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Working Paper

Mental health and labour market participation: Evidence from IV panel data models

IZA Discussion Papers, No. 4883

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Suggested Citation: Frijters, Paul; Johnston, David W.; Shields, Michael A. (2010) : Mental health and labour market participation: Evidence from IV panel data models, IZA Discussion Papers, No. 4883, Institute for the Study of Labor (IZA), Bonn

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DISCUSSION PAPER SERIES

IZA DP No. 4883

Mental Health and Labour Market Participation: Evidence from IV Panel Data Models

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April 2010

Forschungsinstitut
zur Zukunft der Arbeit
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IZA Discussion Paper No. 4883
April 2010

ABSTRACT

Mental Health and Labour Market Participation: Evidence from IV Panel Data Models

A large body of empirical research links mental health and labour market outcomes; however, there are few studies that effectively control for the two-way causality between work and health and the existence of unobserved individual characteristics that might jointly determine health and labour market outcomes. In this study, we estimate the effect of mental health on labour market participation using various models, including instrumental variable models that exploit individual variation observed in panel data. We find robust evidence that a reduction in mental health has a substantial negative impact on the probability of actively participating in the labour market. We calculate that a one standard deviation decrease in mental health decreases the probability of participation by around 17 percentage points. This effect is larger for females and for older individuals. We therefore provide robust evidence that there are substantial costs due to the lost productivity resulting from poor mental health.

JEL Classification: I10, J21, J22

Keywords: labour market participation, mental health, measurement error, causality

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1. Introduction

Mental health disorders are a common condition in both developed and developing countries and the consequences of chronic mental illness for individuals, families and the wider community can be severe and highly costly. The total societal cost of such disorders is substantial, with estimates for the US of close to $200 billion per year (see, for example, Kessler et al., 2008; and also the discussion in Marcotte and Wilcox-Gök, 2001). Depressive disorders alone are estimated to account for around 12% of total years lived with disability worldwide (Moussavi et al., 2007).

One of the most important ways that mental illness impacts on individuals (and their families) is by lowering their ability to actively participate in the labour market. In addition to the loss of income caused by such non-participation, there is also the loss of daily structure, a sense of purpose, and opportunities for social interactions. The erosion of work life can further exacerbate poor mental health. This issue is clearly important when considering policy responses to mental illness and when considering the wider societal costs. Being able to accurately estimate the causal effect that poor mental health has on labour market outcomes, however, is made difficult due to the issues of reverse causality and unobserved individual heterogeneity, as well as the practical issue of measuring mental health.

While many studies have established correlations between mental health and work, there have been only a few studies over the last decade or so that have made use of Instrument Variable (IV) methods in an attempt to gain more reliable causal estimates (see Ettner et al., 1997; Hamilton et al., 1997; Marcotte et al., 2000; Alexandre and French, 2001; Chatterji et al., 2007; Ojeda et al., 2009; and Zhang et al., 2009). The key challenge in this literature is being able to find some exogenous variation in mental health to use for identification, variation that only impacts on labour market outcomes through its impact on mental health. The instruments used so far include information about parental psychological problems, individual experiences of mental illness in the past, religiosity, perceived social support, and participation in physical activity. The results of these studies suggest that mental illness has significant costs in terms of labour market participation and other work-related outcomes such as wages and absenteeism. The magnitude of these costs, however, varies considerably across studies, with some finding relatively small effects of mental health on participation (e.g. Cornwell et al., 2009) and others finding substantial effects for some groups of individuals (e.g. Chatterji et al., 2007; Zhang et al., 2009). While we might expect some variation in the size of this effect across countries, stemming from differences in treatment rates, workplace practices and welfare provision for individuals with mental illness, most of the differential in the estimates likely comes from differences in the instrument choice and empirical models adopted.

The contribution of this paper is not simply to confirm a negative effect of mental illness on labour market participation, as it is inconceivable that any careful empirical analysis would find this not to be the case. Rather we attempt to go further than previous studies by taking advantage of the dynamics in panel data and estimating a variety of models that control for different aspects of the identification problem. In particular, we attempt to address the twin problems of reverse causality and selectivity by using a new instrument to the literature; one which we believe is more reasonable than those used previously. This instrument impacts on a large number of individuals every year, varies for the same individual over time, and is a strong determinant of mental but not physical health. This is the recent death of a close friend (not a spouse or relative). Instead of just using an indicator of whether the event happened in the last year, we allow for a dynamic effect that changes from quarter to quarter in order to improve the precision of our estimates. We get our data from seven waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey. Our conclusion is that the experience of a worsening in mental health leads to a statistically significant fall in labour market participation, that this effect is quantitatively very large, and that it is bigger for females and for older individuals. We find that a one standard deviation decline in mental health leads to a drop in the probability of participation by around 19 percentage points. We also find that the main identification problem comes from the existence of correlated time-varying unobservables rather than individual fixed effects, and that the attenuation bias associated with measurement error is non-trivial.

The remainder of this paper is organised as follows. Section 2 provides some background information on mental health and also further places our study within the existing literature. Section 3 introduces the data, defines the main variables and discusses the empirical models we use. In Sections 4 we present the results, and Section 5 concludes the paper.

2. Background and Literature

Mental health disorders are diverse and wide ranging in their symptoms, diagnosis, treatment and consequences. They range from common anxiety and mood disorders (e.g. generalised anxiety, depression) to low prevalence psychotic disorders (e.g. Schizophrenia). There is a large multi-disciplinary literature showing that mental illness is strongly correlated with a wide variety of detrimental life outcomes, including poorer labour market outcomes, the breakup of family life, homelessness and being both a victim and perpetrator of crime. Bartel and Taubman (1979, 1986) are examples of early research in this area.

There have been many attempts at putting a total societal cost on mental illness, and specific conditions such as depression and alcohol abuse. These estimates are always very large ranging from around $50 billion to around $200 billion per year for the US (see, for example, Rice et al., 1990; Harwood et al., 2000; Greenberg et al., 2003; and Kessler et al., 2008), but it is generally believed that these estimates significantly underestimate the ‘true’ total cost due to the difficulties in fully identifying all of the costs to both the individual and to others (Insel, 20008). One example of this literature is Greenberg et al. (2003) who estimated the total cost of depression in the US to be $83 billion, consisting of direct medical costs (31%), suicide-related mortality costs (7%) and work-related costs (62%). Other examples are Mangalore and Knapp (2007) who estimated the societal cost of schizophrenia in the UK to be £6.7 billion in 2004/5, and Sobocki et al. (2006) who estimated that the total cost of depression in Europe was €118 billion in 2004, or about €253 per inhabitant.

It is a common finding that the work-related costs from lost productivity make up a particularly high proportion of the total societal costs. These work-related costs relate to higher rates of unemployment for those with mental illness, greater absenteeism and lower presenteeism (being ill in the workplace). Broadhead et al. (1990) found that individuals with severe depression are almost five times more likely than healthy individuals to be constrained in their regular activities. Kessler and Frank (1997) found that employees with psychiatric disorders experience substantially more days during which they are unable to work or carry out normal activities. Marcotte et al. (2000) reviewed the US literature and concluded that each year in the US 5-6 million workers “lose, fail to seek, or cannot find employment as a consequence of mental illness.” Stewart et al. (2003) found that workers in the US with depression experienced significantly more health-related ‘Lost Productivity Time’ each week (5.6 hours) compared to workers without depression (1.5 hours). A recent influential study on the labour market costs of mental illness is Kessler et al. (2008), who used US survey data from 2001 to 2003 and found that respondents with a serious mental illness had annual earnings of about $16,000 lower than individuals without such an illness (controlling in a regression model for socioeconomic characteristics). This difference was far higher for males ($26,435) than females ($9,302). Using these estimates the total societal cost was calculated to be $193 billion per year. Similarly the cost of mental illness in the UK is predicted to be high with 8.65 million people (about 17% of the population) living with some form of mental health disorder in 2007. The annual cost is calculated to be around £50 billion, with about half of this cost arising from earnings lost by the many thousands of people unable to work due to their mental illness (McCrone et al., 2008). In Australia, nearly one quarter (24.3%) of Australian youth (aged 12-25) are estimated to suffer from anxiety, affective or substance use disorders, with the financial cost of youth mental illness estimated at A$10.6 billion annually. Lost productivity accounts for about 70% of this total (Access Economics, 2009).

Central to these societal cost estimates is the ability to obtain reliable estimates of the causal impact of mental illness on labour market outcomes, rather than establishing simple correlations. Causal estimates are also needed to better understand the cost of mental illness to an individual, and to design effective mental health policies. The most important labour market outcome is the ability for an individual to be able to actively participate in work, and it is this outcome that we study in this paper. However, the key task is in being able to move beyond a statement of correlation, and this is difficult because of two well-known issues; reverse causality and unobserved individual heterogeneity, the later leading to the possibility of a spurious relationship being mental health and work outcomes. In terms of (1), a large multidisciplinary literature has found that the experience of unemployment is detrimental to mental health (examples from economics are Clark and Oswald, 1994; Theodossiou, 1998; Bender and Theodossiou, 2009), although not all studies agree with this conclusion (e.g. Björkland, 1985; Salm, 2009).

For a number of years economists have been contributing to the understanding of the consequences of mental illness on labour market outcomes. These studies differ in terms of their methodology and identification, and the degree to which they can overcome the empirical difficulties. Broadly three approaches have been used. The simplest methodology is to deal with unobserved individual characteristics by controlling for a wide range of observable characteristics and making the assumption that these will capture or proxy closely all of the relevant (that are directly unobserved) characteristics and traits of an individual. A second approach is to take advantage of panel data and control for (or difference out) fixed individual characteristics, leaving an estimate of the changes in mental health in one year and changes in labour market outcomes in that same year. Neither of these methods, however, controls for the likelihood of reverse causation. Hence a popular approach has been to use Instrumental Variables (IV), to proxy a 'natural experiment' and give some exogenous variation in mental health to aid identification. This means finding a variable(s) that is a strong predictor of mental health that can also be excluded from the main labour market equation. In other words, a desirable instrument only affects labour market outcomes through it effect on mental health. Economists have had to be innovative in their choice of instruments, as identifiable random shocks (e.g. observable policy shocks) to mental health are rare.

Examples of instruments for mental health that have been used include: parental history of mental problems (Ettner et al., 1997; Marcotte et al., 2000); number of childhood psychiatric disorders (Ettner et al., 1997; Chatterji et al., 2007); mental health in the three months before the current survey (Hamilton et al., 1997); religiosity (Alexandre and French, 2001; Chatterji et al., 2007); and proxies for social support (Hamilton et al., 1997; Alexandre and French, 2001; Ojeda et al., 2009); and the frequency of physical activity and stressful life events (Hamilton et al., 1997). Most, but not all of these studies report a detrimental effect of mental illness (defined in many ways across these studies) on labour market outcomes, although the size of the effect differs greatly across studies. For example, Ettner et al. (1997) used childhood and family mental illness as instruments in cross-sectional 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. It is not clear, however, that most of these instruments satisfy the assumption that they can be reasonably excluded from the labour market equation. For example, many studies have found find that depression during childhood causes a substantial decline in human capital accumulation, particularly for women, and that this leads to considerable earnings losses (e.g. Berndt et al., 2000; Fletcher, 2008). This direct effect of childhood disorders on the later outcome violates the assumption of a valid instrument. Similarly, Lipford and Tollison (2003) find that religiosity reduces income by discouraging the acquisition of material wealth and by requiring time commitments that reduce the number of hours worked. More generally, each of these instruments varies little, if at all, over time once a person reaches the labour market, which means reverse causality effects are not well catered for.

In the Australian context a number of recent studies have focused on the relationship between unemployment and mental health (wellbeing), and conversely between mental health and labour market outcomes. Examples of the former are Flatau et al. (2000), Dockery (2005) and Carroll (2007).[1] Most relevant for our study is the recent paper by Zhang et al. (2009), who used pooled cross-sectional data from the Australian National Health Surveys to estimate a joint system of equations modelling the relationship between chronic diseases, including mental disorders, and labour market participation.[2] In particular, the paper identifies the effect of chronic illnesses on labour market participation via a combination of functional form assumptions (e.g. the normality assumption in the multinomial probit model) and standard IV-assumptions implicit in the exclusion restrictions. The paper does not explicitly discuss these restrictions, but it appears from the results tables that characteristics such marital status, immigration status, English language proficiency, children and education are taken to influence participation but not chronic illness. The effect of mental illness is found to be large for men, with older males in particular seeing a decline in the likelihood to participation of around 25 percentage points.

In this paper, we attempt to build on these studies by estimating a number of different models, including a fixed-effects IV (FE-IV) model that benefits from the dynamics that can be captured in seven waves of panel data. Innovatively in this literature this model allows us to simultaneously deal with both reverse causality and unobserved individual heterogeneity. However, the model requires a great deal of variation in the data, both in terms of mental health

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[1] Also see the descriptive analysis by Waghorn and Chant (2006) using Australian cross-sectional survey data.

[2] Another recent paper using Australian data is Cornwell et al. (2009). They do not use an IV approach, and find a relatively small association between mental health disorders and labour market participation. Each additional disorder is estimated to reduce participation by about 1.3 percentage points.

and labour market participation, as well as in the instrument. We use information about whether or not a close friend (not a spouse or relative) has died in the past 12 months, which is a life event that impacts on a large number of people each year and which we believe meets all of the above criteria. A large psychological 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 are predicted to occur shortly after the event (Bebbington and MacCarthy, 1993).

Therefore, the assumption that this instrument is strongly correlated with mental health seems reasonable. Crucially, the death of a close friend is unlikely to influence (except through its effect on mental health) important determinants of labour market outcomes, such as an individual’s productivity, reservation wage or human capital. This instrument itself varies over time, meaning that we cannot only overcome the bias introduced by fixed unobservables, but also overcome reverse causality. This allows us to quantify the endogeneity bias that comes in if time-dependent reverse causality is ignored. The only concern we have is that the death of a close friend might lead to the receipt of inheritance, which if substantial enough, might impact labour supply. We explicitly take account of this in our estimations by controlling for recent windfall financial gains. It turns out, however, that controlling or not for such gains makes no discernable difference to our estimates because the inheritances involved are minimal.

3. Data and Models

To estimate the labour market effects of poor mental health, we use data from waves 2 to 8 (2002-2008) of the Household, Income and Labour Dynamics in Australia (HILDA) survey.[3] HILDA is a household-based longitudinal study that is nationally-representative, with the exception of under-sampling individuals living in more remote areas of Australia. It began in 2001 with a survey of 13,969 persons in 7,682 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, education,

[3] We do not use wave 1 because the instrument information (death of a close friend) was only introduced in wave 2.

income, family formation, health and other specialised topics. In this paper we use observations on adults aged 22-64 inclusive.

A limitation of the data is that it does not contain diagnostic measures of mental illness such as DSM-IV or ICD10. Instead, our measure of mental health, available in all waves, is generated from questions in the mental health module of the Short-Form General Health Survey (SF-36). In this part 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 nothing could cheer you up; (iv) have you felt clam 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; (ix) and 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). 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 is mean zero and standard deviation one.[4] This index is strongly correlated (0.79) with the widely used Kessler Psychological Distress Scale, which was collected in wave 7 of HILDA. 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).

The outcome of interest in this study is labour market participation, which is defined as either being employed, or else as being unemployed but actively looking for work and available to begin work. To get a first feel for the strength of the relationship, Figure 1 shows the nonparametric cross-sectional relationship between the mental health score and participation. The strength and size of the presented relationship is very large, with an improvement in mental health from -2 to 0 (two standard deviations) increasing participation by 20 percentage points. The size of this relationship clearly justifies the use of the SF-36 based measure of mental health. It is nevertheless possible that this raw estimated relationship is upward or downward biased, depending on the effect that participation status has on mental health and on the effect of confounding factors. In the following section we present estimates that control for these observable and unobservable effects. Figure 2 highlights the dynamic relationship, showing that a

[4] We do not use the exact SF-36 summary measure of mental health, the Mental Component Score, because it uses responses to questions which refer directly to people's productivity at work. We feel that in our context a clearer summary measure is one which uses only the nine mental health questions listed.

change in mental health over the last year is associated with a large change in the probability of actively participating in the labour market.

Fortunately, the data are somewhat informative about the actual mechanism by which a decline in mental health is associated with lower labour market participation. In particular, respondents are asked in the survey why they stopped working. For individuals who experienced a one standard deviation drop in mental health in the previous year, the probability that they blamed sickness rather than being fired was 75% compared to 45% for individuals with a small drop or improvement in mental health. Although we should be cautious about inferring too much from these responses, they do suggest that the supply-side responses to poor mental health might dominate the demand-side (being fired) response.

The instrumental variable is constructed from responses in a section of HILDA’s self-completion questionnaire (included only from wave 2 onwards). Respondents are told: “We now would like you to think about major events that have happened in your life over the past 12 months. For each statement cross the yes box or the no box to indicate whether each event happened during the past 12 months”. One of the statements given is: “Death of a close friend”. The proportion of individuals reporting the death of a close friend (with standard errors) for different age groups is shown in Figure 3. Unsurprisingly, the proportion is reasonably constant until around 40, after which the proportion begins to steadily increase. The strength of the instrument is shown in Figure 4. The figure depicts kernel density estimates of the mental health distribution for individuals reporting a death of a friend within the last 12 months and the mental health distribution for all other individuals. It clearly shows that people who have had a close friend die are less likely to have good mental health (index between 0 and 1) and are more likely to have exceptionally poor mental health (index between -1 and -3).

A number of aspects of the data further strengthen the validity argument for this instrument. When we regress the death of a close friend on indicators of physical illness and bodily pain we find no significant relationships. These regression results suggest that the death of a close friend is not impacting upon labour market participation through physical health, a necessary condition for our instrumental variable strategy.

In order to establish the robustness of our main results, and to inform on the various aspects of identification, we fit seven alternative models of mental health and labour market participation. Our preferred specification, which fully utilises the time-variation in our instrument and controls for reverse causality and potential measurement error is Model (6).[5]

The models we fit are:

1. A linear probability model that does not allow for individual fixed effects or reverse causation. This model is similar, for example, to that used by Kessler et al. (2008).
2. A binary probit model that does not allow for individual fixed effects or reverse causation. This model is similar, for example, to that used by Marcotte et al. (2000) and Cornwell et al. (2009).
3. A fixed effects linear probability model that controls for individuals fixed effects but not reverse causality. This model is similar, for example, to that used by Björklund (1995).
4. A 2SLS model that collapses the time-varying instrument into a single event dummy, which is a standard way of modeling events used in the previous literature. This model is similar, for example, to that used by Ettner et al. (1997) and Chatterji et al. (2007).
5. An IV-Probit model with a single event dummy. This model is similar to, for example, that used by Hamilton et al. (1997), Alexandre and French (2001) and Chatterji et al. (2007).
6. An IV-Probit model that uses a 3-degree polynomial of the quarter since the event as the instrument set. We know of no other studies that have estimated this model.
7. An IV-Fixed Effects linear probability model regression model with a 3-degree polynomial as the instrument set.

The IV-Probit models (5 and 6) are our preferred specification, because they respect the binary nature of labour market participation. A limitation of the IV-Probit, however, is its reliance on the assumption of joint normality of the error terms in the mental health and labour market participation equations. In order to determine the importance of this normality assumption, we also present estimates from a linear 2SLS model that does not require this assumption. In addition, Model (6) is preferred to Model (5) because it uses for identification a 3-degree

[5] One potential source of measurement error arises due the miss-match in the time-coverage of the dependent and main independent variables. Participation is measured once a year at the time of the interview while mental health refers to the last 4 weeks. This implies that our mental health measure is a noisy measure. Using an instrument that varies across years should overcome this source of attenuation bias.

polynomial of the quarter since the death of a friend. The polynomial function allows for two years of mental health effects before the death of a friend occurs, which may arise for example if the friend is suffering a terminal illness, and for three years of mental health effects after the death of a friend occurs. Allowing for 'anticipation' and 'adaptation' effects means we are more able to capture the true mental health process than we can with a binary event dummy, which assumes zero anticipation and complete adaptation after one year.

The last model (IV-FE) is included to determine whether the main results are robust to the inclusion of individual fixed effects. The disadvantage of the linear IV-FE model is that it does not respect the binary nature of labour market participation – in the IV-FE model labour market participation can be negative or fractional and so it is difficult to interpret the estimated effect. Unfortunately, more properly defined discrete choice models with endogenous regressors, such as fixed-effect probit or logit models have no consistent estimators.[6]

We include the following time-varying controls in each of the models, including in the first stage IV equations (where we additionally include the death of a close friend as the instrument): sex, age (and age-squared), highest education qualification, marital status, number of children, whether the individual reports windfall income in the last 12 months, whether the individual reports that they have many friends, and whether the individual has lost a spouse, child or relative in the last 12 months. As already noted, we control for windfall income to directly capture the possibility that the death of a close friend leads to a windfall financial gain that could impact on labour market participation. Similar we directly control for the number of friends an individual has, which controls for the possibility that the probability of experiencing the loss of a close friend might be a function of the number of friends a person has. Finally, we control for loss of another family member (spouse, child, other relative), which might directly affect labour market participation and be correlated with the loss of a friend. It turns out, however, that our IV estimates from the various models are little affected by these controls, and that our main finding of a large negative effect of mental health on participation is robust to the exact set of controls.

[6] We undertook a small simulation exercise (available on request) in which we simulated data from a fixed-effect probit model with endogenous regressors (using the relationships found for model 7 in our data), and estimated an IV-FE model. The estimated coefficients differed significantly from the actual coefficients, suggesting that IV-FE models may provide a poor linear approximation of data generating processes defined by fixed-effect probit models, and consequently should be interpreted with some care.

4. Results

4.1. Main Results

The first stage estimates for the IV-Probit and IV-FE models (Models 5, 6 and 7) are provided in Appendix Table A1. They show that the recent death of a close friend is a strongly significant determinant of mental health, as would be expected. Table 1 contains the main results on labour market participation for the seven model specifications, and also gives the *p-values* for the significance of the instrument set. In each specification, a binary labour supply variable is regressed on either observed mental health or instrumented mental health and a set of standard individual-level characteristics. The effects of the individual characteristics on labour market participation are roughly as expected: education strongly increases the probability of labour participation; there is a U-shape in labour market participation with a peak around the age of 35; and males and the childless are more likely to actively participate. Qualitatively, these results hold for all the models. Hence in the remainder of this paper we will concentrate on discussing the effect of the main variable of interest, mental health.

The mental health effect in the cross-section is estimated using linear regression and probit models and is shown in columns 1 and 2. In both models the effect is highly significant and equals 0.06. This implies that a 1 standard deviation increase in mental health increases the probability of labour market participation by 6 percentage points. Importantly, it appears that using a probit model, which respects the binary nature of the dependent variable, provides nearly identical estimates to a linear regression model. In column 3, which shows the fixed-effect results, we observe that the estimated mental health effect drops by over three-quarters: the fixed-effect estimate equals only 0.015. This result indicates that there are either unobserved fixed characteristics that increase the likelihood of being both in the labour force and having good mental health, or that there exists substantial measurement error in our mental health index that is attenuating our estimates (Frank and Gertler, 1991).

In the remaining columns we present instrumental variable estimates. In columns 4 to 6, we present cross-sectional IV models: 2SLS in column 4 and IV Probit in column 5 and 6. Again we find that the estimated mental health effect is similar between the linear regression and probit models, suggesting that the assumption of normality in the IV-Probit model is not driving identification. The magnitude of the 2SLS and IV Probit estimates are much larger than the OLS or FE estimates: in our preferred specification, model 6, we find that a 1 standard deviation increase in mental health leads to a 17 percentage point increase in labour market participation. An explanation for the finding of larger IV estimates is that our measure of mental health contains substantial measurement error, and that this error is amplified when fixed-effects are included in the model, leading to large attenuation bias.

The estimates in columns 4-6 are consistent under the assumption that our instrumental variable – death of a close friend – is randomly determined and can be excluded from the participation equation. A possible concern, however, is that some individuals are more likely than others to have a close friend die. To control for and examine this possibility, we finally estimate an IV-FE model. In this model, the mental health effect is identified by estimating the effect that our instrument has on changes in mental health, and then the effect that these induced changes in mental health have on changes in participation. The estimated IV-FE effects are slightly larger than the 2SLS and IV-Probit estimates, but not considerably: a one standard deviation increase in mental health increases the labour market participation probability by 25 percentage points. We interpret this result as providing additional credibility to the IV-Probit estimates, because the inclusion of fixed-effects seems relatively unimportant.

4.2. Additional Results

Mental illness is often associated with physical illness (comorbidity), and the two can be linked in various ways. To look at how controlling for physical health might affect our results we examined two additional specifications. In the first we simply included in the set of time-varying regressors a measure of physical health (from the physical health component score of the SF-36), which we assumed to be exogenous. In the second specification we again include the measure of physical health but we instrument it with information on whether or not the individual reported to have had a serious injury or illness in the past 12 months. Both specifications give estimated effects of mental health that are very similar to our main estimates in Table 1: in the specification where both mental health and physical health are instrumented, a one standard deviation increase in mental health is predicted to increase participation by around 25 percentage points using the IV-Probit model and 25 percentage points using the IV-FE model. The estimated effects of physical health are smaller with an increase in physical health by one standard deviation predicted to increase labour market participation by around 9 and 7 percentage points, using the IV-Probit and IV-FE models, respectively. An explanation for the smaller estimates is that reduced physical health acts upon labour force outcomes to a large extent through its effect on mental health.

We might expect that the effect on participation of poor mental health will be larger for older than younger workers, for example if it is easier for older workers than younger workers to receive long term disability benefits or to enter early retirement after a health shock. We examine this possibility by estimating 2SLS, IV-Probit and IV-FE models separately for respondents over 40 years and those 40 years or below. These results are presented in Table 2. While the estimates from all three models confirm the hypothesis, the results from the IV-Probit models are clearest, with a one standard deviation increase in mental health leading to a 10 percentage point increase in labour market participation for the younger group compared to a 21 percentage point increase for those over 40 years of age.

Previous studies have also found that the effect of mental health on labour market outcomes may differ by gender. Therefore Table 3 repeats our favoured specifications separately for males and females. The results are again consistent between the three models shown (2SLS, IV-Probit and IV-FE), which is as we would expect because the instrument itself is time-varying and hence should obtain the correct outcome with or without controlling explicitly for fixed-effects. We find that mental health effects are much higher for females than for males, consistent with Marcotte et al. (2001) in their analysis of the US National Comorbidity Survey. Indeed, for males the effect of mental health in the IV-FE model, although large, becomes insignificant. Perhaps this is because of the higher social demands made on men to keep working even if they are in poor mental health. However, not all studies find this result, with Zhang et al. (2009) for example finding that mental illness has a larger effect on males than females.

Finally, it is useful to compare our estimates with those that we would have obtained if we used perhaps the most common instrument in the literature; namely, an indicator(s) of social capital (see Hamilton et al., 1997; Alexandre and French, 2001; Ojeda et al., 2009). To do this we use as an instrument whether or not the individual is a 'member of a club or community organisation'. Using the IV-Probit model and this instrument we find a reduced effect of mental health, with a one standard deviation improvement in mental health leading to an increase in labour market participation of about 9 percentage points (t-statistic = 4.82). Using the IV-FE model, however, we find that a one standard deviation improvement in mental health leads to a *decrease* in labour market participation of about 12 percentage points (t-statistic = 2.11). This counter-intuitive result is perhaps unsurprising because non-participants have more leisure time to participate socially and hence it is likely that labour market participation has a direct negative effect on the instrument, invalidating the underlying assumptions of the model.

Another popular instrument in the literature is religiosity (Alexandre and French, 2001; Chatterji et al., 2007). The IV-Probit estimate of the effect of mental health, using religiosity (0-10 scale of the importance of religion) as an instrument, equals 0.381 (*t*-statistic = 18.17).[7] This is about twice as high as our preferred estimate. As we argued in the introduction, religiosity quite likely affects preferences over work and leisure and therefore forms an imperfect instrument. These results illustrate the strong reliance on the particular instrument for mental health used and we believe that our use of data on the death of a close friend constitutes an improvement in the literature.

5. Conclusion

Mental illness is prevalent and can have serious labour market consequences. In this paper we have focused on the most important labour market outcome; namely, the ability for an individual to actively participate in labour market activities. Not only does work provide income, it also can impart a structure to the day, a sense of purpose, and opportunities for social interaction. Therefore adding to the understanding of the extent to which poor mental health leads to labour market inactivity is an important research topic for policy. Economists have been contributing to knowledge of this issue for many years and a range of empirical techniques have been used to try and overcome the practical empirical problems of reverse causality and unobserved individual heterogeneity, as well as potential measurement error, which make it difficult to make strong causal statements about the consequences of poor mental health.

In this paper we have built on this previous literature by estimating a variety of models that use the dynamics available in panel data, and introducing a new instrument that clearly impacts on the lives of many people each year and that is a significant determinant of mental health. In particular, we use the death of a close friend as an instrument for mental health, which we have argued will only affect labour market participation through its effect on mental health. We have found robust evidence that a worsening in mental health leads to a significant decline in

[7] We cannot present the equivalent IV-FE estimate because HILDA does not contain religiosity questions in each wave.

the probability that an individual will be able to actively participate in the labour market. Moreover, this effect is substantial, with a one standard deviation decrease in mental health reducing the probability of participation by around 17 percentage points. We also find that the effect of poor mental health on participation is larger for females and older individuals, which is consistent with a higher degree of labour market attachment for males and the young. Finally, we find some tentative evidence that mental health effects dominate physical health effects, suggesting that reduced physical health acts upon labour market participation largely through its negative effect on mental health.

We believe that these estimates are valuable to mental health professionals and health policy-makers in lobbying for additional resources to be made available for mental illness research and treatment, and in designing workplace policies and legislation that assists those with poor mental health to be able to stay in the workplace.

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Figure 1: Relationship between Mental Health and Labour Market Participation

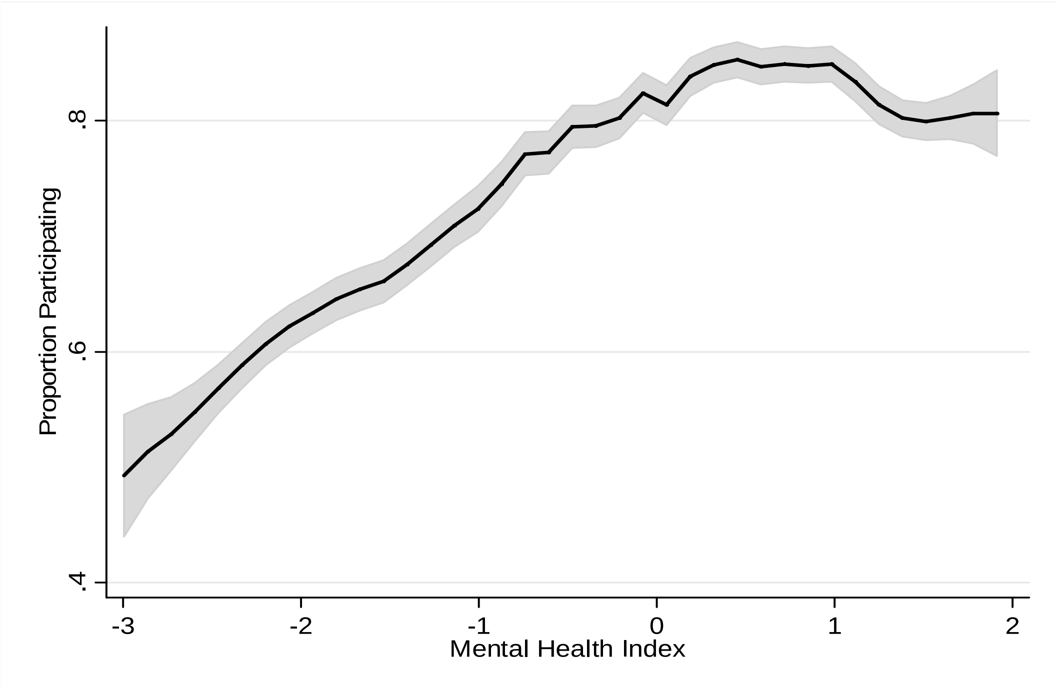
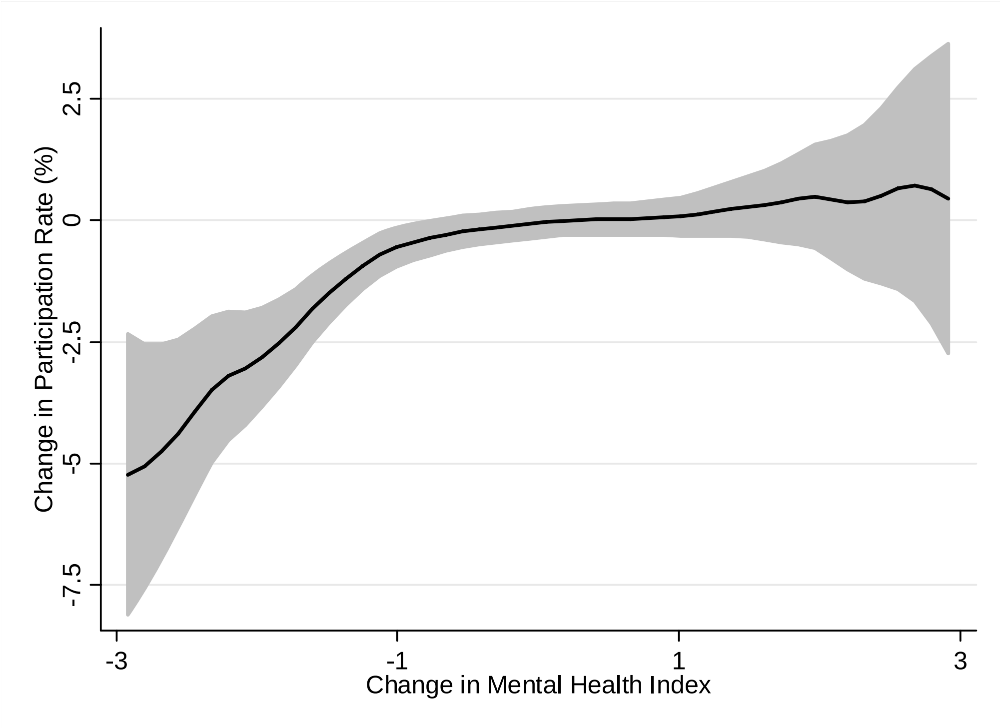


Figure 2: Relationship between the change in Mental Health and the change in Labour Market Participation



Change in Participation Rate (%)
2.5
0
-2.5
-5
-7.5
-3
-1
1
3
Change in Mental Health Index

Figure 3: Percentage Reporting Death of Close Friend in Past Year by Age Group

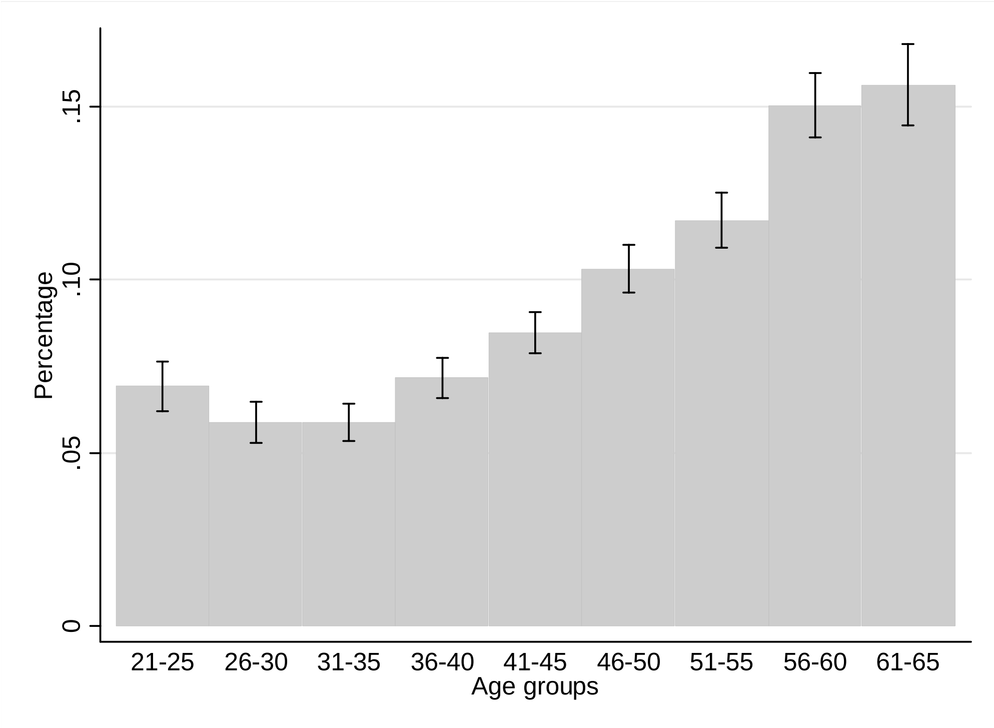


Figure 4: Density Estimates of Mental Health

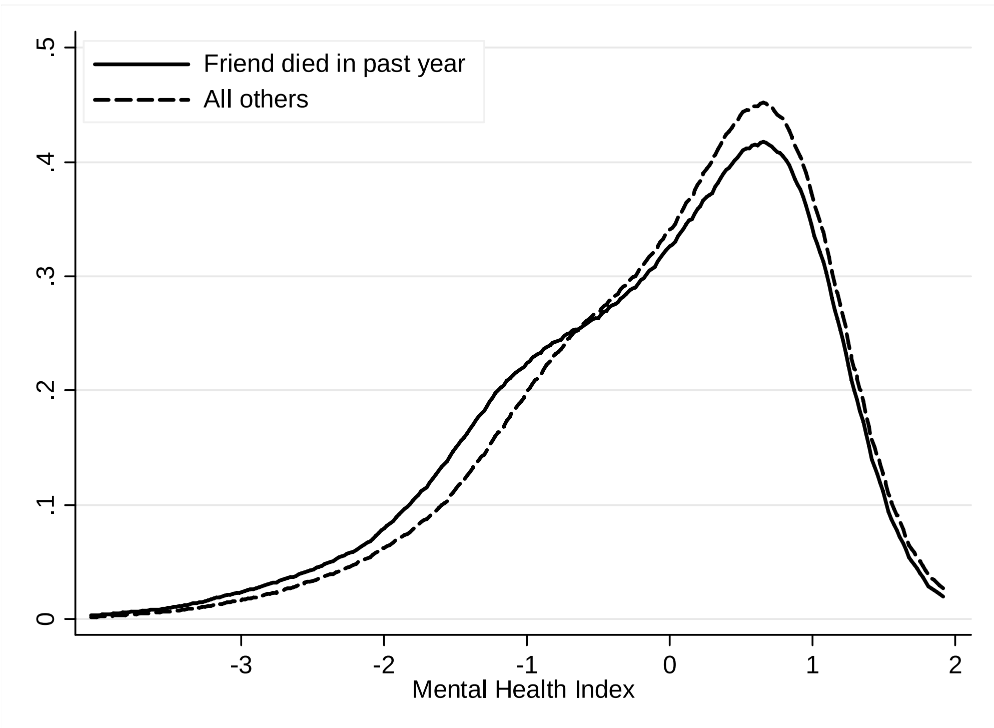


Table 1: Estimated Effect of Mental Health on Labour Market Participation

	OLS (1)	PROBIT (2)	FE (3)	2SLS (4)	IV-PROBIT (5)	IV-PROBIT (6)	IV-FE (7)
Mental health	0.061***	0.058***	0.015***	0.214***	0.197***	0.173***	0.246**
	(0.003)	(0.003)	(0.003)	(0.044)	(0.036)	(0.043)	(0.111)
Male	0.139***	0.149***	-	0.109***	0.120***	0.126***	-
	(0.006)	(0.006)		(0.011)	(0.011)	(0.012)	
Age	0.053***	0.044***	0.049***	0.053***	0.044***	0.044***	0.054***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
Age squared /100	-0.072***	-0.061***	-0.061***	-0.073***	-0.061***	-0.061***	-0.065***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)
University degree	0.161***	0.133***	0.202***	0.136***	0.117***	0.120***	0.174***
	(0.009)	(0.006)	(0.036)	(0.011)	(0.009)	(0.009)	(0.042)
Diploma/Certificate	0.104***	0.083***	0.112***	0.091***	0.071***	0.073***	0.118***
	(0.009)	(0.007)	(0.023)	(0.010)	(0.008)	(0.008)	(0.025)
High school graduate	0.078***	0.054***	0.040	0.060***	0.039***	0.042***	0.029
	(0.011)	(0.008)	(0.034)	(0.013)	(0.010)	(0.010)	(0.037)
Married/De facto	0.041***	0.052***	-0.024***	0.011	0.022*	0.027*	-0.032***
	(0.009)	(0.011)	(0.009)	(0.012)	(0.013)	(0.014)	(0.011)
Divorced/Separated	0.018	0.031***	-0.040***	0.026*	0.038***	0.038***	-0.019
	(0.013)	(0.012)	(0.014)	(0.014)	(0.012)	(0.012)	(0.019)
Number of children	-0.062***	-0.061***	-0.052***	-0.058***	-0.056***	-0.057***	-0.047***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Instrument	-	-	-	Binary event dummy	Binary event dummy	Quarter since event cubic	Quarter since event cubic
Instrument *p*-value	-	-	-	0.0000	0.0000	0.0000	0.0002
Sample size	53636	53636	53636	53636	53636	53636	53636

Note: Clustered standard errors in parentheses. *, ** and *** denote significance at .10, .05 and .01 levels. Columns 1,3,4,6 and 7 present coefficients from linear regression models. Columns 2 and 5 present marginal effects calculated at the mean values of the explanatory variables. Included in each model but not shown are controls for windfall income and for number of friends. The error correlation coefficients in the IV-Probit models (rho) equal -0.483 (p = 0.0001) and -0.440 (p = 0.0053). First-stage estimates for models 5 and 7 are presented in Appendix Table A1.

Table 2: Estimated Effect of Mental Health on Labour Market Participation by Age

	2SLS		IV-PROBIT		IV-FE	
	Aged ≤ 40	Aged > 40	Aged ≤ 40	Aged > 40	Aged ≤ 40	Aged > 40
Mental health	0.146**	0.247***	0.099	0.214***	0.233	0.257*
	(0.069)	(0.054)	(0.063)	(0.054)	(0.267)	(0.132)
Male	0.135***	0.088***	0.145***	0.105***	-	-
	(0.017)	(0.013)	(0.011)	(0.017)		
Age	-0.024***	0.147***	-0.013*	0.114***	-0.008	0.114***
	(0.007)	(0.010)	(0.007)	(0.011)	(0.010)	(0.011)
Age squared/100	0.044***	-0.164***	0.024**	-0.130***	0.033**	-0.122***
	(0.012)	(0.010)	(0.011)	(0.011)	(0.016)	(0.010)
University degree	0.134***	0.136***	0.103***	0.134***	0.198***	0.185***
	(0.015)	(0.016)	(0.008)	(0.015)	(0.057)	(0.070)
Diploma/Certificate	0.105***	0.080***	0.075***	0.073***	0.135***	0.084**
	(0.014)	(0.013)	(0.008)	(0.013)	(0.045)	(0.034)
High school graduate	0.067***	0.042**	0.043***	0.033*	0.063	-0.093
	(0.016)	(0.020)	(0.010)	(0.018)	(0.051)	(0.070)
Married/De facto	0.016	0.054**	0.023	0.073***	-0.023	0.010
	(0.017)	(0.021)	(0.016)	(0.025)	(0.014)	(0.025)
Divorced/Separated	0.027	0.068***	0.033**	0.073***	0.016	0.010
	(0.019)	(0.022)	(0.014)	(0.018)	(0.033)	(0.034)
Number of children	-0.066***	-0.024***	-0.053***	-0.026***	-0.058***	-0.027***
	(0.004)	(0.006)	(0.003)	(0.006)	(0.013)	(0.006)
N	23843	29793	23843	29793	23843	29793

Note: Clustered standard errors in parentheses. *, ** and *** denote significance at .10, .05 and .01 levels. The 2SLS models correspond to column 4 in Table 1. The IV-Probit models correspond to column 6 in Table 1. The IV-FE models correspond to column 7 in Table 1. Included in each model but not shown are controls for windfall income and for number of friends. First-stage estimates are not presented but are available upon request.

Table 3: Estimated Effect of Mental Health on Labour Market Participation by Gender

	2SLS		IV-PROBIT		IV-FE	
	Females	Males	Females	Males	Females	Males
Mental health	0.322***	0.124**	0.235***	0.093**	0.340**	0.058
	(0.079)	(0.049)	(0.061)	(0.044)	(0.155)	(0.143)
Age	0.066***	0.040***	0.058***	0.022***	0.064***	0.039***
	(0.004)	(0.003)	(0.005)	(0.002)	(0.007)	(0.006)
Age squared/100	-0.090***	-0.057***	-0.078***	-0.034***	-0.073***	-0.053***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.007)	(0.006)
University degree	0.172***	0.069***	0.164***	0.053***	0.127**	0.206***
	(0.017)	(0.015)	(0.020)	(0.008)	(0.061)	(0.057)
Diploma/Certificate	0.129***	0.038***	0.109***	0.025***	0.143***	0.051
	(0.015)	(0.013)	(0.015)	(0.009)	(0.035)	(0.033)
High school graduate	0.081***	0.038**	0.066***	0.021*	0.024	0.022
	(0.019)	(0.017)	(0.017)	(0.011)	(0.053)	(0.052)
Married/De facto	-0.057***	0.076***	-0.050***	0.097***	-0.048**	-0.010
	(0.020)	(0.015)	(0.017)	(0.016)	(0.019)	(0.014)
Divorced/Separated	0.048**	-0.011	0.033*	0.018*	-0.010	-0.028
	(0.022)	(0.019)	(0.020)	(0.011)	(0.031)	(0.021)
Number of children	-0.095***	-0.018***	-0.092***	-0.013***	-0.078***	-0.018***
	(0.006)	(0.004)	(0.010)	(0.004)	(0.008)	(0.004)
N	28544	25092	23843	29793	28544	25092

Note: Clustered standard errors in parentheses. *, ** and *** denote significance at .10, .05 and .01 levels. The 2SLS models correspond to column 4 in Table 1. The IV-Probit models correspond to column 6 in Table 1. The IV-FE models correspond to column 7 in Table 1. Included in each model but not shown are controls for windfall income and for number of friends. First-stage estimates are not presented but are available upon request.

Appendix Table A1: First-Stage Models of Mental Health

	IV-PROBIT (5)		IV-PROBIT (6)		IV-FE (7)	
Death of friend in past year	-0.172***	(0.018)	-		-	
Quarters since death of friend	-		-0.028***	(0.008)	0.005	(0.006)
Quarters since death of friend squared / 10	-		0.007	(0.010)	-0.018**	(0.008)
Quarters since death of friend cubed / 100	-		0.002	(0.004)	0.008***	(0.003)
Male	0.195***	(0.016)	0.192***	(0.016)	-	
Age	-0.005	(0.005)	-0.006	(0.005)	-0.019***	(0.007)
Age squared /100	0.011*	(0.006)	0.013**	(0.006)	0.021***	(0.008)
University degree	0.153***	(0.022)	0.143***	(0.022)	0.121*	(0.066)
Diploma/Certificate	0.083***	(0.022)	0.082***	(0.022)	-0.028	(0.043)
High school graduate	0.112***	(0.027)	0.109***	(0.027)	0.047	(0.061)
Married	0.188***	(0.023)	0.186***	(0.023)	0.032	(0.025)
Divorced/Separated	-0.048	(0.034)	-0.046	(0.034)	-0.086**	(0.035)
Number of children	-0.025***	(0.008)	-0.025***	(0.008)	-0.019**	(0.008)
Windfall income	0.044***	(0.011)	0.042***	(0.011)	0.019**	(0.008)
Many Friends	0.177***	(0.004)	0.178***	(0.004)	0.067***	(0.003)
Death of spouse/child in past year	-0.398***	(0.072)	-		-	
Death of relative in past year	-0.098***	(0.014)	-		-	
Quarters since death of spouse/child	-		-0.097***	(0.031)	-0.086***	(0.025)
Quarters since death of spouse/child squared / 10	-		0.083**	(0.042)	0.075**	(0.033)
Quarters since death of spouse/child cubed / 100	-		-0.017	(0.014)	-0.016	(0.011)
Quarters since death of relative	-		-0.017**	(0.007)	-0.003	(0.005)
Quarters since death of relative squared / 10	-		0.013	(0.009)	0.002	(0.007)
Quarters since death of relative cubed / 100	-		-0.003	(0.003)	0.000	(0.002)

Note: Clustered standard errors in parentheses. *, ** and *** denote significance at .10, .05 and .01 levels. These models correspond to models 5, 6 and 7 in Table 1.