0.008)	(0.006)	(0.007)
2011	-0.030***	0.006	-0.031***	-0.003	-0.012*	-0.017**
	(0.006)	(0.009)	(0.005)	(0.008)	(0.007)	(0.007)
2012	-0.039***	-0.004	-0.036***	-0.010	-0.012*	-0.019***
	(0.006)	(0.009)	(0.005)	(0.009)	(0.007)	(0.007)
2013	-0.043***	-0.015	-0.044***	-0.014	-0.010	-0.016**
	(0.006)	(0.009)	(0.005)	(0.009)	(0.007)	(0.007)
Constant	0.818***	0.793***	0.843***	0.811***	0.083**	0.091**
	(0.027)	(0.043)	(0.025)	(0.041)	(0.033)	(0.038)
Within R^2	0.021	0.020	0.021	0.023	0.004	0.007
Observations	30789	34409	30789	34409	26132	23187

Notes: Estimated coefficients from OLS fixed effects models presented and robust standard errors in parenthesis. Demographic, financial and regional controls are measured at time t-1. *, **, *** Indicates significance at the 10%, 5 % and 1% levels respectively.

Table A5. Full results from OLS-FE models of poor mental health, by gender.

	Severe depressive episode					
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Employment						
Stable employment (ref)						
Chronic non-employment	0.033*	0.018*				
	(0.019)	(0.010)				
Exit from employment	0.021	0.005				
	(0.015)	(0.010)				
Entry to employment	0.012	-0.000				
	(0.017)	(0.011)				
Participation						
Stable participation (ref)						
Chronic non-participation			0.014	0.034***		
			(0.020)	(0.011)		
Exit from participation			0.037**	0.008		
			(0.016)	(0.010)		
Entry to participation			0.020	0.018		
			(0.023)	(0.011)		
Unemployment						
Never unemployed (ref)						
Chronic unemployment					0.031	0.011
					(0.019)	(0.020)
Exit from unemployment					0.014	-0.007
					(0.010)	(0.012)
Entry to unemployment					0.032**	0.021
					(0.014)	(0.016)
Number of children	0.009**	-0.003	0.009**	-0.004	0.007*	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Number of adults	-0.000	0.004	0.000	0.005	-0.002	0.006
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Coupled	-0.029**	-0.019	-0.029**	-0.019	-0.033**	-0.031*
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.016)
Separated	0.008	0.009	0.008	0.009	-0.006	-0.007
	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.023)
Postgraduate	0.038	-0.031	0.038	-0.030	0.018	-0.047
	(0.043)	(0.034)	(0.043)	(0.034)	(0.051)	(0.037)
Undergraduate	0.033	-0.022	0.032	-0.021	0.021	-0.041
	(0.038)	(0.031)	(0.038)	(0.031)	(0.044)	(0.033)
Certificate	0.007	0.024	0.006	0.026	0.009	0.021
	(0.026)	(0.021)	(0.026)	(0.021)	(0.030)	(0.027)
Year 12	-0.020	0.009	-0.021	0.010	-0.023	0.008
	(0.034)	(0.030)	(0.034)	(0.030)	(0.039)	(0.036)
Mild disability	0.018***	0.017**	0.018***	0.017**	0.011	0.014
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)
Moderate disability	0.039***	0.069***	0.039***	0.069***	0.023**	0.062***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)
Physical health (SF-36)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Smoker	0.001	0.005	0.001	0.006	0.015	-0.000
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.012)
Ln equiv. hh dispos inc	0.004	-0.002	0.004	-0.002	0.003	-0.004
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Non-pos hh dispos inc	0.046*	-0.003	0.047*	-0.003	0.040	-0.020
	(0.025)	(0.035)	(0.025)	(0.035)	(0.026)	(0.039)
Ln equiv. hh nonlab inc	-0.002	-0.003**	-0.002	-0.003**	-0.001	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Non-pos nonlab inc	-0.017*	-0.016	-0.017*	-0.016	-0.009	-0.016
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)
Homeowner	0.001	-0.001	0.001	-0.001	0.004	-0.006

	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Home equity	-0.012*	-0.012	-0.012*	-0.012	-0.010	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Inner regional	-0.000	0.024	-0.000	0.023	0.012	0.006
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.015)
Outer regional	0.002	0.014	0.002	0.013	0.010	0.022
	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)	(0.027)
Remote	-0.016	0.014	-0.015	0.015	0.004	0.007
	(0.024)	(0.032)	(0.024)	(0.032)	(0.027)	(0.043)
Non-respondent (*t+1*)	0.012	0.003	0.012	0.003	0.009	-0.010
	(0.010)	(0.012)	(0.010)	(0.012)	(0.011)	(0.014)
Wave (year) dummies						
2003 (ref)						
2004	0.000	0.011	0.000	0.011	0.004	0.013
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)
2005	0.001	-0.001	0.001	-0.001	0.001	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
2006	0.000	0.015**	-0.000	0.015**	0.000	0.018**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
2007	-0.004	0.003	-0.004	0.003	-0.003	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
2008	0.010	0.006	0.010	0.006	0.013*	0.005
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)
2009	-0.007	0.000	-0.007	-0.000	-0.005	-0.000
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)
2010	0.005	0.010	0.005	0.010	0.011	0.007
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)
2011	0.005	0.004	0.005	0.004	0.013	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
2012	-0.007	0.007	-0.006	0.007	-0.002	0.010
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.010)
2013	-0.003	0.005	-0.003	0.004	-0.001	0.008
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Constant	0.240***	0.288***	0.241***	0.286***	0.209***	0.289***
	(0.039)	(0.044)	(0.039)	(0.044)	(0.044)	(0.051)
Within R^2	0.013	0.011	0.013	0.011	0.010	0.010
Observations	30789	34409	30789	34409	26132	23187

Notes: Estimated coefficients from OLS fixed effects models presented and robust standard errors in parenthesis. Demographic, financial and regional controls are measured at time t, does not include personal disposable income. *, **, *** Indicates significance at the 10%, 5 % and 1% levels respectively.

Table A6. Sensitivity analysis: Selected results from OLS-FE models of various labor market outcomes using point in time labor market outcomes.

	Employment		**Participation**		**Unemployment**	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Stable MH (ref)						
Chronic depressive episodes	-0.029**	-0.032**	-0.040***	-0.028**	-0.009	0.008
	(0.013)	(0.013)	(0.012)	(0.013)	(0.008)	(0.008)
Exit depressive episode	-0.016**	-0.005	-0.013*	-0.008	0.004	0.001
	(0.007)	(0.008)	(0.007)	(0.008)	(0.004)	(0.004)
Enter depressive episode	-0.028***	-0.014	-0.024***	-0.013	0.002	-0.002
	(0.008)	(0.008)	(0.007)	(0.008)	(0.005)	(0.004)
Within R^2	0.014	0.015	0.019	0.015	0.002	0.003
Observations	30789	34409	30789	34409	26132	23187

Notes: Estimated coefficients presented and robust standard errors in parenthesis. All models control for demographic, financial and regional variables, measured at t-1 (i.e. the previous interview). Models also include wave dummies and a control for attrition. *, **, *** indicates significance at the 10%, 5 % and 1% levels respectively.

Table A7. Sensitivity analysis: Selected results from OLS-FE models of poor mental health using point in time measures of labor market transitions.

	Men		Women	
	With income	**Without income**	**With Income**	**Without income**
A: Employment				
Stable employment (ref)				
Chronic non-employed	0.003	0.004	-0.001	0.001
	(0.016)	(0.016)	(0.009)	(0.009)
Exit from employment	-0.002	-0.000	0.007	0.009
	(0.011)	(0.011)	(0.007)	(0.007)
Entry to employment	-0.013	-0.013	-0.006	-0.005
	(0.010)	(0.010)	(0.007)	(0.007)
Within R^2	0.013	0.013	0.012	0.011
N	30789	30789	34409	34409
B: Participation				
Stable participation (ref)				
Chronic non-participation	0.010	0.011	0.011	0.013
	(0.019)	(0.019)	(0.010)	(0.010)
Exit from participation	0.012	0.014	0.004	0.006
	(0.012)	(0.012)	(0.008)	(0.008)
Entry to participation	-0.016	-0.015	-0.012	-0.011
	(0.012)	(0.012)	(0.008)	(0.008)
Within R^2	0.013	0.013	0.012	0.012
N	30789	30789	34409	34409
C: Unemployment				
Never unemployed (ref)				
Chronic unemployment	0.013	0.016	-0.019	-0.018
	(0.036)	(0.036)	(0.041)	(0.041)
Exit from unemployment	-0.004	-0.004	0.004	0.004
	(0.016)	(0.016)	(0.019)	(0.020)
Entry to unemployment	-0.009	-0.007	-0.025	-0.023
	(0.021)	(0.021)	(0.026)	(0.026)
Within R^2	0.009	0.010	0.010	0.010
N	26132	26132	23187	23187

Notes: Estimated coefficients presented and robust standard errors in parenthesis. All models control for demographic, financial and regional variables, measured at time t (i.e. the current interview). Models also include wave dummies and a control for attrition. *, **, *** indicates significance at the 10%, 5 % and 1% levels respectively.