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EFFECTS OF PSYCHIATRIC DISORDERS ON LABOR MARKET OUTCOMES: A LATENT VARIABLE APPROACH USING MULTIPLE CLINICAL INDICATORS

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ABSTRACT

In this paper, we estimate the effect of psychiatric disorders on labor market outcomes using a structural equation model with a latent index for mental illness, an approach that acknowledges the continuous nature of psychiatric disability. We also address the potential endogeneity of mental illness using an approach proposed by Lewbel (2012) that relies on heteroscedastic covariance restrictions rather than questionable exclusion restrictions for identification. Data come from the US National Comorbidity Survey – Replication and the National Latino and Asian American Study. We find that mental illness adversely affects employment and labor force participation and also reduces the number of weeks worked and increases work absenteeism. To assist in the interpretation of findings, we simulate the labor market outcomes of individuals meeting diagnostic criteria for mental disorder if they had the same mental health symptom profile as individuals not meeting diagnostic criteria. We estimate potential gains in employment for 3.5 million individuals, and reduction in workplace costs of absenteeism of $21.6 billion due to the resultant improvement in mental health.

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KEY WORDS: mental health; labor supply; employment; endogeneity; simulation; structural equation model

1. INTRODUCTION

The wide-ranging labor market consequences associated with mental illness have been well documented.[1] Mental disorders are associated with unemployment, lower earnings, work absences, reduced labor supply, and lower on-the-job productivity (Ettner *et al.*, 1997; Chatterji *et al.*, (2007, 2011); Marcotte *et al.*, 2000; Marcotte and Wilcox-Gok, 2003; Ojeda *et al.*, 2010; Hamilton *et al.*, 1997; Schmitz, 2011; Banerjee *et al.*, 2014). The annual earnings loss associated with serious mental illness in the US was estimated to be over $193 billion in 2001–2003 alone (Kessler *et al.*, 2008). The main emphasis in the economics literature on mental illness and labor market outcomes has been on testing whether the observed association between mental illness and labor market outcomes reflects a causal relationship. Mental illness may be endogenous to labor market outcomes in a structural sense, if these outcomes are determined simultaneously, and/or in a statistical sense, if there are difficult-to-measure characteristics, such as personality traits and family background, which are correlated with mental illness and directly related to labor market outcomes. In prior work, researchers have

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[1]A recent OECD (2012) report highlights the labor market burden of mental illness across different countries.

addressed the potential endogeneity of mental disorders with respect to labor market outcomes using a variety of approaches.[2] In most prior studies, there are conceptual as well as empirical concerns about the identification strategy, and dealing with identification issues is the focus of this literature.

Although there has been much interest in testing for causality between mental disorders and labor market outcomes, one relatively neglected issue in the economics literature has been the measurement of mental health itself. Many of the more recent economic studies in this area are based on state-of-the-art surveys that include fully structured, diagnostic psychiatric interviews. These studies typically use an indicator variable (1, if an individual meets diagnostic criteria for a particular mental disorder and 0, otherwise) as the regressor of primary interest. Dichotomous indicators are easy to interpret, and, in epidemiological work, they are useful for measuring and tracking changes in disease prevalence. However, the shortcoming of using such a measure in examining the effect of mental illness on labor market outcomes is that it dichotomizes a health condition that is inherently continuous, and it assumes away any heterogeneity in the population in the way psychiatric symptoms affect work capacity. In other words, using dichotomous indicators for mental illness ignores individuals who do not pass the threshold for clinical diagnosis of any particular mental disorder, but, nonetheless, could have a range of sub-threshold symptoms that cause significant work-related impairments. Likewise, there is heterogeneity in the number, type, and severity of mental health symptoms among those meeting diagnostic criteria.[3]

In Figure 1, for example, we show a schematic diagram of the diagnostic criteria from the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) used for a single disorder, Major Depressive Episode (MDE). As the diagram indicates, many individuals who experience symptoms will not meet the threshold for MDE; however, their symptoms may still affect their labor market performance, and they would be coded as ‘healthy’ in a study using binary indicators based on diagnostic criteria. This issue has been recognized by policymakers in the USA. Notably, in the 1980s, screening criteria for federal disability benefits programs were modified such that more consideration was given to work functioning rather than strict psychiatric diagnosis, and non-severe, multiple impairments potentially were viewed as work disabling (Lahiri *et al*., (1995, 2008); Autor and Duggan, 2003).

In this paper, we estimate the effect of mental illness on labor market outcomes using a Multiple Indicator and Multiple Cause model (Joreskog and Goldberger, 1975) with a continuous latent measure of mental illness that is derived from the varied symptoms and determinants of psychiatric disorders. Notably, our approach incorporates the high levels of co-morbidity between different psychiatric conditions because the latent index is constructed based on all psychiatric symptoms, not just those that correspond to a particular disorder.

Data come from two unique and recently publicly available datasets, the National Comorbidity Survey Replication (NCS-R) and the National Latino and Asian American Study (NLAAS) that include fully structured diagnostic assessments of mental disorders and also rich data on the correlates of mental disorders. We study the impact of mental illness on a wide range of labor market outcomes (employed, in labor force, number of weeks worked for pay in the past 12 months, and number of full days of work missed during the last 30 days conditional on being employed) to account for the manifold effects of mental illnesses. The mental illness measure incorporates symptoms of four psychiatric disorders – MDE, panic attack, social phobia and generalized anxiety disorder (GAD).

Our main contribution to the existing literature is the use of a continuous latent index for mental illness to assess the impact on a range of labor market outcomes.[4] In addition, we also address the potentially endogenous nature of the mental illness variable by using covariance instruments, proposed in Lewbel (2012), which, to our knowledge, have not been used previously in this literature. Lewbel argues that identification based on higher moments is reasonable in many classes of models where there are measurement error problems or the error

[2]See, for example, Frijters *et al*., 2010; Ettner *et al*., 1997; Ojeda *et al*., 2010; Chatterji *et al*., (2007, 2011); Lu *et al*., 2009; DeSimone, 2002; Renna, 2008; Bartel and Taubman, 1979,1986; Mitchell and Anderson, 1989; Chang and Yen, 2011.

[3]For example, in our sample, among those meeting diagnostic criteria for MDE, only about 2% had fewer than six symptoms; whereas, 45% had more than 9 symptoms.

[4]Overall health has been modeled as a latent variable in earlier studies (for example, Bound, 1991; Bound *et al*., (1999, 2010); Cai, 2010; Gupta and Larsen, 2010; Garcia-Gomez *et al*., 2010).

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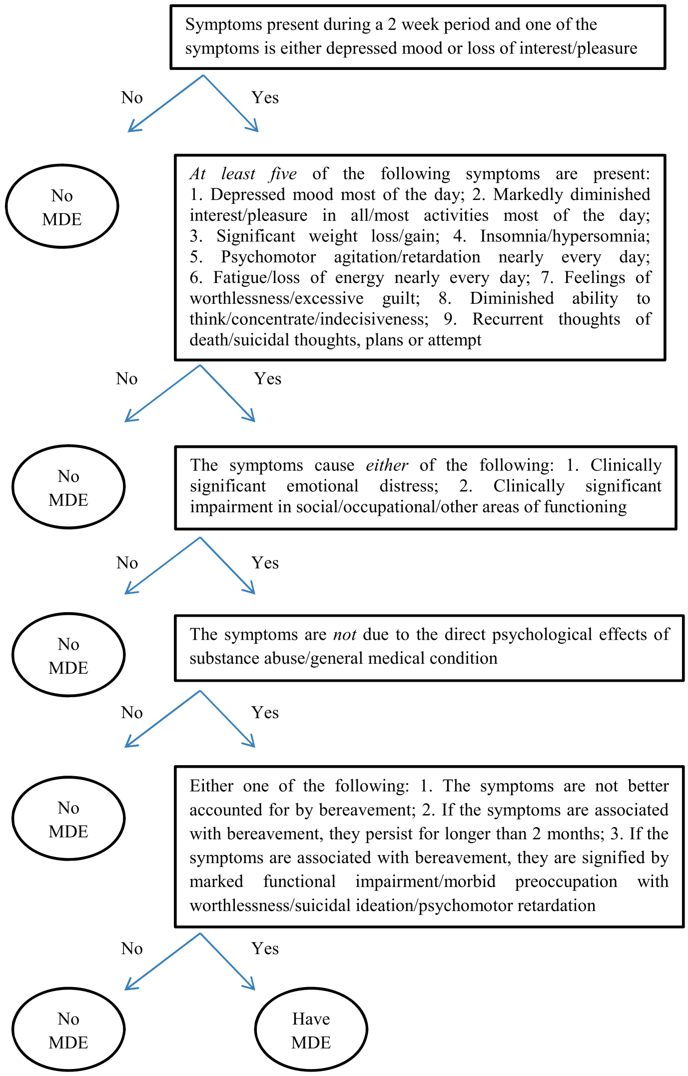

Figure 1. Diagnostic criteria for major depressive episode (MDE) in the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition

correlations are due to an unobserved common factor. Further, this identification strategy is most useful in situations where the conventional instruments are either weak or unavailable. This makes a strong case for using this approach in our context. We show the usefulness of our approach by conducting a counterfactual simulation exercise, whereby, we simulate the employment effects of amelioration of mental health of individuals who are in most need of treatment, by using the ‘Rank and Replace’ method, discussed further in the succeeding text (McGuire *et al*., 2006; Cook *et al*., (2009, 2010)).

2. PSYCHIATRIC DISABILITY AND LABOR MARKET OUTCOMES

A growing body of research suggests that both cognitive and non-cognitive skills are important in determining labor market outcomes (Cunha & Heckman, 2007; Heckman, 2007; Heckman, Stixrud & Urzua, 2006).

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Symptoms of mental disorders can be viewed as a component of non-cognitive skills. In addition, mental health can be framed as a component of an individual's stock of health capital; in this way, this paper also fits into the broader theoretical and empirical literature on the effects of health on human capital outcomes (Grossman, 1972; Currie & Madrian, 1999).

The symptoms of mental illness may impair an individual's ability to obtain and maintain employment and may detract from a person's earnings, by affecting factors such as productivity, mood, energy level, memory, concentration, decisiveness, motivation, and social relations. Also, because psychiatric disorders tend to have early onset in the lifespan, these disorders can have indirect effects on labor market outcomes through their impact on earlier outcomes such as academic achievement, educational attainment, and occupational choice (Mullahy & Sindelar, 1993). Conceptually, these mechanisms are similar to the pathways through which other non-cognitive skills such as motivation and self-efficacy are thought to affect labor market outcomes.

However, in the case of mental illness, there are additional mechanisms through which symptoms can affect labor market outcomes, given that mental disorders are health conditions and are often highly stigmatized. Employers may be unable or unwilling to accommodate an employee with mental health problems. Workers with mental health problems may have reduced job mobility compared with other workers because of concerns about losing health insurance coverage. Individuals with psychiatric disorders may face workplace discrimination, or may fear workplace discrimination, affecting their labor market outcomes (Currie & Madrian, 1999).

In this section, we briefly review recent studies in economics that have examined the impact of psychiatric disorders on labor market outcomes of individuals. These papers can be roughly divided into two groups – papers that use a binary indicator for the presence/absence of a mental disorder and papers that use varied aggregate measures of mental illness or psychological distress, based often on the number of recorded symptoms.

Most papers utilizing a binary measure of mental disorder are based on either the 1990 NCS, the 2001–2003 Collaborative Psychiatric Epidemiologic Surveys (CPES – the current paper draws on these data as well), or the National Survey on Drug Use and Health, because these three groups of surveys are the only large-scale surveys to include diagnostic interviews and a range of standard measures of mental health. For example, Ettner *et al.* (1997) use data from NCS to examine the effect of psychiatric disorders on employment, and among those employed, income, and work hours. Using an instrumental variable (IV) approach, with the number of psychiatric disorders of the respondent's parents and number of psychiatric disorders experienced by the respondent before age 18 as identifying instruments, the authors find that the presence of any mental disorder detracts from employment by about 11 percentage points or a little more, depending on the specification of the model, for both men and women. They also find significant reduction in work hours for men – by almost 3 days, and fall in income for women by more than $5000, conditional on employment.

Similarly, Chatterji *et al.* (2007) examine the employment effects of mental disorders for a population that comprised mostly immigrants – Latinos and Asians. They use data from NLAAS and use IV estimation, with the number of psychiatric disorders prior to age 18, religious attendance and seeking religious or spiritual means to handle problems as instruments. The authors find that among Latinos, mental disorders have an adverse effect on employment and absenteeism, similar to US-born population, whereas, there is no such clear evidence for Asians. Ojeda *et al.* (2010) also examine the effect of nativity and mental health on employment and full-time work using National Survey on Drug Use and Health and three different set of instruments and find that mental illness lowers employment rates for US-born men but has no significant impact on immigrants.

Finally, Chatterji *et al.* (2011) using the NCS-R dataset and an identification method proposed in Altonji *et al.* (2005), where the selection along unmeasured factors is set equal to selection along measured factors, find reduction in the probability of current labor force participation by 9 and 19 percentage points for men and women, respectively, and reductions in the order of 14 and 13 percentage points in the likelihood of being currently employed.

As a group, these studies show large effects of mental disorders on labor market outcomes, but individuals are classified as not having mental illness if they do not meet the diagnostic threshold for any particular disorder, even though they may be having sub-threshold levels of symptoms for several different disorders,

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or sub-threshold levels of symptoms that are particularly harmful for labor market outcomes.[5] Studies based on symptom scales show that higher levels of symptoms are associated with worse labor market outcomes. Hamilton *et al.* (1997), for example, use the Psychiatric Symptom Index as a measure of mental illness, with a higher score indicating higher symptomatology of depression, anxiety, anger, and cognitive disturbance. Consistent with the previous findings in the literature, the authors observe significant adverse effect of mental illness on employability. Another example is Lu *et al.* (2009), who examine the impact of mental health on employment outcomes in China using the China Health Surveillance Baseline 2001 Survey. The mental health index is generated from eight questions in the SF-36 survey relating to mental health. The authors find improved mental health to increase the likelihood of being employed by 0.12 for men and 0.17 for women, but no significant effect on annual earnings. One problematic issue with this approach is that because the mental health index is not standardized, it is difficult to interpret the unstandardized treatment effect.

Finally, Frijters *et al.* (2010) examine the relationship between mental health and labor force participation in Australia. The authors use data from the Household Income and Labour Dynamics survey for 2002 to 2008 and a subset of questions from the mental health module of the Short Form General Health Survey (SF-36) to create a mental health index. The linear probability and probit models indicate a six percentage point increase in the likelihood of labor force participation when mental health improves by one standard deviation. When the possible endogeneity is accounted for, by using recent death of a close friend as an instrument, the estimates indicate much larger effects from improved mental health.

One possible limitation of these studies based on symptom scales is it is unclear which symptoms are driving the effects on labor market outcomes. Moreover, all the symptoms used in the construction of the mental illness scale are added up with equal weights, thus ignoring the differential impact of the psychiatric symptoms on the labor market. Also, the symptoms included in the scales are not necessarily part of the diagnostic criteria used to determine psychiatric diagnosis, which makes it hard to interpret findings.

The main contribution of the paper is that we use a structural equation modeling framework with a latent construct for mental illness, whereby we simultaneously estimate the determinants of labor market outcomes and mental illness, and also the loadings of different symptoms on mental health. Using this approach, we are able to create a latent index of mental illness that is more nuanced and better at capturing the underlying continuous and highly co-morbid nature of psychiatric disability.

3. EMPIRICAL MODEL

In order to examine the impact of mental illness on labor market outcomes, we use the following structural equation model involving an unobserved mental illness construct:[6]

$$k = a'x + \beta\eta + \delta, \tag{1}$$

$$\mathrm{K} = \begin{cases} 1 & \mathit{if} \quad k > 0 \\ 0 & \mathit{if} \quad k \leq 0 \end{cases}, \text{ for binary labor market outcomes} \tag{1'}$$

$$\eta = \gamma'x + \zeta, \tag{2}$$

$$y = \lambda\eta + \in. \tag{3}$$

The labor market variables of interest like employment and labor force participation are denoted by k(K); η is a latent index for mental illness; x is a vector ($q \times 1$) of control variables (e.g., age, race/ethnicity, and

[5]Broadhead *et al.* (1990) find that even milder forms of depression substantially increased the number of disability days in a 3 month follow up period.

[6]Note that our modeling approach is not the same as that in Banerjee *et al.* (2014) where we use four latent indices for psychiatric disorders. In that framework, we were unable to address endogeneity issues because of absence of identifying instrumental variables for individual psychiatric disorders.

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education); y is a vector $(k \times 1)$ of psychiatric symptoms of all the four mental disorders considered in the analysis; δ, ζ (scalars), and $\in$ ($(k \times 1)$ vector) are error terms. We are primarily interested in two structural parameters. The treatment effect is captured by β, which provides an estimate of the effect of increase in the mental illness score (worsening mental health condition) on the labor market outcomes. The relative weights of the psychiatric symptoms, as they load up on the underlying mental illness variable, are captured by λ.

Substituting (2) into (1) and (3) yields the following $k+1$ reduced form equations without the unobserved mental health variable, but with cross-equation restrictions on the parameters (for example, Agee and Crocker, 2008):

$$k = (a' + \beta\gamma')x + (\delta + \beta\zeta), \tag{4}$$

$$y = \lambda\gamma' x + (\in + \lambda\zeta). \tag{5}$$

These equations can be written in compact notation as

$$R = \Pi' x + v, \tag{6}$$

where $R = \begin{bmatrix} k \\ y \end{bmatrix}$; $\Pi = [a + \gamma\beta' \; \vdots \; \gamma\lambda']$; $c = \begin{bmatrix} \delta \\ \in \end{bmatrix}$; $d = \begin{bmatrix} \beta \\ \lambda \end{bmatrix}$, and $v = c + d\zeta$.

The covariance matrix of the composite error term can be written as

$$\Omega = \text{var}(v) = \Theta + dd'\sigma_\zeta^2 + 2\sigma_{c,\zeta} d'$$

where $\Theta = \text{var}(c)$; $\sigma_\zeta^2 = \text{var}(\zeta)$; *and* $\sigma_{c,\zeta} = \text{cov}(c, \zeta)$.

One important point to note is that Ω involves $d = [\beta\lambda']'$, the structural parameters of interest. In order to identify the model, we impose two normalization constraints. Because the latent variable η is unobserved and does not have a natural scale of measurement, for identification of λ, one requires normalization of one element of λ. The choice of the normalized factor loading is arbitrary, and the other elements in λ are interpreted relative to the normalized factor. In our context, the symptom 'depressed mood' is normalized to one. The second normalization constraint imposed is that the intercept in the mental illness Equation (2) is constrained to zero.

Initially, we assume $\text{cov}(\delta, \zeta) = 0$ and consider the latent mental health index η as exogenous. Subsequently, we address its endogeneity by allowing $\text{cov}(\delta, \zeta) \neq 0$ and use instrumental variable(s) for the endogenous η in order to achieve identification. We use different specifications of the model, each using a different set of instruments: (1) an external instrument (w); (2) covariance instruments; and (3) both external and covariance instruments. First, following past research (Ettner *et al.*, 1997; Chatterji *et al.*, (2007, 2011)), we use the number of psychiatric disorders with onset prior to age 18 as an external instrument for the possibly endogenous mental illness latent variable. Note that there are conceptual as well as empirical issues about the validity of this instrument (Chatterji *et al.*, 2011). It can reasonably be argued that disorders that occur in childhood represent underlying individual traits that can manifest later on in life. The age of onset of some disorder classes (e.g., anxiety disorders) is usually during childhood (Kessler *et al.*, 2005a). We also experimented with another external instrument 'parent/parental figure's experience of a period of sadness for at least 2 weeks or a period of constant anxiety/nervousness for at least 1 month during most of the respondent's childhood' that can potentially avoid the aforementioned problems.

As an alternative to this standard IV method, we use an approach suggested in Lewbel (2012) that is based on the heteroskedasticity of the error term estimated from Equation (2). Lewbel (2012) shows that β can be estimated consistently using $(z - \bar{z})\hat{\zeta}$ as instruments[7] in Equation (2) under the assumption that $\text{cov}(z, \zeta^2) \neq 0$ and

[7]We refer to these instruments as 'covariance instruments' in the paper.

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$\mathrm{cov}(z, \delta\zeta) = 0$. The vector z is a set of covariates, which could be the entire vector of exogenous variables (x, w), and $\bar{z}$ is the mean of z. The identification comes from the vector of variables that are uncorrelated with the covariance of heteroskedastic errors. The residual $\widehat{\zeta}$ of Equation (2) was computed using the estimated residuals from the reduced form (5) of the Multiple Indicator and Multiple Cause model. The reduced form residual can be written as

$$u_{ij} = \lambda_j \zeta_i + \epsilon_{ij}, i = 1,2,\ldots, N; = 1,2,\ldots, k,$$

where N denotes the sample size and k the number of indicators (symptoms). The aforementioned one-way error component structure is standard in panel data models, and $\widehat{\zeta}_i$ can be obtained by averaging the residuals over symptoms. Because the applicability of the Lewbel (2012) approach hinges on the assumption of heteroskedasticity of the error term ζ, we conducted a Breusch-Pagan (1979) test, which resoundingly rejected the null hypothesis of homoskedasticity. Our model (Equations (1)–(3)) was estimated using the 'sem' module in Stata 12 (StataCorp, 2012).

4. DATA

We employ data from two sources, the NCS-R (Kessler *et al*., 2004) and the NLAAS (Alegria *et al*., 2004).[8] These data sources, when combined with the National Survey of American Life, comprise the CPES, which is collected by the University of Michigan Survey Research Center. Data collected for the NCS-R and the NLAAS are based on a multi-stage area probability sample including the following four steps: first stage sampling of US Metropolitan Statistical Areas and counties; second stage sampling of area segments; selection of the housing units from the area segments in the third stage; and finally, randomly selecting the eligible respondents from the selected housing units (Heeringa *et al*., 2004). The richness of the data lies in detailed information on the distributions, risk factors, and correlates of mental disorders and also health services use, in addition to socioeconomic, demographic, physical health conditions, and employment outcomes of the individuals.

The NCS-R is a nationally representative household survey of the non-institutionalized, English-speaking population who are 18 years and older and living in the coterminous states of the USA. The survey comprised two parts – Part I including a core diagnostic assessment, with a sample size of 9282; and Part II being administered to all the respondents from Part I of the survey who met lifetime criteria for any disorder as well as a probability sample of new respondents (sample size = 5692). The response rate for the survey was 70.9% (Heeringa *et al*., 2004), and the data were collected between February 2001 and April 2003.

The NLAAS included non-institutionalized Latino and Asian Americans residing in the coterminous states in the USA. Latinos were categorized under the following heads: Mexican, Cuban, Puerto Rican, and all other Latinos; whereas, Asian Americans were classified based on their ancestry or national origin as follows: Chinese, Filipino, Vietnamese, and all other Asians. The data collection process was completed by late fall 2003. The Latino sample comprised 2554 individuals, with a response rate of 75.5%, and the Asian American sample included 2095 individuals with a response rate of 65.6% (Heeringa *et al*., 2004).

Our preliminary sample comprised respondents from the NCS-R (Part II) and the NLAAS ($N = 10{,}341$). Individuals in the age group of 25 to 64 were included in the study because those younger than 25 may have been continuing with their education and thus would not be part of the labor force (14.2% of the original sample dropped) and those 65 years and older would have reached their retirement age and thus some would have exited the labor market (10.7% of the original sample excluded). Those with missing values for current work status (0.13%), psychiatric symptoms (0.11%), and those belonging to a racial group other than African

[8]The reason for using the pooled NCS-R/NLAAS rather than only the NCS-R was that we could take advantage of an expanded sampling frame.

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Americans, non-Latino Whites, Latinos, and Asians (2.16%) were excluded from the analysis. The working sample size is 7566, including 3331 men and 4235 women.

The dependent variables are measures of labor market outcomes at the time of the survey: (i) employment status; (ii) labor force participation; (iii) number of weeks worked in the past 12 months conditional on employment; and (iv) number of work absences in the last 30 days among employed individuals. The employment outcome is a binary indicator for whether the individual is currently employed for pay (either part time or full time); the labor force participation outcome is also a binary indicator, indicating whether the respondent is currently a part of the labor force (employed/unemployed versus not in the labor force). Both of these variables are created from a survey question about the individual's current work status (employed/unemployed/not in labor force). The continuous measures of labor market outcomes (iii) and (iv) are generated from the stem questions regarding the number of weeks worked for pay/profit, either part time or full time in the past 12 months and the number of full days of work missed in the last 30 days. We restricted the sample for these measures to those who were employed at the time of the survey.

In the NCS-R and the NLAAS, the diagnostic battery for each disorder is administered in the following manner. First, there is a set of screener questions that are asked to every respondent in the survey. For example, in the case of MDE, the screener questions include the following: (1) 'Have you ever in your life had a period of time lasting several days or longer when most of the day you felt sad, empty or depressed'; (2) 'Have you ever had a period of time lasting several days or longer when most of the day you were very discouraged about how things were going in your life'; and (3) 'Have you ever had a period of time lasting several days or longer when you lost interest in most things you usually enjoy like work, hobbies, and personal relationships'. Second, if the respondent answered in the affirmative to any one of the screener questions, the entire battery of questions corresponding to the disorder is then asked. Clinical diagnosis of a psychiatric disorder is then made based on the responses to the questions. In Figure 1, we depict how a determination is made for MDE in the DSM-IV.

The latent index for mental illness is generated from the model using an array of questions that relate to the symptoms of four psychiatric disorders MDE, social phobia, panic attack, and GAD and the correlates of mental illness, including demographic, socioeconomic, and health conditions variables. We focus on these four disorders because they are the most prevalent psychiatric disorders in our sample, with no missing values for the symptoms.[9] We did not include a few prevalent disorders in our study because the diagnostic battery of questions for those disorders were not administered to all individuals in the CPES. For example, specific phobia is a widely prevalent psychiatric disorder, with a 12-month prevalence rate of 8.7% (Kessler *et al.*, 2005b); however, the symptoms associated with the disorder were asked only to respondents from the NCS-R. To address concerns of simultaneity between work outcomes and psychiatric symptoms, we did not include a handful of symptoms (e.g., fear or avoidance of a social or performance situation that interfered with one's ability to work, worry/anxiety/nervousness interferes with one's ability to work) that were closely related to work outcomes.

The covariates (x) we use as predictors of work outcomes and mental illness comprise age, marital status (married, widowed/divorced/separated with single as the reference), race/ethnicity (Asian, Latino, African American, with non-Latino Whites as the reference category), education (12 years, 13–15 years, 16 or more years, with less than 12 years as the reference category), any health conditions (either arthritis/rheumatism, stroke, heart attack, diabetes, ulcer, or cancer at any point during their lifetime), and region (midwest, south, west with northeast as the baseline). We estimate our model for each gender separately, because the prevalence of mental disorders and labor market outcomes differs significantly for women and men.[10]

[9]In our sample, about 25% of individuals met criteria for one of the four disorders; whereas, close to 28% met criteria for any mental disorder in the past 12 months, thus highlighting the highly prevalent and comorbid nature of the conditions, which are incorporated in our analysis.

[10]The structural equation model with the continuous outcomes, number of weeks worked in the past year, and number of full days of work missed in the past month among employed individuals is estimated for the full sample to avoid estimation with a relatively small sample size when differentiated by sex.

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The first identifying instrument (external) is the number of psychiatric disorders that occurred prior to age 18 (excluding childhood disorders, which by definition have age of onset before age 18, such as ADHD).[11] We also use covariance instruments, without and with the external instrumental variable. In order to implement the Lewbel (2012) approach, we use a subset of (x, w) covariates as the vector z, namely, a binary indicator for whether an individual is married or not and a dichotomous measure for the presence of any physical chronic conditions. These two variables were chosen because the correlation between the endogenous mental illness variable and the covariance instruments was strongest for these variables (−0.249 and 0.233, respectively) from the vector (x, w), and the covariance instruments generated using these variables were significantly and strongly predictive of mental illness after accounting for the other demographic and socio-economic factors that predicted mental illness. This is reassuring given the fact that instruments based on higher moments are expected to be noisier than those based on standard exclusion restrictions.[12]

5. RESULTS

5.1. Descriptive statistics

The survey weighted means of the labor market outcomes, covariates, and mental illness measures used in the study are presented in Table I. Rates of employment and labor force participation are substantially higher for men compared with women (84% vs. 69% for employment; 86% vs. 75% for labor force participation). The average age is 43 years for both men and women; higher proportion of men are married compared with women (70% vs. 64%), and a substantial proportion of individuals have chronic physical health conditions (34% men vs. 38% women).

5.2. Structural equation model results

In Table II, we report the coefficients from the estimated model of the impact of mental illness on the likelihood that an individual is employed. In columns (1) and (5), we do not address the endogeneity of mental illness; in columns (2) and (6), we present estimates using the 'number of psychiatric disorders with onset prior to age 18' as an external instrument for the potentially endogenous mental illness latent variable; in columns (3) and (7), we use instruments suggested in Lewbel (2012), (i) covariance instrument physical chronic conditions and (ii) covariance instrument married; finally, in columns (4) and (8), we use the covariance instruments mentioned previously along with the external instrument number of psychiatric disorders with early onset. As anticipated, we find significant dampening effect of mental illness on employment regardless of the model specification. An increase in the mental illness score by one standard deviation reduces the likelihood of employment by almost 19 percentage points for men and 10 percentage points for women. Because the unemployment situation in 2002 (our sample period) was very similar to that in 2015, we expect these effects to be currently valid under the assumption that the mental health profile of the individuals remained largely unchanged. The estimated effect of mental illness is much larger after accounting for potential confounders because of simultaneity in the relationship between mental illness and employment. Moving on to the predictors of mental illness, we find that each of our instrumental variables are statistically significant and are fairly good predictors of mental illness, based on the large F-statistics (minimum was 27.00) on the identifying instrumental variable(s) obtained from the first-stage regression.[13]

[11]These disorders were dysthymia, major depressive disorder, major depressive episode, agoraphobia, generalized anxiety disorder, panic attack, panic disorder, post-traumatic stress disorder, social phobia, alcohol abuse, alcohol dependence, drug abuse, drug dependence, anorexia, binge eating disorder, bulimia, and intermittent explosive disorder.

[12]The correlation between the predicted mental illness score and the covariance instruments is shown in Appendix Table AI.

[13]The first stage results (not reported) were obtained by estimating Equations (2) and (3). Note that if our mental illness measure were to be observed directly, one would estimate only Equation (2) to obtain results from the first stage. However, because mental illness is modeled as a latent variable in our context, the first stage refers to the joint estimation of the MIMIC model (Equations (2) and (3)).

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Table I. Weighted means

Variables	Men (N = 3331) (%[a])	Women (N = 4235) (%[a])
Labor market outcomes		
Employed	84.21	69.20
In labor force	86.24	75.13
Weeks worked in the past year conditional on employment[b]	50.46 (0.20)	49.41 (0.19)
Days missed in the past month conditional on employment[b]	1.08 (0.13)	1.22 (0.10)
Mental illness indicators		
Major depression		
Depressed mood	8.61	13.70
Diminished pleasure	6.23	10.27
Significant weight change	6.13	11.64
Insomnia or hypersomnia	8.07	12.64
Restlessness or retardation	4.76	7.09
Fatigue	7.28	12.75
Worthlessness	3.99	6.98
Indecisiveness	7.76	12.57
Suicidal thoughts	6.03	10.41
Frequently severe emotional distress	7.30	11.66
Severe emotional distress	8.19	13.13
Length of depressive episode[b]	71.02 (11.05)	107.77 (14.81)
Panic attack		
Sweating	4.38	6.37
Trembling	2.54	4.65
Choking	5.47	9.75
Chest pain or nausea	4.64	9.30
Dizziness or unreality	5.23	8.91
Social phobia		
Afraid meeting new people	7.42	9.38
Afraid talking to authority	6.37	8.66
Shy at social gathering	6.25	7.77
Shy performing	8.22	11.06
Shy of unknown people	5.95	7.57
Shy at disagreement	4.91	7.68
Shy with others watching	3.36	5.75
Shy using public restroom	2.66	3.74
Shy in dating situation	5.28	6.27
Uncomfortable getting attention	6.84	9.15
Fear of embarrassment	9.21	11.84
Fear of social situation	8.89	11.52
Avoid social situations	8.67	10.97
Social situations cause intense anxiety	8.22	10.72
Recent occurrence after age 18	9.58	12.21
Generalized anxiety disorder (GAD)		
Excess anxiety	6.19	10.52
Length of GAD episode[b]	76.13 (14.29)	122.47 (21.25)
Difficult to control worry	5.84	9.82
Restlessness	5.57	9.66
Tired	4.43	8.51
Irritable	4.98	8.64
Difficulty concentrating	4.83	9.13
Tense muscles	3.60	7.36
Sleeping problems	5.38	8.93
Excessive nervousness	4.68	9.14
Significant emotional distress	5.77	9.79
Worry not always due to physical causes	2.09	2.50

(*Continues*)

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Table I. (Continued)

Variables	Men ($N = 3331$) (%[a])	Women ($N = 4235$) (%[a])
Socio-demographic variables		
Age[b]	42.78 (0.37)	43.40 (0.34)
Asian	4.88	4.85
Latino	13.19	11.63
African American	10.46	11.81
Married	70.44	63.98
Divorced	14.80	21.45
12 years of education	30.40	28.54
13–15 years of education	26.83	29.89
16 or more years of education	27.65	28.61
Midwest	23.92	22.28
South	33.23	35.14
West	24.28	23.91
Physical chronic conditions		
Chronic conditions	34.16	38.25

[a]Means of binary variables expressed in percentage terms;
[b]Continuous variable; Standard error in parenthesis;
Statistics are adjusted for complex survey design.

Examining the indicators (symptoms), which are the strongest indicators of mental health, we find that the length of a depressive episode, severe emotional distress, indecisiveness, and insomnia/hypersomnia are the most crucial in the context of employment for both men and women.[14] In addition, we find that the symptom of fatigue is detrimental for women but not so much for men. The results of the effect of mental ill health on labor force participation of men and women are presented in Table III. The estimated effects as well as the factor loadings (not reported) are very similar to those obtained in the previous table and are not discussed in the paper.

Overall, our findings suggest that the range of depressive and anxiety disorder symptoms considered in this analysis significantly affects individuals' performance in the labor market at the extensive margin. While it seems likely that many individuals with severe mental impairments would be either out of the labor force or be unemployed, those with mild to moderate psychiatric impairments would also perhaps perform poorly in the labor market, although in very different ways (e.g., in the form of reduced labor supply and increased absenteeism). In order to assess the impact of mental illness on the intensive margin of labor market outcomes, we focus on the number of weeks worked in the past year and number of full days of work missed in the past month for the employed group of individuals.

The estimated structural parameters for the model with continuous work outcomes are reported in Table IV. We find poor mental health to be associated with significant reductions in the number of weeks worked ($\beta = -1.862$) when we do not account for the endogeneity of mental illness (column (1)). Accounting for the potential confounds, we find much larger effects, with estimated reductions in the number of weeks worked in the past year by about 4 weeks (column (3)) using our covariance instruments specification. We also find that mental illness increases work absenteeism in the past month by almost 1 day in our model specification without the use of any instrumental variables. Consistent with previous findings, we observe a magnified effect after accounting for the role of latent confounding factors. Using the covariance instruments, we find mental illness to cause an increase in work absenteeism by more than 2 days in the past month for employed individuals.[15]

[14]Note that because it is a community-based survey, the CPES does not include diagnostic criteria for some serious mental disorders, such as schizophrenia, which have been found to be associated with functional impairments and poor work outcomes (for example, Harvey *et al*., 2012).
[15]Although the point estimate is larger using only the external instrument (column 6) relative to not using any instrument, the coefficient loses significance because of the larger standard errors. The use of the covariance instruments helps to regain the significance of the mental illness variable (columns 7 and 8).

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Table II. Effect of mental illness on employment

	Men				Women			
	(1) No instruments	(2) IV	(3) Lewbel IV, no external instrument	(4) Lewbel IV with external instrument	(5) No instruments	(6) IV	(7) Lewbel IV, no external instrument	(8) Lewbel IV with external instrument
Labor market equation								
Employed								
Mental Illness	−0.253*	−0.327*	−0.444*	−0.390*	−0.135*	−0.187*	−0.305*	−0.248*
	(0.04)	(0.10)	(0.09)	(0.07)	(0.03)	(0.06)	(0.09)	(0.07)
	[−0.188]	[−0.243]	[−0.330]	[−0.289]	[−0.099]	[−0.137]	[−0.224]	[−0.182]
Mental illness equation								
Mental Illness								
No. early onset of psychiatric disorders		0.070*		0.063*		0.093*		0.076*
		(0.01)		(0.01)		(0.01)		(0.01)
Cov instrument physical chronic conditions			0.180*	0.167*			0.151*	0.121*
			(0.03)	(0.03)			(0.03)	(0.02)
Cov instrument married			−0.123*	−0.109*			−0.187*	−0.158*
			(0.04)	(0.04)			(0.02)	(0.02)
First stage F-statistic on instrument(s)		95.18	27.72	77.9		244.95	119.11	195.64
[p-value]		[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]
Measurement model equations								
Depressed mood	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Diminished pleasure	0.776*	0.777*	0.777*	0.777*	0.774*	0.774*	0.774*	0.774*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Significant weight change	0.735*	0.735*	0.735*	0.736*	0.870*	0.870*	0.870*	0.870*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Insomnia or hypersomnia	0.955*	0.955*	0.955*	0.955*	0.940*	0.940*	0.940*	0.940*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Restlessness or retardation	0.574*	0.574*	0.574*	0.574*	0.542*	0.543*	0.543*	0.543*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Fatigue	0.869*	0.869*	0.869*	0.869*	0.944*	0.944*	0.944*	0.944*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Worthlessness	0.518*	0.519*	0.519*	0.519*	0.536*	0.537*	0.537*	0.537*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Indecisiveness	0.934*	0.934*	0.934*	0.934*	0.935*	0.935*	0.935*	0.935*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Suicidal thoughts	0.742*	0.742*	0.742*	0.743*	0.779*	0.779*	0.779*	0.780*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Frequently severe emotional distress	0.872*	0.872*	0.872*	0.872*	0.859*	0.859*	0.859*	0.859*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

(Continues)

Table II. (Continued)

	Men				Women			
	(1) No instruments	(2) IV	(3) Lewbel IV, no external instrument	(4) Lewbel IV with external instrument	(5) No instruments	(6) IV	(7) Lewbel IV, no external instrument	(8) Lewbel IV with external instrument
Severe emotional distress	0.973*	0.973*	0.973*	0.973*	0.966*	0.966*	0.966*	0.966*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Length of depressive episode	1.017*	1.018*	1.020*	1.022*	0.971*	0.972*	0.973*	0.974*
	(0.17)	(0.17)	(0.17)	(0.17)	(0.12)	(0.12)	(0.12)	(0.12)
Sweating	0.172*	0.173*	0.173*	0.173*	0.121*	0.121*	0.121*	0.122*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Trembling	0.087*	0.087*	0.087*	0.087*	0.061*	0.061*	0.061*	0.061*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Choking	0.246*	0.247*	0.246*	0.248*	0.243*	0.243*	0.243*	0.244*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Chest pain or nausea	0.252*	0.253*	0.253*	0.254*	0.235*	0.235*	0.235*	0.236*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Dizziness or unreality	0.237*	0.238*	0.238*	0.239*	0.196*	0.196*	0.196*	0.197*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Afraid meeting new people	0.345*	0.348*	0.347*	0.349*	0.230*	0.231*	0.231*	0.232*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Afraid talking to authority	0.284*	0.286*	0.285*	0.287*	0.201*	0.202*	0.202*	0.203*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Shy at social gathering	0.303*	0.305*	0.304*	0.306*	0.211*	0.212*	0.212*	0.213*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Shy performing	0.300*	0.302*	0.301*	0.304*	0.236*	0.237*	0.237*	0.238*
	(0.04)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Shy of unknown people	0.276*	0.278*	0.277*	0.279*	0.182*	0.183*	0.183*	0.184*
	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Shy at disagreement	0.264*	0.266*	0.265*	0.267*	0.168*	0.169*	0.169*	0.170*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Shy with others watching	0.206*	0.207*	0.207*	0.208*	0.145*	0.146*	0.146*	0.146*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Shy using public restroom	0.157*	0.158*	0.157*	0.158*	0.120*	0.120*	0.121*	0.121*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Shy in dating situation	0.243*	0.245*	0.244*	0.246*	0.162*	0.163*	0.163*	0.164*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Uncomfortable getting attention	0.312*	0.314*	0.313*	0.315*	0.220*	0.221*	0.221*	0.222*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Fear of embarrassment	0.349*	0.352*	0.350*	0.353*	0.261*	0.262*	0.262*	0.263*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Fear of social situation	0.332*	0.334*	0.333*	0.336*	0.250*	0.252*	0.252*	0.253*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)

(Continues)

Table II. (Continued)

	Men				Women			
	(1) No instruments	(2) IV	(3) Lewbel IV, no external instrument	(4) Lewbel IV with external instrument	(5) No instruments	(6) IV	(7) Lewbel IV, no external instrument	(8) Lewbel IV with external instrument
Avoid social situations	0.363*	0.366*	0.364*	0.367*	0.254*	0.256*	0.255*	0.256*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Social situations cause intense anxiety	0.335*	0.338*	0.337*	0.340*	0.248*	0.250*	0.249*	0.250*
	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Recent occurrence after age 18	0.365*	0.368*	0.367*	0.370*	0.258*	0.260*	0.259*	0.261*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
Excess anxiety	0.469*	0.471*	0.471*	0.473*	0.408*	0.409*	0.409*	0.410*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Length of GAD episode	0.786*	0.788*	0.790*	0.793*	0.582*	0.584*	0.585*	0.586*
	(0.19)	(0.19)	(0.19)	(0.19)	(0.12)	(0.12)	(0.12)	(0.12)
Difficult to control worry	0.449*	0.450*	0.450*	0.452*	0.388*	0.389*	0.389*	0.390*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Restlessness	0.431*	0.432*	0.433*	0.434*	0.373*	0.374*	0.374*	0.375*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Tired	0.342*	0.343*	0.343*	0.345*	0.366*	0.367*	0.367*	0.367*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Irritable	0.406*	0.407*	0.407*	0.409*	0.363*	0.364*	0.364*	0.364*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Difficulty concentrating	0.406*	0.407*	0.407*	0.409*	0.363*	0.364*	0.364*	0.365*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Tense muscles	0.300*	0.301*	0.301*	0.302*	0.324*	0.325*	0.325*	0.326*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Sleeping problems	0.419*	0.421*	0.421*	0.422*	0.373*	0.374*	0.374*	0.375*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Excessive nervousness	0.379*	0.381*	0.381*	0.382*	0.358*	0.359*	0.359*	0.360*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Significant emotional distress	0.441*	0.443*	0.443*	0.444*	0.396*	0.397*	0.397*	0.398*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Worry not always due to physical causes	0.189*	0.189*	0.189*	0.190*	0.109*	0.109*	0.109*	0.110*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
N	3331	3331	3331	3331	4235	4235	4235	4235

Standard errors for unstandardized coefficients in parentheses; standardized coefficients presented in brackets;
*$p < 0.01$;
results are adjusted for complex survey design; covariates in the Labor market and Mental illness equation not reported for brevity; length of depressive episode and length of GAD episode indicator variables standardized to mean 0 and standard deviation 1; columns (1) and (5) represent model that does not account for endogeneity of mental illness; columns (2) and (6) use number of early onset of psychiatric disorders as an instrument; columns (3) and (7) use covariance instruments suggested in Lewbel (2012); columns (4) and (8) use covariance instruments suggested in Lewbel (2012) and an external instrument number of early onset of psychiatric disorders; the coefficient on mental illness in the first equation of the measurement model is constrained to 1 as a normalization.

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Table III. Effect of mental illness on labor force participation

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No instruments	IV	Lewbel IV, no external instrument	Lewbel IV with external instrument	No instruments	IV	Lewbel IV, no external instrument	Lewbel IV with external instrument
Labor market equation								
In labor force								
Mental illness	−0.231*	−0.322*	−0.431*	−0.381*	−0.138*	−0.189*	−0.298*	−0.245*
	[−0.182]	[−0.253]	[−0.339]	[−0.299]	[−0.108]	[−0.148]	[−0.234]	[−0.192]
	(0.04)	(0.09)	(0.10)	(0.07)	(0.02)	(0.06)	(0.09)	(0.07)
Mental Illness equation								
Mental Illness								
No. early onset of psychiatric disorders		0.070*		0.063*		0.093*		0.076*
		(0.01)		(0.01)		(0.01)		(0.01)
Cov instrument physical chronic conditions			0.182*	0.169*			0.152*	0.122*
			(0.03)	(0.03)			(0.03)	(0.02)
Cov instrument married			−0.120*	−0.107*			−0.186*	−0.158*
			(0.04)	(0.04)			(0.02)	(0.02)
First stage F-statistic on instrument(s)		95.18	27.72	77.9		244.95	119.11	195.64
[p-value]		[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]
N	3331	3331	3331	3331	4235	4235	4235	4235

Standard errors for unstandardized coefficients in parentheses; standardized coefficients presented in brackets;
*$p < 0.01$;
results are adjusted for complex survey design; covariates in the labor market and mental illness equation not reported for brevity; measurement model equations not reported for brevity; columns (1) and (5) represent model that does not account for endogeneity of mental illness; columns (2) and (6) use number of early onset of psychiatric disorders as an instrument; columns (3) and (7) use covariance instruments suggested in Lewbel (2012); columns (4) and (8) use covariance instruments suggested in Lewbel (2012) and an external instrument number of early onset of psychiatric disorders.

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Table IV. Effect of mental illness on number of weeks worked in past year and days missed in past month conditional on being employed for full sample

	Weeks worked in past year conditional on employment				Days missed in past month conditional on employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No instruments	IV	Lewbel IV, no external instrument	Lewbel IV with external instrument	No instruments	IV	Lewbel IV, no external instrument	Lewbel IV with external instrument
Labor market equation								
Mental illness	−1.862***	−5.903***	−4.161**	−4.890***	0.754***	1.287	2.402**	1.934**
	[−0.075]	[−0.236]	[−0.167]	[−0.196]	[0.055]	[0.094]	[0.175]	[0.141]
	(0.59)	(2.05)	(1.95)	(1.65)	(0.24)	(0.87)	(1.08)	(0.75)
Mental Illness equation								
Mental illness								
No. early onset of psychiatric disorders		0.062***		0.056***		0.062***		0.055***
		(0.01)		(0.01)		(0.01)		(0.01)
Cov instrument physical chronic conditions			0.114***	0.106***			0.114***	0.106***
			(0.03)	(0.03)			(0.03)	(0.03)
Cov instrument married			−0.200***	−0.183***			−0.199***	−0.182***
			(0.03)	(0.02)			(0.03)	(0.02)
First stage F-statistic on instrument(s)		93.00	47.32	67.37		94.85	45.60	67.11
[p-value]		[0.00]	[0.00]	[0.00]		[0.00]	[0.00]	[0.00]
N		5525	5525	5525	5477	5477	5477	5477

Standard errors for unstandardized coefficients in parentheses; standardized coefficients presented in brackets;
$^{**}p < 0.05$;
$^{***}p < 0.01$;
results are adjusted for complex survey design; covariates in the labor market and mental illness equation not reported for brevity; measurement model equations not reported for brevity; columns (1) and (5) represent model that does not account for endogeneity of mental illness; columns (2) and (6) use number of early onset of psychiatric disorders as an instrument; columns (3) and (7) use covariance instruments suggested in Lewbel (2012); columns (4) and (8) use covariance instruments suggested in Lewbel (2012) and an external instrument number of early onset of psychiatric disorders.

5.3. Validity of the instruments

In order to test for the validity of the instruments used in the analysis, we conducted a set of Hausman tests for overidentifying restrictions. First, we tested for the validity of the additional instrument 'number of psychiatric disorders with onset prior to age 18', using 'parent/parental figure's experience of a period of sadness for at least 2 weeks or a period of constant anxiety/nervousness for at least 1 month during most of the respondent's childhood' as the baseline instrument. Certainly we would expect the latter to be potentially less troubling as an instrument than the former. Because the parental mental health information is available in the NCS-R sample only and not in NLAAS, we conducted this test using the NCS-R sample. We fail to reject the validity of the additional instrument for both the men (*Hausman statistic* $H = 0.01 < 26.30 = X^2_{16}$) and women ($H = 0.22 < 26.30 = X^2_{16}$) samples in the model with employment as the outcome variable. In the second step, using 'number of psychiatric disorders with onset prior to age 18' as a valid instrument for mental illness, we test for the validity of the two additional covariance instruments 'covariance instrument physical chronic conditions' and 'covariance instrument married'. Again, we fail to reject the validity of the additional covariance instruments (Men: $H = 0.92 < 27.59 = X^2_{17}$; Women: $H = 0.76 < 27.59 = X^2_{17}$) in the same model. The instruments also passed the Hausman test for instrument validity in our model for the other labor market outcomes (Table V).[16] The results of the tests for the validity of the instruments thus provide greater confidence in our causal estimates of the effect of mental illness.

6. COUNTERFACTUAL SIMULATIONS

To aid in interpretation of the findings, we simulate what would happen if individuals meeting diagnostic criteria for mental illness ($D = 1$) had the same symptom profiles as individuals not meeting diagnostic criteria for mental illness ($D = 0$).

In other words, we create a counterfactual group of $D = 1$ individuals with identical profile of symptoms as $D = 0$ individuals but retaining their own, original demographic, socioeconomic, and other health characteristics. In order to implement this, we apply the 'Rank and Replace' method used previously in research on health care disparities (McGuire *et al.*, 2006; Cook *et al.*, (2009, 2010)). The procedure is outlined as follows: (i) Rank the $D = 1$ and $D = 0$ group individuals separately by their mental illness score[17] and obtain the percentile scores of the ranked individuals in each group; (ii) Rank the combined sample of $D = 1$ and $D = 0$ individuals in increasing order of their percentile scores previously computed; (iii) Replace the symptoms of $D = 1$ individual with symptoms of higher ranked (healthier) $D = 0$ individual; and (iv) Using coefficients from previously estimated model (with two covariance instruments and one external instrument) obtain predicted value of labor market outcome with simulated mental health profile of $D = 1$ individuals and original mental health profile of $D = 0$ individuals.

In Table VI, we present results of the labor market benefits from improved mental health of the diagnosed individuals. We find almost 18 percentage point increase in the likelihood of employment and labor force participation for men; and slightly lower 11 percentage point increases, respectively, for women. Further, individuals are predicted to work an additional 2 weeks longer in a given year as a result of improved mental health. We also conducted counterfactual simulations of the labor market effects of worsening mental health of undiagnosed individuals ($D = 0$), to match the symptom profile of diagnosed individuals ($D = 1$). We find substantial adverse impact of poor mental health on all the labor market outcomes, and the magnitude of the effects is very similar to those obtained in Table VI (Table VII). The 'Rank and Replace' method is useful for this analysis as it acknowledges two important facts. First, within the $D = 1$ and $D = 0$ groups, there is substantial variation in

[16] For the outcome number of weeks worked in the past year we, however, reject the validity of the external instrument 'number of psychiatric disorders with onset prior to age 18' using our full sample ($H = 33.98 > 26.30 = X^2_{16}$). This result is not surprising because, as has been noted earlier, there are conceptual and empirical concerns about the validity of this instrument (Chatterji *et al.*, 2011). Thus, for this outcome variable, estimate under column 3 with only Lewbel instrument is most credible.

[17] The mental illness score is computed from Equation (3).

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Table V. Chi-square statistics for the validity of instruments

Hausman statistic	Employed	In Labor force	Weeks worked in past year conditional on employment	Days missed in past month conditional on employment	Critical value
Full sample:					
IV[a]			33.98	1.68	$X^2_{16} = 26.30$
Lewbel IV[b]			7.00	2.30	$X^2_{17} = 27.59$
Male:					
IV[a]	0.01	0.04			$X^2_{16} = 26.30$
Lewbel IV[b]	0.92	0.97			$X^2_{17} = 27.59$
Female:					
IV[a]	0.22	0.09			$X^2_{16} = 26.30$
Lewbel IV[b]	0.76	0.32			$X^2_{17} = 27.59$

[a]Instrumental variable (number of early onset of psychiatric disorders);
[b]Lewbel instruments (covariance instrument physical chronic conditions and covariance instrument married).

mental health levels. Second, given that the need-for-treatment group utilizes and adheres to effective treatment, the improvement in mental health would not be uniform across the distribution of mental health scores.

In order to put the individual level labor market effects into perspective, we calculate the societal impact of amelioration of mental health of the diagnosed group of individuals. We compute the gains in employment by using the number of individuals, 24- to 64-year-old, that are in the labor force[18] (BLS, 2002a), the prevalence rate of any mental disorder,[19] and the estimated increase in the likelihood of employment. We find that a total of 3.5 million individuals (1.91 million men and 1.57 million women) would gain employment from improved mental health. Further, we also calculate the workplace cost of absenteeism – this was carried out in two steps.[20] First, we compute the monetary value of the lost work days in a year per person. We used the estimated value of the reduction in missed days due to improved mental health, obtained earlier, and the median weekly wages (following Greenberg *et al*., 1993) obtained from the Bureau of Labor Statistics (2002b). Second, we calculate the societal cost of absenteeism for the working age employed individuals. To this effect, we use the employment figures for the 24- to 64-year-old individuals (BLS 2002a) and the prevalence rate of any mental disorder.[21] We find that the workplace cost of absenteeism is $21.6 billion in 2002 dollars.[22]

7. DISCUSSION

Our primary contribution in this paper is the use of a continuous measure of mental illness, moving away from the oft-used dichotomous indicator for meeting diagnostic criteria for mental illness, to assess the impact on a broad range of labor market outcomes. We believe this measure is more nuanced and better able to capture heterogeneity in the manner in which psychiatric disorders limit work functioning and lead to poor work-related outcomes. Another contribution to the literature is obtaining identification without the use of exclusion

[18]Here, we assume that individuals who are out of the labor force do not re-enter the labor force as a result of improved mental health. This provides a conservative estimate of the increase in employment.
[19]The disorders considered are MDE, panic attack, social phobia, and GAD. The prevalence rate for any mental disorder is 16.75% for men and 26.11% for women, computed from our dataset.
[20]We compute the workplace cost of absenteeism for the overall sample because our model for the number of days missed at work in the past month was estimated on the full sample.
[21]The disorders considered are MDE, panic attack, social phobia, and GAD. The prevalence rate for any mental disorder in the overall sample is 21.63%, computed from our dataset.
[22]We use employment, labor force participation, and median weekly wages data from 2002 (BLS (2002a, b)) to arrive at the employment gain and societal cost estimates, because the NCS-R and the NLAAS were conducted between 2001 and 2003.

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Table VI. Labor market benefits from improved mental health of diagnosed individuals ($D = 1$)

Mean predicted outcome	Full sample		Men		Women	
	Symptoms of $D = 1$ (Original mental health profile)	Symptoms of $D = 0$ (Simulated mental health profile)	Symptoms of $D = 1$ (Original mental health profile)	Symptoms of $D = 0$ (Simulated mental health profile)	Symptoms of $D = 1$ (Original mental health profile)	Symptoms of $D = 0$ (Simulated mental health profile)
Employment			0.70	0.88	0.63	0.74
			(0.01)	(0.01)	(0.01)	(0.01)
Labor force participation			0.72	0.89	0.68	0.79
			(0.01)	(0.01)	(0.01)	(0.00)
No. weeks worked among employed	48.24	50.27				
	(0.11)	(0.04)				
No. days missed among employed	1.80	1.00				
	(0.04)	(0.02)				

MDE, Major Depressive Episode; GAD, generalized anxiety disorder.
Standard errors in parentheses; mental disorders considered are MDE, panic attack, social phobia and GAD.

Table VII. Adverse labor market outcomes due to worsening mental health of undiagnosed individuals ($D = 0$)

Mean predicted outcome	Full sample		Men		Women	
	Symptoms of $D = 0$ (Original mental health profile)	Symptoms of $D = 1$ (Simulated mental health profile)	Symptoms of $D = 0$ (Original mental health profile)	Symptoms of $D = 1$ (Simulated mental health profile)	Symptoms of $D = 0$ (Original mental health profile)	Symptoms of $D = 1$ (Simulated mental health profile)
Employment			0.87	0.69	0.72	0.59
			(0.00)	(0.01)	(0.01)	(0.01)
Labor force participation			0.89	0.71	0.78	0.65
			(0.00)	(0.01)	(0.01)	(0.01)
No. weeks worked among employed	50.39	48.04				
	(0.03)	(0.06)				
No. days missed among employed	0.98	1.91				
	(0.01)	(0.03)				

MDE, Major Depressive Episode; GAD, generalized anxiety disorder.
Standard errors in parentheses; mental disorders considered are MDE, panic attack, social phobia and GAD.

restrictions, using an approach suggested in Lewbel (2012). This approach based on higher moments appears to work well in our context, suggesting that the use of covariance instruments can potentially address the endogeneity of mental illness with respect to labor market outcomes.

We find evidence that poor mental health adversely affects the likelihood of being employed and labor force participation of both men and women. The effects are much larger across all model specifications after addressing the endogeneity of mental illness, and the impact is greater for men compared with women. In case of the continuous work outcomes, we find mental illness to reduce the number of weeks worked and increase work absence for employed individuals.

We find an increase in the likelihood of employment of 18 and 11 percentage points for men and women, respectively, when their mental health condition improves to match that of those who do not meet criteria for any mental illness. These estimates are comparable with the 11 percentage point increase for both men and women found in Ettner *et al.* (1997). We also calculate the workplace cost of absenteeism to be $21.6 billion, which is much lower than $36.2 billion found by Greenberg *et al.* (2003) for depression alone using the NCS-R. The estimate of Greenberg *et al.* (2003), however, is not directly comparable with our estimate because they do not examine the causal effect of depression on absenteeism, merely association between the two. In our counterfactual simulation exercise, we have attempted to highlight some of the potential benefits from greater utilization and/or evidence-based treatment of mental illness. A more thorough treatment, including direct costs of inpatient, outpatient, and pharmaceutical costs, and also other benefits in terms of improved productivity of treated individuals should be undertaken in future research.

Although we have included four highly prevalent psychiatric disorders in the present study, which belong to the class of affective disorders, we have not included some other disorders that are less prevalent but are potentially more work-disabling. In the future, we plan to include psychiatric symptoms from bipolar disorder, dysthymia, agoraphobia, post-traumatic stress disorder, and specific phobia in the analysis to obtain a more complete picture of how affective disorders limit employment opportunities and performance of individuals.

APPENDIX I

Table AI. Correlation between predicted mental illness (MI) score and covariance instruments

Covariance instruments $(z - \bar{z})\hat{\zeta}$	Predicted MI score
Early onset of disorders	0.386
Married	−0.249
Physical chronic conditions	0.233
Age	−0.005
Age^2	−0.009
Asian	−0.298
Latino	−0.004
African American	0.036
Divorced	0.170
12 years of education	0.022
13 to 15 years of education	0.042
16 or more years of education	−0.162
Midwest	0.053
South	0.063
West	−0.151

The predicted MI score is obtained from Equation (3), and the covariance instruments are defined in Section 3.

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