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THE EFFECT OF MENTAL HEALTH ON EMPLOYMENT: EVIDENCE FROM AUSTRALIAN PANEL DATA

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ABSTRACT

To what extent does poor mental health affect employment outcomes? Answering this question involves multiple technical difficulties: two-way causality between health and work, unobservable confounding factors and measurement error in survey measures of mental health. We attempt to overcome these difficulties by combining 10 waves of high-quality panel data with an instrumental variable model that allows for individual-level fixed effects. We focus on the extensive margin of employment, and we find evidence that a one-standard-deviation decline in mental health reduces employment by 30 percentage points. Further investigations suggest that this effect is predominantly a supply rather than a demand-side response and is larger for older than young workers.

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1. INTRODUCTION

Mental health disorders are common in both developed and developing countries, and the consequences of chronic disorders for individuals, families and wider communities can be severe and costly. In comparison with any type of physical health condition, the prevalence estimates for mental health disorders are daunting. The World Health Organisation (WHO, 2010) estimates that some 450 million people worldwide suffer from mental health disorders and many more have lesser mental health problems. Worldwide, depressive disorders alone account for around 12% of total years lived with disability (Moussavi *et al.*, 2007). In the USA, it is estimated that 26% (about 58 million) of adults suffer from a diagnosable mental disorder in any given year and that around 15 million adults have a major depressive disorder (Kessler *et al.*, 2005a). The total societal cost of such mental health disorders is substantial, with estimates for the USA of up to $200bn per year (see, e.g. Rice *et al.*, 1990; Harwood *et al.*, 2000; Greenberg *et al.*, 2003; and Kessler *et al.*, 2008).

One of the most important ways that poor mental health impacts on individuals and families is by lowering the ability of adults to be actively employed. For example, Greenberg *et al.* (2003) estimated that of the total cost of depression in the USA ($83bn), 62% was accounted for by work-related costs, with the remainder being due to direct medical costs (31%) and suicide-related mortality costs (7%). For those in employment, poor mental health can lead to the necessity of more days of sickness absence and a lowering of productivity in the workplace. In the latter context, Stewart *et al.* (2003) found that workers in the USA with depression

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experienced significantly more health-related 'lost productivity time' each week (5.6 h) compared with workers without depression (1.5 h). Moreover, the impact of poor mental health is particularly costly in a lifecycle perspective because many mental health conditions begin early in life (see Paus *et al.*, 2008; Prager, 2009) and are often chronic or reoccurring throughout adulthood. For example, the median age of onset of common mood disorders is around 30 years (Kessler *et al.*, 2005b).

Although it is straightforward to establish the size of correlations between mental health and various labour market outcomes, as a large literature has already performed, identifying the causal effects of poor mental health is more difficult. This is due to the well-established issues of reverse causality (where work affects mental health, as well as mental health affecting work) and unobserved individual heterogeneity correlated with both health and labour market outcomes (e.g. cognitive ability, childhood circumstances and family background). There is also a high likelihood of measurement error in this context, as measuring mental health is difficult, and researchers are usually constrained by the information collected in surveys. Although hard to obtain, causal estimates are important when formulating policy responses to poor mental health and when attempting to calculate wider societal costs.

In many contexts, researchers have made use of readily identifiable policy changes to aid in identifying causal effects of important health inputs, such as using changes in the level of taxation to identify the causal effects of consumption on health (e.g. smoking and alcohol) or increases in compulsory years of schooling to identify the causal effect of education on health. In contrast, identifying policy changes that shift only the mental health of a subset of the population is considerably more difficult. The key challenge in this literature has therefore been to find a valid instrumental variable for mental health.

The majority of studies within the economics literature have used cross-sectional data from North America and relied on time-invariant individual-level characteristics as instrumental variables. Prime examples of the instruments used are parental psychological problems (Ettner *et al.*, 1997; Marcotte *et al.*, 2000; Chatterji *et al.*, 2011), individual experiences of mental illness in the past (Ettner *et al.*, 1997; Hamilton *et al.*, 1997; Chatterji *et al.*, 2007, 2011), degree of religiosity (Alexandre and French, 2001; Chatterji *et al.*, 2007), perceived social support (Hamilton *et al.*, 1997; Alexandre and French, 2001; Ojeda *et al.*, 2010) and participation in physical activity (Hamilton *et al.*, 1997). The results of these studies most often suggest that mental illness has significant and substantive costs in terms of labour market participation and other work-related outcomes, such as wages and absenteeism. For example, Ettner *et al.* (1997) used childhood and family mental illness as instruments in two stage least squares (2SLS) models and found that a diagnosis of any psychiatric disorder during the past 12 months reduces female employment by around 14 percentage points and male employment by around 13 percentage points. Alexandre and French (2001) used religiosity and a social support proxy as instruments in bivariate probit models and found that depression decreases the probability of being employed by 19 percentage points. Chatterji *et al.* (2007) estimated 2SLS and bivariate probit models identified with childhood psychiatric disorders and religiosity instruments. They found that a diagnosis of any psychiatric disorder during the past 12 months reduces Latino female employment by around 26 percentage points. A large negative effect on employment of having a recent psychiatric disorder is also found in a more recent contribution by Chatterji *et al.* (2011) using a general US sample and 2SLS and bivariate probit models. In contrast, the study found no wage effects. The instruments used in this latter study were having a parent who experienced psychiatric symptoms (when the adult survey respondent was a child) and the individual's own early onset of a disorder.

In this paper, we build upon the existing studies by using an instrumental-variables fixed-effects (IV-FE) model, which is identified via a new time-varying source of plausibly exogenous variation in mental health. This estimation technique makes use of 10 waves of high-quality Australian panel data and simultaneously tackles the problems of reverse causality, unobserved confounders and measurement error. The instrument we use is the recent death of a close friend, which affects a large number of individuals in our sample, varies considerably for the same individual over time and is shown to be a strong determinant of mental health. Importantly, we provide evidence that the death of a close friend is associated with a real deterioration in mental health and that it is not solely capturing short-term bereavement—the death of a close friend significantly lowers mental health for several years and in the cross-section is associated with an increased propensity to have a doctor-diagnosed depression or anxiety condition. We also provide a number of placebo tests that

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support the assumption that the instrument affects labour market outcomes only through its effect on mental health, and we explicitly control for other variables that might co-move with death of a close friend. As far as we are aware, the use of this instrument is new in this literature.

We focus in this paper on the extensive margin of employment, and our main conclusion is that a one-standard-deviation worsening in mental health leads to a substantial (around 30 percentage points) drop in employment. We also find that older individuals have a larger adverse employment response to worsening mental health than younger workers, suggesting that there might be different pathways and opportunities to leave the labour market for older workers in the face of poor mental health. Moreover, our empirical investigations suggest that the movement out of employment following a worsening of mental health is predominantly a supply rather than a demand-side response, in that the probability of getting fired does not drive the employment change.

2. DATA, DEFINITIONS AND SAMPLE CHARACTERISTICS

To estimate the labour market effects of poor mental health, we use data from waves 2 to 11 (2002–2011) of the Household, Income and Labour Dynamics in Australia (HILDA) survey.[1] HILDA is a household-based longitudinal study that is nationally representative, except for an under-sampling of individuals living in more remote areas of Australia. It began in 2001 with a survey of 13 969 persons in 7682 households. Each year since, interviews have been conducted with all willing members of each household who are at least 15 years old at the time of the interview. In these interviews, information is collected on labour force dynamics, employment conditions, education, income, family formation, health and other specialised topics. In this paper, we use observations on adults aged 21–64 years, who have non-missing information on our dependent and independent variables and who are included in at least two waves (necessary for our fixed-effects identification strategy). These restrictions leave us with an estimation sample of 12 911 individuals and 80 737 observations.

Our measure of mental health is generated from nine questions included in the Short-Form General Health Survey (SF-36), which have been consistently asked in every wave of the survey. Respondents are asked how much of the time during the past 4 weeks: (i) did you feel full of life; (ii) have you been a nervous person; (iii) have you felt so down in the dumps that nothing could cheer you up; (iv) have you felt calm and peaceful; (v) did you have a lot of energy; (vi) have you felt down; (vii) did you feel worn out; (viii) have you been a happy person; and (ix) did you feel tired. For each of these nine questions, individuals could select one of six responses, ranging from all of the time (1) to none of the time (6). Appendix Table AI contains a summary of the responses. We construct a mental health index by taking the mean of individuals' responses (with some questions reverse coded) and then standardising such that the index has a mean of zero and a standard deviation of one and is increasing in good mental health. This index is strongly correlated (−0.76) with the widely used Kessler Psychological Distress Scale, which was collected only in wave 7 of HILDA. It is also strongly predictive of current doctor-diagnosed depression or anxiety: according to a univariate probit model, a one-standard-deviation increase in the index is estimated to reduce the probability of depression or anxiety by 8.5 percentage points (relative to mean of 11.1%). More generally, the 'SF-36 is a highly recommended measure with superior psychometric properties. It has been used extensively in Australia for both population health and clinical research' (Marosszeky, 2005). It has also been shown to be useful in screening for psychiatric disorders internationally (Ware *et al.*, 1993).

Summary statistics for the employment outcome and individual-level characteristics are presented in Table I. For the whole sample, we see that 77% of the respondents aged 21–64 years are employed. However, when we break down these results for individuals who are above ($0 < \text{index}$) and below ($\text{index} \leq 0$) the average value for the mental health index, we find clear evidence that individuals with poor mental health systematically differ from individuals with good mental health. In particular, individuals with poorer mental health have

[1]We do not use wave 1 because the information used to form our instrumental variable (death of a close friend) and other key covariates were only included in waves 2–11.

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Table I. Sample means of outcomes and key covariates by mental health level

	All respondents	Below average (index ≤ 0)	Above average (0 < index)
Employed	0.770	0.703	0.820***
Death of friend in the past 3 years	0.185	0.200	0.173***
Death of spouse in the past 3 years	0.013	0.018	0.009***
Death of relative in the past 3 years	0.235	0.251	0.224***
Male	0.469	0.427	0.500***
Age	42.199	41.971	42.371**
University degree	0.266	0.241	0.285***
Diploma/certificate	0.336	0.334	0.339
High school graduate	0.142	0.141	0.143
Married/cohabitating	0.722	0.682	0.753***
Divorced/separated	0.115	0.137	0.097***
Number of children	0.715	0.743	0.694***
Windfall income ($0000s)	0.264	0.225	0.294***
Many friends	4.479	4.042	4.806***
Sample size	80 737	34 610	46 127

Figures are sample means.
**Denotes 0.5 significance level for two-group mean-comparison *t*-tests, relative to the group with below-average mental health.
***Denotes 0.1 significance level for two-group mean-comparison *t*-tests, relative to the group with below-average mental health.

substantively lower employment rates by around 12 percentage points. Moreover, those with poorer mental health are more likely to be female, less educated and unmarried and to report having fewer friends.

Figure 1 shows nonparametric regression estimates (with 95% CIs) of the changes in the mental health index (*x*-axis) against changes in employment (*y*-axis).[2] The graph suggests that negative changes in mental health are strongly associated with decreases in employment but that there is a near-zero association for positive changes in mental health. However, it is important to note that this relationship could be driven by the effect of changes in employment on mental health, rather than mental health on employment (the issue of reverse causality). It is for this reason that we present instrumental-variables estimates in the forthcoming Section 4.

3. METHODOLOGY

3.1. Estimation approach

Estimation is based on an individual-level fixed-effects regression model of labour market outcomes (Y_{it}). In particular, for individual i in year t, we assume that Y_{it} is given by

$$Y_{it} = \alpha_i + MH_{it}\delta + X_{it}\beta + \varepsilon_{it} \tag{1}$$

where MH_{it} is the individual's measured mental health, X_{it} is a vector of characteristics that vary across time and ε_{it} is a random error term. The coefficient δ is the parameter of primary interest and represents the impact that mental health has on Y_{it}. The parameter α_i is an individual-level fixed effect and captures all time-invariant characteristics that are associated with both an individual's mental health and labour market outcomes. In particular, family history of mental health problems will be captured by the fixed effect and so will individual characteristics such as cognitive ability, which have been shown in the literature to be both positively correlated with mental health outcomes and a range of labour market outcomes, especially wages.

Consistent estimation of δ in Eqn 1 relies on the assumption that, conditional on the individual-level fixed-effect α_i and the time-varying characteristics X_{it}, mental health is exogenously determined. This assumption is unlikely to hold. Research by Clark and Oswald (1994), Theodossiou (1998) and Bender and Theodossiou

[2]For each nonparametric regression, an Epanechnikov kernel function and a rule-of-thumb bandwidth were used.

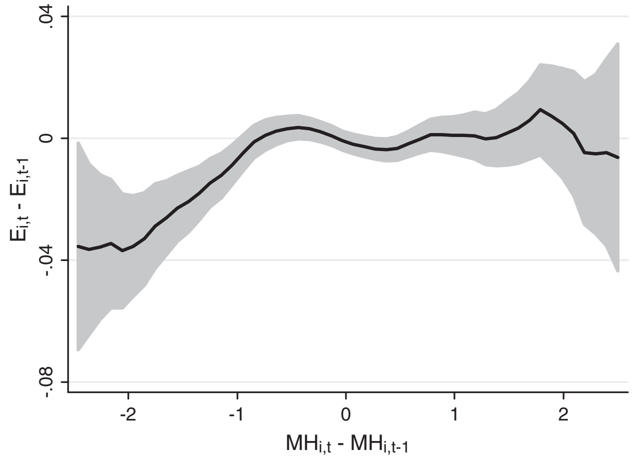

Figure 1. Nonparametric regression estimates of the relationship between changes in mental health (*x*-axis) and employment (*y*-axis)

(2009), for example, shows that the experience of unemployment is detrimental to mental health. Therefore, a positive δ estimate may merely reflect the positive effect of employment on mental health.

Estimation of Eqn 1 is further complicated by the possibility of measurement error in mental health (Frank and Gertler, 1991). Although our mental health measure is derived from a widely used and validated survey module, it is likely to be a noisy proxy of underlying mental health if individual survey responses are tainted by differences in interpretation and social desirability of particular responses. Another potential source of measurement error arises from the mismatch in the time coverage of the mental health measure and employment outcome: employment is measured once a year at the time of the interview, and the mental health question we use refers to the last 4 weeks. If these sources of measurement error are classical, they can be overcome by our IV approach. The instrumentation is particularly important in the fixed-effects specification because the attenuation bias arising from measurement error is known to be amplified when the cross-sectional information is removed via fixed effects.[3]

The strong likelihood of endogeneity and attenuation biases motivates our use of an IV-FE estimation procedure. The fixed-effects first-stage equation in this procedure is given by

$$MH_{it} = \theta_i + Z_{it}\pi + X_{it}\gamma + v_{it} \tag{2}$$

where θ_i is an individual-level fixed effect and Z_{it} is an instrumental variable representing the recent death of a close friend. Importantly, the inclusion of the fixed effects in Eqns 1 and 2, coupled with our choice of IV, implies that identification of δ in Eqn 1 is driven by changes in labour market outcomes for individuals whose mental health has been affected by the death of a friend.

The vector of characteristics (X_{it}) in Eqn 2 includes variables representing age, education, marital status, children, windfall income, friendships and the deaths of relatives. Naturally, given our IV-FE modelling framework, we can only include time-varying variables as covariates, and we have chosen this set for two reasons. First, variables are included if they are important time-varying, exogenous determinants of employment (e.g. marital status, children and achieving a higher level of education). Second, variables are included if they are potentially associated with our instrumental variable—the death of a close friend. The variables such as

[3]One way to view non-classical measurement error is as response heterogeneity. The vignette studies of Meijer *et al.* (2011) have shown that respondents might differ in their interpretation of subjective health questions in that some respondents rated the health of the same hypothetical person differently than others. The response heterogeneity these authors found was strongly dependent on fairly stable characteristics, such as nationality and wealth and gender or changing characteristics we control for, such as age. The measurement error that remains after taking out fixed effects is therefore arguably random.

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windfall income and number of friends are included because these variables are potentially associated with the death of a close friend and employment status (i.e. we are attempting to capture as best we can any other time-varying changes that could be driven by the death of a close friend). Other variables that we might typically include in a cross-sectional labour supply model are not included because they are either mainly time-invariant (e.g. state of residence) or because they are particularly endogenous in our context (e.g. income is strongly determined by employment status, so it is inappropriate to include).[4]

3.2. Using death of a close friend as an instrumental variable

The cornerstone of this paper is the power and validity of the instrument we use for causal identification and therefore whether it makes a contribution to the literature. The instrument must be strongly correlated with mental health and uncorrelated with labour market outcomes, except through mental health. We believe that the recent death of a close friend meets these criteria. A large psychology literature has clearly demonstrated that stressful life events have a substantial impact on mental health (e.g. Faravelli and Pallanti, 1989; Newman and Bland, 1994; Kessler, 1997). In particular, 'loss' events, such as the death of a friend, are predicted to increase depressogenic symptoms (e.g. Finlay-Jones and Brown, 1981; Brown and Eales, 1993). Kendler *et al.* (1999) found that the death of someone in an individual's social network has the largest effect of all independent life events. Furthermore, the symptoms start to occur shortly after the event (Bebbington and MacCarthy, 1993).

The instrumental variable is constructed from responses in a section of HILDA's self-completion questionnaire. Respondents are told 'We now would like you to think about major events that have happened in your life over the past 12 months'. One of the listed events is 'Death of a close friend'. As our main instrument, we use death of a close friend summed over the last 3 years, which involves adaptation to such an event after 3 years, and we will later provide some evidence in support of this time scale.[5] Figure 2 shows the proportion of individuals reporting the death of a close friend in the last 3 years (with standard errors) for different age groups. This major life event is experienced by many adults of working age, with around one in 10 adults aged younger than 36 years old reporting the death of a close friend, increasing to about one in three by age 61–65 years.

The strength of the instrument between individuals is demonstrated in Figure 3, which provides kernel density estimates of our standardised mental health index separately for those who reported the death of a close friend in the last 3 years and also for those who did not (an Epanechnikov kernel function and a rule-of-thumb bandwidth are used). It shows a leftward shift in the whole distribution (a worsening of mental health), which is particularly evident in the left-hand tail, with those reporting a death more concentrated amongst those with very low levels of mental health. [6]

The instrument is also strongly related to mental health within individuals. The results in column 1 of Table II present estimates from a linear fixed-effects model that includes a dummy variable for death of a close friend in the past 3 years, together with controls for other time-varying characteristics. As already suggested by Figure 1, we find that death of a close friend is associated with a significant drop in mental health, with the size of the effect approximately one-quarter of the effect associated with the death of a spouse or child, and towards double the effect associated with the death of a close relative (e.g. parent).[7] Importantly, the first-

[4]Including partner characteristics and labour market outcomes as additional control variables has only a very small influence on our estimated mental health effects and does not alter any of our conclusions.

[5]By allowing for lagged effects on mental health, we are also inherently allowing for lagged effects in employment, such that the death of a friend in the previous 3 years is allowed to impact upon current employment probabilities.

[6]Using information from wave 9 of HILDA, we also find that the death of a friend increases the probability of a current doctor-diagnosed depression or anxiety condition by 3.4 percentage points ($t = 2.63$) and the use of prescription medication for depression or anxiety by 2.4 percentage points ($t = 3.24$).

[7]We do not use the 'death of a close relative' as an instrumental variable because it is conceivable that the death of a parent, or at least the unobserved correlated event 'parent has a terminal illness', may reduce an individual's labour supply through pathways other than mental health. In particular, it is possible that individuals reduce their labour supply in order to care for a terminally ill parent. It is far less likely, however, that an individual will reduce their labour supply to care for a terminally ill friend; although, of course in a very small number of instances, this will also occur.

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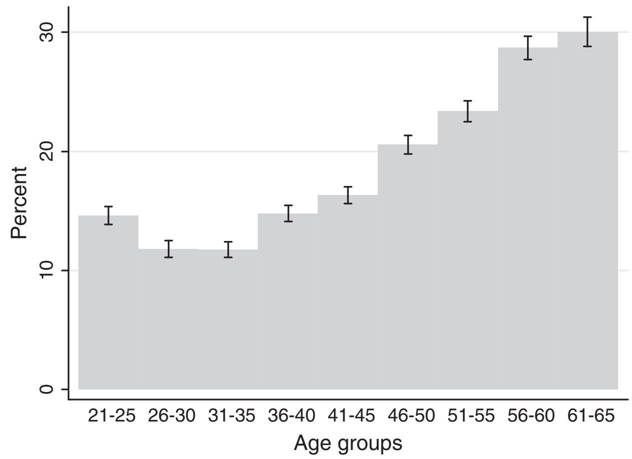

Figure 2. Percentage reporting death of close friend in past 3 years

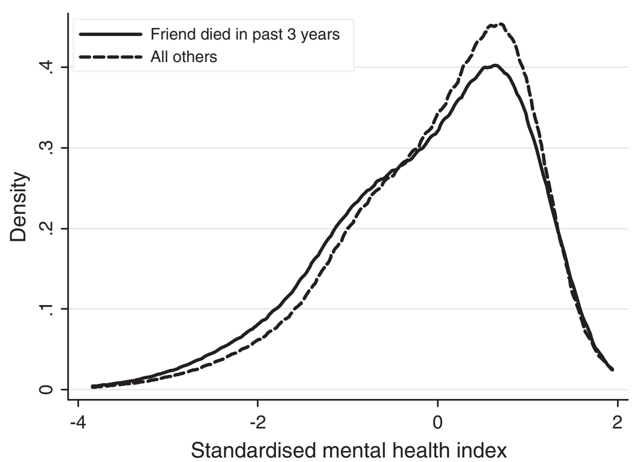

Figure 3. Kernel density estimates of the standardised mental health index

stage F-statistic equals 24.09, which is well above the value of 10 commonly suggested as a cutoff point for a strong instrument.

To justify our decision to use death of a close friend in the last 3 years as our exogenous variation with the fixed-effects framework, we also provide the results in column 2 from a model where we include separate dummies to capture the number of years since the event. We do this because a large literature has shown that there is an adaptation process following major life events (see, e.g. Frijters *et al.*, 2011), although there is still uncertainty regarding the speed and extent of adaptation to different events. The results suggest that the effect of such a death on mental health is larger if it happened within the last year but that around 60% of the effect still remains after 3 years. However, for this particular event, the data tell us that full adaptation has taken place by 3–4 years. We note that the first-stage F-statistic for this specification is lower at 6.10. We can also test the validity of this aggregation with a Stock and Yogo (2002) over-identification test of whether using a 3-year window is appropriate by noting that such a window involves three instrumental variables with restrictions on the coefficients. The over-identification test statistic equals 0.421 with p-value 0.810. Thus, we cannot reject the null hypothesis that the instruments are valid.

We also include a number of time-varying covariates in the Table II models, which attempt to capture pathways that might plausibly link the death of a close friend to labour market outcomes other than through decreased mental health (note that the fixed effects control for all time-invariant confounders). The most

Table II. First-stage equation and instrumental variable validation models

	Mental Health			Physical health
	1	2	3	4
Death of friend in the past 3 years	−0.042*** (0.008)	—	—	−0.008 (0.009)
Death of friend 0–1 years past	—	−0.041*** (0.010)	—	—
Death of friend 1–2 years past	—	−0.023** (0.010)	—	—
Death of friend 2–3 years past	—	−0.030*** (0.011)	—	—
Death of friend 3–4 years past		0.002 (0.012)		
Death of friend 0–1 year future	—	—	−0.001 (0.010)	—
Death of spouse in the past 3 years	−0.170*** (0.033)	−0.170*** (0.033)	−0.169*** (0.034)	0.009 (0.035)
Death of relative in the past 3 years	−0.025*** (0.007)	−0.025*** (0.007)	−0.028*** (0.008)	−0.012* (0.008)
F-statistic	24.09	6.10	0.02	0.93
F-statistic *p*-value	<0.0001	0.0001	0.898	0.335
Sample size	80 737	72 160	72 897	80 737

Figures are estimated coefficients from linear fixed-effects regression models. Standard errors clustered at the individual level are shown in parentheses. The dependent variable in models 1, 2 and 3 is a standardised mental health index ($SD = 1$) and in model 4 is a standardised physical functioning index ($SD = 1$). Included in each model but not shown are the set of covariates in Table III and year dummy variables. The *F*-statistic is from a test of the null hypothesis that the death of friend coefficient(s) equals zero.
*Denotes 0.10 significance level.
**Denotes 0.05 significance level.
***Denotes 0.1 significance level.

important of these are windfall income (i.e. a close friend might leave a bequest) and the death of a spouse or relative, which could be correlated with death of a friend if an individual considers their spouse or relative to also be a close friend. To capture any other time-varying aspects of friendship on mental health (or work), we also control for whether the individual reports to have many friends. However, it turns out that including or excluding these variables does not change the main result of this paper.

Table II also includes two placebo tests that provide additional support for the validity of our instrument. First, if our instrument is valid, then we would not expect the death of a close friend 1 year in the future to affect an individual's mental health today. This is shown to be the case in column 3, where the coefficient on death of a friend in the future is not significantly different from zero (t-statistic $= -0.13$). This suggests that our results are not driven by unobservable time-varying heterogeneity. Second, although we expect that the death of a close friend will impact on mental health, we do not expect it to affect physical health to any large extent. This is shown to be true in column 4, where death of a close friend is not associated with a continuous measure of physical functioning, which is extracted from the SF-36 questionnaire. Again, if the instrument simply reflected unobservable time-varying heterogeneity (such as changes in socioeconomic status or disability benefit status), then we would expect these unobservable time-varying heterogeneities to impact upon both physical and mental health. This result also implies that our IV-FE estimates are not capturing any effect of changes in physical health (comorbidity).

4. RESULTS

4.1. Main estimates

The IV-FE employment estimates are presented in Table III alongside equivalent ordinary least squares (OLS), 2SLS and IV-Probit estimates, which are provided for comparative purposes.[8] We also provide the full first-stage estimates for our main IV-FE model (column 4).

[8]We note that we are using a linear probability model because we are unaware of an estimator for a non-linear fixed-effects model with an endogenous covariate. However, we provide the estimate from an IV-Probit model to check that our main employment result is not driven by the linearity assumption. This also provides us with an estimate that can be compared with estimates from previous studies, which often have used a bivariate probit specification.

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Table III. Ordinary least squares, 2SLS and instrumental-variables fixed-effects regression models of employment

	OLS (1)	2SLS second stage (2)	IV-probit second stage (3)	IV-FE first stage (4)	IV-FE second stage (5)
Mental health	0.069*** (0.003)	0.229*** (0.042)	0.215*** (0.033)	—	0.299*** (0.110)
Death of friend	—	—	—	−0.042*** (0.008)	—
Age	0.049*** (0.002)	0.051*** (0.002)	0.044*** (0.002)	−0.012** (0.005)	0.043*** (0.005)
Age squared/100	−0.066*** (0.002)	−0.069*** (0.002)	−0.060*** (0.002)	0.012** (0.005)	−0.061*** (0.004)
University degree	0.180*** (0.009)	0.154*** (0.011)	0.134*** (0.010)	0.042 (0.048)	0.168*** (0.033)
Diploma/certificate	0.140*** (0.009)	0.120*** (0.010)	0.099*** (0.010)	0.000 (0.033)	0.096*** (0.024)
High school graduate	0.101*** (0.011)	0.081*** (0.012)	0.058*** (0.011)	−0.014 (0.045)	0.059* (0.031)
Married/cohabitating	0.055*** (0.008)	0.028** (0.011)	0.033*** (0.012)	0.026 (0.018)	−0.036*** (0.010)
Divorced/separated	−0.008 (0.012)	0.010 (0.013)	0.019 (0.012)	−0.093*** (0.028)	−0.009 (0.018)
Number of children	−0.062*** (0.003)	−0.058*** (0.003)	−0.057*** (0.004)	−0.020*** (0.006)	−0.046*** (0.004)
Windfall income	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	0.001 (0.001)	−0.003*** (0.001)
Many friends	0.002 (0.002)	−0.026*** (0.008)	−0.024*** (0.006)	0.075*** (0.003)	−0.022*** (0.008)
Death of spouse	−0.095*** (0.021)	−0.048** (0.024)	−0.032 (0.023)	−0.170*** (0.033)	0.031 (0.025)
Death of relative	−0.022*** (0.005)	−0.007 (0.006)	−0.008 (0.006)	−0.025*** (0.007)	0.004 (0.005)
First-stage *F*-statistic	—	110.99	111.03	—	24.09
Number of individuals	12911	12911	12911	12911	12911
Sample size	80 737	80 737	80 737	80 737	80 737

The dependent variable in models 1, 2, 3 and 5 is employment. The dependent variable in model 4 (first-stage equation) is mental health. Figures are estimated coefficients in models 1, 2, 4 and 5. Figures are estimated marginal effects in model 3. Standard errors clustered at the individual level are shown in parentheses. Included in each model but not shown are year dummy variables.
OLS, ordinary least squares; IV-FE, instrumental-variables fixed-effects.
*Denotes 0.10 significance level.
**Denotes 0.5 significance level.
***Denotes 0.1 significance level.

The IV-FE estimates (column 5) suggest that a one-standard-deviation decrease in mental health leads to a 30-percentage-point decrease in the probability of being employed, which is statistically significant at the 1% level.[9] This effect is roughly equivalent to nearly double the effect of having a degree level qualification (effect equals 0.168) relative to the omitted category of being a high school dropout. The substantive size clearly suggests that the loss of a close friend generates more than just a short-term bereavement-related fall in mental health.[10]

The IV-FE estimate is only about 25% larger than the 2SLS estimate (effect equals 0.229) and the marginal effect from the IV-Probit model (0.215) but about four-fold larger than the OLS estimate (effect equals 0.069). A major difference between the OLS model and the three IV models (2SLS, IV-Probit and IV-FE) is that the latter models can account for reverse causality and measurement error. The very large difference between the OLS and IV estimates therefore suggests the presence of either strong reverse causality or large measurement error in the index of mental health symptoms.[11] The smaller differences between the 2SLS, IV-Probit and IV-FE estimates suggest that the instrumental variable is not strongly associated with time-invariant characteristics that determine employment.

To explore if there is heterogeneity in the effect of mental health on employment, we present separate estimates by gender and two broad age groups in Table IV. They show that employment for both genders is significantly and substantively affected by worsening mental health but the estimated effect is a little larger for women (32 percentage points) than men (27 percentage points). For women, this effect is roughly equivalent to a tripling of the predicted employment difference between those with a university degree and those reporting to have no qualifications. We also find evidence of a larger employment response for those over the age of 40 years (0.431) compared with younger individuals (0.262), which might reflect different pathways or opportunities outside of the labour market available for older workers.

4.2. Further exploring the employment effect

We now try to shed some light on the mechanism through which a decline in mental health leads to lower employment. In particular, we ask the following two questions: (i) is the employment effect of poor mental health driven by supply-side responses (e.g. voluntary quits) or demand-side responses (e.g. being fired)? and (ii) are supply-side effects explained by workers voluntarily leaving the workforce or by non-workers (or marginally attached workers) postponing (re)employment?

We attempt to answer these questions by estimating IV-FE models with additional outcome variables and by using a number of subsamples defined by employment status and job type 3 years prior to the measurement of the outcome (*t*-3). Specifically, we examine three outcomes: employment, being fired or made redundant and unemployment. The subsamples are defined by past employment, past employment in a full-time job, past employment in a managerial or professional occupation, past employment in other occupations (i.e. manual jobs and low-skill non-manual jobs) and past employment in the private sector. This limited set of past employment conditions is chosen so that the estimation sample sizes remain sufficiently large for our data-hungry

[9]If instead of using the binary indicators of death of a close friend in the last 3 years, we rather include three separate dummies for a death in the last year, 1–2 years ago and 2–3 years ago (as suggested by the adaptation profile reported in Table II), then the significant employment effect equals 0.273 (p-value = 0.018).

[10]A potential issue that could bias the main estimate is panel attrition. Although we have not been able to explicitly model this within the IV-FE framework, we have explored this issue by testing whether mental health, employment and death of a friend (our key variables) in period t are predictive of non-response in period $t+1$ (mean level of non-response equals 7.3%). The results from fixed-effects regression models show that none of these three variables are statistically significant predictors. For example, the estimated effect of mental health equals −0.002 with associated t-statistic of −1.13. This result, however, can only tentatively suggest that attrition is not biasing our results.

[11]With classical measurement error, the downward bias in an OLS coefficient estimate is a factor of $var(signal)/[var(signal) + var(noise)]$, which would indicate a noise-to-signal ratio of 3 : 1. However, if mental health is strongly correlated with other variables in the outcome equations (which it is), then the noise-to-signal ratio can be much lower and still produce the same reduction in the OLS coefficient.

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Table IV. Instrumental-variables fixed-effects regression models of employment for gender and age subgroups

	Female (1)	Male (2)	Aged ≤40 years (3)	Aged >40 years (4)
Mental health	0.319** (0.151)	0.273* (0.159)	0.262 (0.181)	0.431** (0.189)
Age	0.042*** (0.008)	0.044*** (0.008)	−0.011 (0.010)	0.111*** (0.012)
Age squared/100	−0.069*** (0.005)	−0.053*** (0.005)	0.014 (0.012)	−0.121*** (0.010)
University degree	0.135*** (0.043)	0.167*** (0.048)	0.201*** (0.044)	0.130** (0.062)
Diploma/certificate	0.120*** (0.031)	0.020 (0.032)	0.115*** (0.035)	0.053 (0.037)
High school graduate	0.089** (0.043)	−0.023 (0.042)	0.075* (0.041)	−0.053 (0.067)
Married/cohabitating	−0.060*** (0.015)	−0.019 (0.015)	−0.021* (0.011)	−0.033 (0.031)
Divorced/separated	−0.020 (0.027)	0.009 (0.023)	0.012 (0.030)	0.004 (0.037)
Number of children	−0.077*** (0.006)	−0.014*** (0.005)	−0.061*** (0.009)	−0.021*** (0.006)
Windfall income	−0.003*** (0.001)	−0.003*** (0.001)	−0.003** (0.001)	−0.003*** (0.001)
Many friends	−0.024** (0.012)	−0.019 (0.012)	−0.022 (0.016)	−0.027** (0.011)
Death of spouse	0.038 (0.042)	0.023 (0.026)	−0.001 (0.039)	0.083* (0.043)
Death of relative	0.005 (0.008)	0.002 (0.006)	0.003 (0.009)	0.006 (0.007)
First-stage *F*-statistic	14.16	9.76	8.16	10.67
Number of individuals	6720	6191	7434	7551
Sample size	42 569	37 471	35 795	43 537

The dependent variable in all models is employment. Figures are estimated coefficients. Standard errors clustered at the individual level are shown in parentheses. Included in each model but not shown are year dummy variables.
*Denotes 0.10 significance level.
**Denotes 0.5 significance level.
***Denotes 0.1 significance level.

instrumental-variables estimation approach. The 3-year lag is chosen because our identification strategy is based on death of a close friend in the past 3 years.

Row (1) in Table V presents estimated IV-FE mental health coefficients for the sample of individuals for whom we observe employment status 3 years ago. Effectively, this is a replication of the IV-FE employment model shown in Table III for a reduced time span and is presented solely to provide a comparison point for the estimates in rows (2)–(6). Rows (2) and (3) present estimates for those who were previously employed (part-time or full-time employment and full-time employment). Our hypothesis is that if the employment effect shown in row (1) is driven by non-workers postponing employment, then the estimated employment effect for past employees should be substantially smaller than the row (1) estimate. Conversely, if the employment effect shown in row (1) is driven by workers being fired or voluntarily leaving the workforce, then the estimated

Table V. Estimated mental health coefficients from instrumental-variables fixed-effects models conditional on past employment status

	Sample size	First-stage *F*-statistic	Employed	Fired	Unemployed
Conditional on employment 3 years ago					
(1) Employment status non missing	58011	23.97	0.240** (0.099)	−0.048 (0.057)	−0.000 (0.049)
(2) Employed	45188	24.22	0.218** (0.090)	−0.038 (0.062)	−0.013 (0.041)
(3) Employed full time	31909	11.51	0.217* (0.119)	−0.029 (0.091)	−0.020 (0.053)
Conditional on job type and employment 3 years ago					
(4) Managerial/professional occupation	17529	8.38	0.105 (0.131)	0.017 (0.090)	−0.037 (0.056)
(5) All other occupations	27654	14.56	0.267** (0.125)	−0.061 (0.087)	−0.003 (0.058)
(6) Employed in the private sector	49015	25.05	0.255** (0.100)	−0.027 (0.058)	−0.002 (0.051)

Figures are estimated coefficients on a standardised mental health index ($SD = 1$) from linear regression models. Standard errors clustered at the individual level are shown in parentheses. Included in each model but not shown are the covariates in Table III and year dummy variables.
*Denotes 0.10 significance level.
**Denotes 0.5 significance level.
***Denotes 0.1 significance level.

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employment effect for past employees should be similar to or even larger than the row (1) estimate. The employment estimate in row (1) equals 0.24, whereas the employment estimates for past employees (row 2) and past full-time employees (row 3) equal 0.218 and 0.217, respectively. Therefore, these employment estimates support the idea that the mental health effect is equally strong for workers and non-workers: following deterioration in mental health, workers increasingly leave the workforce and non-workers postpone re-entry.

We further test whether workers are leaving the workforce voluntarily by estimating models of being fired and being unemployed. The results for these outcomes consistently show that mental health does not significantly increase the probability of being fired (regardless of past employment status) and correspondingly does not significantly increase the probability of unemployment. These results suggest that workers are in the main voluntarily leaving the workforce after a decline in mental health and that the effects are therefore primarily supply-related rather than demand-related.[12]

Finally, rows (4)–(6) in Table V present results on the types of workers who are most likely to quit. The estimated employment effects are largest for low-skill occupations and for those employed in the private sector (0.267 and 0.255, respectively). Given that the deterioration in on-the-job human capital and networks is likely to be largest in high-skill and arguably in public sector jobs, these results are consistent with the hypothesis that the types of workers who are most likely to quit are those for whom the penalty for leaving the workforce (and potentially returning when mental health improves) is lowest.

5. CONCLUSIONS

Poor mental health and specific disorders such as depression and anxiety are highly prevalent, and a large interdisciplinary literature has linked poor mental health to detrimental labour market outcomes. However, quantifying the causal effects of poor mental health on labour market outcomes, rather than the straightforward calculation of associations, is a difficult empirical challenge. Most of the existing economics literature uses North American cross-sectional survey data to study this issue and have chosen a variety of time-invariant individual characteristics as instruments to aid causal identification. The most commonly used instruments (sources of exogenous variation) have been parental mental health problems (as retrospectively reported by the adult survey respondent), previous spells of poor mental health (of the adult respondent earlier in their life), religion and various measures of social capital. One weakness of using cross-sectional data in this context is the inability to directly control for selection based on unobservable characteristics.

In this paper, we contribute to the literature that has focussed on obtaining robust causal estimates of mental health on labour market outcomes by using a novel time-varying instrumental variable model that controls for individual-level fixed effects using 10 years of high-quality panel data. Such a model simultaneously controls for reverse causality between mental health and work, unobservable confounders and classical measurement error. This model is identified with a new time-varying instrumental variable representing the recent death of a close friend (not a family member). We show that this major life event is a powerful predictor of mental health (first-stage F-statistic in fixed-effects model is 24.09), and we argue that it is a valid instrument because the only alternative pathways through which it could affect labour market outcomes can be reasonably dismissed with our data. The death of a friend is not associated with positive financial windfall gains (via bequests) nor does it affect physical health today or mental health in the past. These placebo tests therefore support the argument that the instrument works solely through mental health and that it does not reflect other unobserved time-varying characteristics. However, one weakness of our data is that we do not observe longitudinal clinical

[12]If we examine the intensive margin (hours of work and wages) using the same IV-FE methodological approach, we find that the mental health effects are statistically insignificant. These results suggest that the employer is not reacting to the mental health shocks by changing wage rates or contracted hours and that the main effects on employment are thus supply-driven. However, we do not emphasise these results because there is the real possibility that those who lost their job would have reacted much more strongly in hours and wages if they had retained their jobs (effect heterogeneity in the presence of endogenous selection), making it hard to give a causal interpretation on the found effects of the intensive margin.

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diagnosis of mental health disorders; instead, we construct an index of mental health on the basis of reported symptoms that mostly captures symptoms of depression and anxiety (rather than psychosis, e.g.). Yet, we are able to confirm that our measure is strongly correlated with a one-time reported clinical diagnosis available in one wave of our panel data.

Our focus in this paper has been on the extensive margin of employment, where we have investigated the extent to which individuals who experience a mental health decline remain in employment. We find robust evidence that a worsening of mental health leads to substantially reduced employment. Moreover, the size of this effect is substantial, with a one-standard-deviation worsening of mental health leading to a 30-percentage-point reduction in the probability of being employed. This effect is large for both men and women and is consistent with the large adverse employment effects of poor mental health found in a number of North American studies (e.g. Alexandre and French, 2001; Chatterji *et al.*, 2007, 2011). Further investigations suggest that this employment effect is larger for older than younger workers possibly reflecting different pathways and opportunities out of employment for older workers and that the movement out of employment following a deterioration in mental health is mainly supply rather than demand-side driven in that those subject to a mental health deterioration were not more likely to be fired and hence voluntarily reduced their labour supply.

Overall, we believe that obtaining causal estimates of the effect of mental health on labour market outcomes has important policy benefits. For example, our estimates, combined with those from previous North American studies, provide useful information for policy makers in lobbying for additional resources to be made available for mental illness treatment and prevention and in helping to design workplace policies that minimise the costs of poor mental health.

APPENDIX

Table A1. Summary of the nine SF-36 questions used to form mental health index

	All of the time (1)	Most of the time (2)	A good bit of the time (3)	Some of the time (4)	A little of the time (5)	None of the time (6)
1. Did you feel full of life?	4.76	40.14	24.25	19.39	8.60	2.85
2. Have you been a nervous person?	1.03	2.56	5.45	16.70	35.71	38.55
3. Have you felt so down in the dumps that nothing could cheer you up?	0.63	1.66	3.51	9.98	22.33	61.89
4. Have you felt calm and peaceful?	4.51	36.92	23.04	21.62	11.04	2.86
5. Did you have a lot of energy?	3.29	32.44	26.26	22.51	11.30	4.20
6. Have you felt down?	0.90	2.94	5.70	18.98	44.00	27.48
7. Did you feel worn out?	1.90	6.88	13.39	30.21	37.16	10.48
8. Have you been a happy person?	7.51	51.44	19.86	14.92	5.26	1.00
9. Did you feel tired?	3.27	10.18	16.65	35.05	31.31	3.53

The preamble to this set of questions is, 'How much of the time during the past 4 weeks'. Figures represent percentage of respondents giving each response, with each row totalling to 100%. Sample size equals 80 737.

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