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THE EFFECT OF DEPRESSION ON LABOR MARKET OUTCOMES

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ABSTRACT

We estimated the effect of depression on labor market outcomes using data from the 2004-2009 Medical Expenditure Panel Survey. After accounting for the endogeneity of depression through a correlated random effects panel data specification, we found that depression reduces the likelihood of employment. We did not, however, find evidence of a causal relationship between depression and hourly wages or weekly hours worked. Our estimates are substantially smaller than those from previous studies, and imply that depression reduces the probability of employment by 2.6 percentage points. In addition, we examined the effect of depression on work impairment and found that depression increases annual work loss days by about 1.4 days (33 percent), which implies that the annual aggregate productivity loses due to depression-induced absenteeism range from $700 million to 1.4 billion in 2009 USD.

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1. Introduction

Mental health problems are prevalent among U.S. adults. It is estimated that about 26 percent of adults have some type of mental disorder broadly defined, and 6 percent suffer from severe mental illness (Kessler et al, 2005). The costs associated with mental illness include direct medical costs for mental health treatment and indirect costs in the form of time away from work (absenteeism) and reduced productivity while at work (presenteeism). The National Institute of Mental Health (NIMH) estimated that the total annual cost for people with severely debilitating mental disorders exceeds $300 billion each year, a large fraction of which falls on payers of medical services and employers (NIMH, 2002).

Among various mental health conditions, depression is of interest for two reasons. First, it is one of the most common mental health problems among adults. In 2011, 6.6 percent of adults aged 18 or older in the U.S. (15.2 million people) experienced at least one major depressive episode during the past year (National Survey on Drug Use and Health, 2011). Second, the social cost of depression is surprisingly high: in high-income countries, unipolar depression (also known as major depressive disorder or major depression) is the leading cause of burden of disease and accounts for 8.2 percent of total disability-adjusted life years (DALYs). In contrast, heart diseases only account for 6.3 percent of total DALYs (WHO, 2008).

A correct understanding of the economic costs associated with mental health problems has important policy implications. Historically, mental health conditions are covered less generously than physical illness by private insurance, which has contributed to under-treatment of mental health problems.[1] Legislators at both the federal and state level responded by enacting mental health parity laws that aim to expand coverage for mental health conditions. However, it is still unclear whether these parity laws influence health outcomes (GAO, 2011), and if mental health conditions do not significantly affect individuals' labor market opportunities, the benefits of expanding mental health coverage may justify the costs.

There is a well-documented cross-sectional association in the economics literature between poor mental health and reduced likelihood of employment, lower wages, and fewer hours worked. Mental disorders are characterized by poor concentration, fatigue, sadness, reduced cognitive ability, excessive guilt, or even thoughts of suicide (NIMH, 2011). These symptoms reduce human capital accumulation, which in turn limits potential wages and the benefits of participating in the formal labor market. (Ettner et al, 1997). Among the employed, the onset of symptoms can result in absenteeism (absence from work) and presenteeism (attending work while sick). Furthermore, when employers learn an individual has a mental health condition they are sometimes less likely to hire him due to the inability or unwillingness to provide needed accommodations, or they may even engage in outright discrimination. (Chatterji et al, 2011).

The main difficulty in attributing poor labor market outcomes to the presence of mental health problems in a cross section of individuals is endogeneity. As pointed out by Chatterji et al (2011), mental health status is endogenous in both a structural and statistical sense: reverse causality poses a threat to identification if mental health and labor market outcomes are determined simultaneously. For example, job loss could

[1] According to the National Survey on Drug Use and Health in 2007, among the 24.3 million adults with serious psychological distress, only 44.6 percent used mental health services in the past year.

trigger an episode of depression for an individual with a predisposition. In addition, unobserved physical and mental health status as well as unobserved productivity may lead to omitted variable bias. In most cases, this type of endogeneity will lead to an over-estimation of the negative impact of poor mental health on labor market outcomes, such as employment, wages, work hours and work loss days, in non-causal analyses.[2] To address this endogeneity problem, researchers have primarily relied on instrumental variables or exclusion restrictions in multiple equation models. Nonetheless, it is difficult to find valid instruments that affect mental health but have no impact on labor market outcomes. The instruments that have been used in the literature fall into two broad categories: personal characteristics and social support.[3] However, the exogeneity of these instruments is difficult to validate. For example, the same personal characteristics that affect mental health may be correlated with productivity and labor market outcomes, and greater support from families or communities may also be related to better labor market opportunities.

We exploited the longitudinal dimension of the Medical Expenditure Panel Survey (MEPS) to estimate the causal relationship between depression and labor market outcomes. The MEPS is well suited to this analysis because it contains a clinically validated measure of depression that is collected contemporaneously with several labor market outcomes. We estimated fixed effects and correlated random effects (CRE) models (Chamberlain, 1980), which require no exclusion restrictions for identification and allow unobserved heterogeneity to be correlated with the regressors. This is an

[2] It is possible that certain types omitted variables could result in the under-estimation of the impact of poor mental health for some outcomes. For example, unobserved generosity in mental health coverage could bias the effect of poor mental health towards zero in a wage equation.

[3] See Chatterji et al (2007) for a comprehensive review of the instruments that have been used in the literature.

attractive alternative method of measuring causal effects when the primary threats to causal inference are unobservable dimensions of productivity and health status.

2. Literature Review

Previous research indicates that the positive relationship between poor mental health and unemployment is strong and robust, but that the associations with wages and works hours are less consistent, and sensitive to the type of mental disorder and modeling approach. For example, Ettner et al. (1997) analyzed the National Co-morbidity Survey (NCS) and found that psychiatric disorders (mainly major depression) reduced the probability of employment by approximately 11 percentage points among both men and women. Conditional on employment, they also found weak evidence of a small reduction in weekly hours worked for men and a substantial reduction in income for both men and women. They confirmed these results using instrumental variables models where the number of psychiatric disorders of an individual's parent and the number of disorders diagnosed before the age of 18 were the instruments for current mental health status. Chatterji et al (2011) used the more recent National Co-morbidity Survey-Replicate (NCS-R) data and estimated a set of constrained bivariate probit models using the method proposed by Altonji et al (2005). They found that past year psychiatric disorders were associated with reductions of 9 (19) percentage points in the probability of labor force participation and 14 (13) percentage points in the probability of employment for men (women). However, they failed to find an effect of psychiatric disorders on hours worked or earnings when accounting for the endogeneity of mental health status using similar instruments to Ettner et al. (1997).[4]

There are two studies which used causal methods to investigate the labor market consequences of depression, specifically. Alexandre and French (2001) found that depression lead to a 19 percentage point reduction in employment and 8 fewer annual weeks worked, using instruments based on the respondent's attitudes towards religion, and a proxy for individual and family social support. Cseh (2008) employed fixed effects models to account for the unobserved heterogeneity using the National Longitudinal Survey of Youth 1979 (NLSY79). To our knowledge, this is the only study that uses panel data techniques for identification. Relative to analyses that did not account for endogeneity, this study found a much smaller reduction in wages for men, and no effect on the wages of women.

Other studies have identified a strong association between mental health problems and work impairment. Kessler and Frank (1997) used the NCS to demonstrate that among the employed, individuals with psychiatric disorders in the past month had more work loss days or work cutback days. Kessler et al. (1999) showed that past month major depression increased short term work-disability days by 1.5 to 3.2 days per month. Likewise, Lim et al. (2000) found that depression, anxiety disorders and personality disorders were strong predictors of work impairment.

[4] One concern with the use of instruments based on parental or past mental health status is that these factors could impact current productivity through past human capital accumulation. In support of this possibility, Farahati et al (2003) found that children with mentally ill parents were more likely to drop out of high school, while Fletcher (2010) found that depression was associated with fewer years of schooling completed, higher probability of high school dropout, and lower probability of college attendance.

Finally, researchers have uncovered different impacts of mental health conditions across social groups. In particular, Chatterji et al (2007) found that poor mental health reduced employment among Latinos as well as Asian males, but not Asians females. Latinos were also more likely to have work absences than Asians in the presence of psychiatric disorders and mental distress. Ojeda et al (2009) determined that the labor supply of immigrants to the U.S. was less affected by mental health problems than the labor supply of natives.

3. Theoretical Framework and Empirical Methods

3.1 A simple theoretical model of labor supply

We follow the standard labor supply model with health capital (Currie and Madrian, 1999). The inter-temporal utility function for individual i is

$$U_i = \sum_{t=1}^{T} \left(\frac{1}{1+\delta} \right)^t U_{it}, \qquad (1)$$

where δ is a constant discount rate. We further assumed that the utility in period t takes the form:

$$U_{it} = U_1(C_{it}) + U_2(H_{it}, L_{it}), \qquad (2)$$

where C_{it} is a composite commodity with price normalized to one, H_{it} is the current health capital, and L_{it} is the leisure consumed by the individual in that period. The individual maximizes his overall utility subject to the following constraints:

$$
\begin{aligned}
&H_{it} = H(H_{i,t-1}, V_{it}, \mu_i),\\
&Q_{it}\omega_{it} + A_{it} = C_{it},\\
&L_{it} + V_{it} + Q_{it} + S_{it} = \Omega,\\
&\omega_{it} = \omega(H_{it}, X_{it}, M_i, m_i),\\
&S_{it} = S(H_{it}, Z_{it}, \theta_i).
\end{aligned}
\tag{3}
$$

The first constraint is the health production function where current health capital, H_{it}, depends on past health capital as well as time spent in health production, V_{it}. μ_i is unobserved heterogeneity in health production. The second and third constraints are a budget and time constraint, respectively. The budget constraint limits expenditure on the composite commodity to no more than the sum of unearned income A_{it} and labor income $Q_{it}\omega_{it}$, while the time constraint ensures that the sum of sick time, S_{it}, hours worked, Q_{it}, time devoted to health production, V_{it}, and leisure, L_{it}, equal total time available (Ω). The fourth constraint specifies the wage is a function of health capital, a vector of individual characteristics, X_{it}, observed job and employer characteristics, M_i, and unobserved productivity, m_i. In the last constraint, sick time S_{it} is a function of current health capital, a vector of exogenous determinants, Z_{it}, individual-specific propensity to get sick, θ_i. The individual chooses the optimal consumption path, $C_{it} > 0$, hours worked, $Q_{it} \geq 0$, time inputs into health production, $V_{it} \geq 0$, to maximize his lifetime utility subject to (3). The first-order conditions with respect to Q_{it} are given by

$$
\frac{\partial U_2}{\partial L_{it}} \geq \left(1+\delta\right)^t \omega_{it}\lambda_{it}, \quad t = 1, \ldots, T, \tag{4}
$$

where λ_{it} is the marginal utility of wealth in period t. It follows that the conditional labor supply function in period t is

$$Q_{it} = Q\left(\lambda_{it}, (1+\delta)^t, H_{it}, \omega\left(H_{it}, X_{it}, M_i, m_i\right)\right). \quad (5)$$

One of the distinct features of this model is that the health stock is an endogenous choice. Individuals can affect the health stock by altering time devoted to health production. From the quasi-reduced form equation of labor supply as a function of health, it is clear that there are several determinants of labor supply that are unobserved to the econometrician. Some of these, such as unobserved determinants of sickness and health production, and unmeasured productivity have a large genetic component, while unobserved preferences may be established prior to adulthood. Under these assumptions, one can further decompose all the unobserved factors into time-invariant and time-varying components. Denote α_i and ε_{it} as all the time-invariant and time-varying determinants of labor supply, respectively, where $\alpha_i = \mu_i + m_i$. Equation (5) then becomes:

$$Q_{it} = Q(X_{it}, H_{it}, M_{it}, \alpha_i, \varepsilon_{it}), \quad (6)$$

which serves as the basis of our empirical analysis.

3.2 Empirical models

One basic estimating equation for (6) is:

$$Y_{it} = f(X'_{it}\beta + D_{it} \cdot \gamma + \alpha_i + \varepsilon_{it}), \quad (7)$$

where Y_{it} is the labor market outcome of interest for individual i in time period t, X_{it} is a vector of covariates including demographics, human capital, and observed physical health status. We use the binary indicator D_{it} to denote whether the individual is depressed in time period t. The time-invariant parameter α_i captures unobserved components of physical and mental health status and unmeasured productivity. The error term ε_{it} is assumed to be uncorrelated with all regressors from all time periods (strong exogeneity). The choice of $f(\cdot)$ is dependent on the outcome Y_{it}. For employment status, we specify (7) as

$$\Pr(Y_{it}=1)=\Phi(X_{it}'\beta+D_{it}\gamma+\alpha_i), \tag{8}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. In the case of continuous outcomes such as hourly wage and weekly hours worked, (7) is the identity function. Since hourly wage is highly skewed to the right, we used the log transformation of the hourly wage as the dependent variable. In addition, we estimated a set of ordered probit models using the *conditional* sample to investigate whether depression affects full-time versus part-time work status. We created three categories of weekly hours worked: less than 30 hours a week, between 30 and 40 hours a week, and at least 40 hours a week (full-time). The reason why we made a distinction between those who work part-time for 30 or more hours per week is that some employers offer fringe benefits (such as health insurance) to those who work at least 30 hours a week.[5]

We are also interested in absenteeism, which is captured in the MEPS using a count variable indicating the number work loss days during the reference period. We modeled work loss days using the zero-inflated ordered probit (ZIOP) specification developed by Harris and Zhao (2007). This model is more appropriate than a standard count data model for two reasons. First, the distribution of work loss days is highly skewed, with over 70 percent of employed individuals reporting zero work loss days and

[5] According to the data from National Compensation Survey, 24 percent of the part-time workers in private industry have access to medical care benefits (Employee Benefits in the United States- March 2012). URL: http://www.bls.gov/news.release/archives/ebs2_07272010.pdf

only around 10 percent reporting more than 7 annual work loss days. The ZIOP specification allowed us to account for this right skewness by combining work loss days at the higher end of its distribution into discrete categories (Meyerhoefer and Zuvekas, 2010). Second, the ZIOP model facilitates the investigation of the effect of depression at both the extensive and intensive margins by separately modeling two different latent processes that generate the zero counts of work loss days. In particular, zero counts were reported because individuals remained healthy during the sample period, or because they did get sick, but remained at work while they were ill (i.e. presenteeism).

Let $\tilde{r}$ be a latent variable underlying the first data generating process determining sickness:

$$\tilde{r}_{it} = X'_{1it}\beta + D_{it}\gamma + \alpha_i + \eta_{it}. \tag{9}$$

The individual is healthy if $\tilde{r} \le 0$, but when the individual becomes sick $\tilde{r} > 0$. If the error term η_{it} follows a standard normal distribution, then the probability of sickness is

$$\Pr(r_{it} = 1 \mid X_{1it}, D_{it}) = \Pr(\tilde{r}_{it} > 0 \mid X_{1it}, D_{it}) = \Phi(X'_{1it}\beta + D_{it}\gamma + \alpha_i). \tag{10}$$

Conditional on illness, the actual work loss days of each individual is a discrete variable ($\tilde{y} = 0,1,\ldots,J$), which is assumed to be determined by the latent process:

$$\tilde{y}^* = X'_{2it}\pi + D_{it}\varphi + \alpha_i + \nu_{it}, \tag{11}$$

where $\tilde{y} = j$ when $c_j < \tilde{y}^*_{it} < c_{j+1}$, ($j = 0,1,\ldots,J$) are cutoffs estimated jointly with $(\beta', \gamma, \pi', \varphi)'$, and ν_{it} is standard normally distributed. Therefore, presenteeism occurs when $\tilde{y} = j = 0$. For notational simplicity, we suppress individual and time subscripts as well as unobserved heterogeneity, and denote $\tilde{X}_1 = (X'_1, D)'$ and $\tilde{X}_2 = (X'_2, D)'$. Then the two latent processes map to the observed data as $y = r\tilde{y}$, such that the density of y is given by

$$\Pr(y) = \begin{cases} \Pr(y=0 \mid \tilde{X}_1, \tilde{X}_2) & = & \left[1-\Phi(\tilde{X}_1'\tilde{\beta})\right] + \Phi(\tilde{X}_1'\tilde{\beta})\Phi(-\tilde{X}_2'\tilde{\pi}), \\ \Pr(y=j \mid \tilde{X}_1, \tilde{X}_2) & = & \Phi(\tilde{X}_1'\tilde{\beta})\left[\Phi(c_{j+1}-\tilde{X}_2'\tilde{\pi}) - \Phi(c_j - \tilde{X}_2'\tilde{\pi})\right], \\ \Pr(y=J \mid \tilde{X}_1, \tilde{X}_2) & = & \Phi(\tilde{X}_1'\beta)\left[1-\Phi(c_J - \tilde{X}_2'\tilde{\pi})\right], \end{cases} \tag{12}$$

where $j = 1, \cdots, J-1$. We estimated this model using the conditional sample of workers and computed an overall marginal effect of depression on work loss days as

$$ME = \sum_i ME_i \times L_i, \tag{13}$$

where L is the weighted average of work loss days in each category, and ME_i is the marginal effect of depression on the probability of being in category i.

Although one could in principle model α_i using fixed effects, this estimation strategy does not yield consistent parameter estimates of most nonlinear specifications when the time series dimension of the panel is fixed (Cameron and Trivedi, 2005). As an alternative Chamberlain (1980) proposed a random effects estimator that is consistent when T is fixed and allows α_i to be correlated with all regressors in all time periods. Again, denote $\tilde{X} = (X', D)'$ and $\tilde{\beta} = (\beta', \gamma)'$, and note that α_i can be modeled using a linear projection containing the regressors from all time periods:

$$\alpha_i = \tilde{X}_{i1}'\lambda_1 + \tilde{X}_{i2}'\lambda_2 + \cdots + \tilde{X}_{iT}'\lambda_T + u_i, \tag{14}$$

where u_i is orthogonal to $\tilde{X}$ by construction, and is assumed to be distributed as $N(0, \sigma_u^2)$. Substituting (14) into (7), we have

$$Y_{it} = f(\tilde{X}_{i1}'\lambda_1 + \cdots + \tilde{X}_{it}'(\tilde{\beta} + \lambda_t) + \cdots + \tilde{X}_{iT}'\lambda_T + u_i + \varepsilon_{it}). \tag{15}$$

Jakubson (1988) described a two-step procedure for consistent estimation of $\tilde{\beta}$ in labor supply models. First, consistent estimates of the reduced-form parameters are obtained from equation-by-equation estimation of (15), followed by identification of the structural parameters $\tilde{\beta}$, through minimum distance estimation:

$$\min D(\psi) = (\hat{\pi} - H\psi)'\hat{\Omega}^{-1}(\hat{\pi} - H\psi), \tag{16}$$

where ψ denotes the vector of structural parameters, $\hat{\pi}$ is the vector of reduced-form parameters obtained from the first step, $\hat{\Omega}$ is the variance-covariance matrix of $\hat{\pi}$, and H is a design matrix that maps the structural parameters to the reduced-form parameters. Where possible we confirmed the estimates of our nonlinear CRE models with linear models containing individual fixed effects.

4. Data

To estimate our empirical models we used the 2004-2009 Medical Expenditure Panel Survey (MEPS), subset to individuals aged 18-64 who were not full-time students. The MEPS is a nationally representative overlapping panel survey designed to provide estimates of health care use, expenditures, and health insurance coverage for the U.S. civilian non-institutionalized population. The MEPS contains detailed information on respondents' health status, demographic and socio-economic characteristics, and employment information. Each panel of respondents was interviewed in 5 rounds covering 2 calendar years.

Our indicator variable for major depression was calculated using the Patient Health Questionnaire (PHQ-2) index, collected during MEPS interview rounds 2 and 4. The PHQ-2 is a validated screening tool for depressive disorders (Kroenke et al, 2003) that is derived from two questions that ask whether the respondent was bothered by "having little interest or pleasure in doing things" and whether he was "feeling down, depressed and hopeless" during the past two weeks. For each question, respondents rate themselves on scale of 0-3 based on the frequency of depressed mood and decreased interest in usual activities. The PHQ-2 index is the sum of scores from the above two items and ranges from 0-6. As suggested by Kroenke et al (2003), we coded individuals as suffering from major depression if the value of the PHQ-2 index was greater or equal to 3.[6] Some respondents had missing values for the PHQ-2 index either because they were ineligible for the Self-Administrated Questionnaire (SAQ) containing the PHQ-2 questions, or they did not respond to the SAQ.[7] We excluded individuals ineligible for the SAQ from our estimation sample, and for those where were eligible but did not respond, we imputed a PHQ-2 index value using a generalized linear model.[8]

Respondents were asked to report on labor market outcomes in all 5 rounds, but since the SAQ is only administrated in rounds 2 and 4 (in the middle of the each year), we used the outcome variables collected during these same rounds. We considered individuals with a current main job on the interview date as employed, but excluded the self-employed from our estimation sample because the MEPS does not contain their wage

[6] Kroenke et al (2003) found that PHQ-2 ≥ 3 had a sensitivity of 83% and a specificity of 92% for major depression.

[7] All adults above 18 as of the interview date were asked to fill out the SAQ, with the exception of those made ineligible because they were deceased, institutionalized, moved out of the U.S, or moved to military facilities.

[8] We used a GLM with a log link to account for the right skewness of the distribution of the PHQ-2 index. In the imputation regressions, we included socio-demographic characteristics, the Physical Component Summary (PCS) scores, and Mental Component Summary (MCS) scores. Both PCS and MCS scores were calculated based on the questions in SF-12 Health Survey. The correlation between MCS score and the PHQ-2 index is quite high (the correlation coefficient is -0.72, with the negative sign the result of opposite scaling on the MCS).

information.[9] We converted hourly wage data and all monetary measures of productivity costs to constant 2009 dollars using the urban CPI.

The MEPS question designed to measure workplace productivity loss asks respondents "the number of times {the person} lost half-day or more from work because of illness, injury, mental or emotional problems" during the interview round. We constructed work loss days assuming that respondents lost a full day of work. While we believe this to be the most likely duration of work loss, it means that our estimates represent the upper bound of the effect of depression on absenteeism. However, when we computed aggregate productivity loss estimates from the work loss day models, we did so assuming only half a day was lost to identify the lower bound, and a full day was lost to identify the upper bound estimate. Due to the fact that the length of reference period varies across respondents, we normalized work loss days to a 12-month period.

We controlled for a full set of socio-demographic and employment characteristics in our models. Our main control variables include age and its square, gender, race and ethnicity, marital status, region (Northeast, South, Midwest, West), urban residence, years of education completed before entering the survey, union status, employer size (less than 25 employees, between 25-99 employees, between 100-500 employees, more than 500 employees), benefits provided by the employer (sick pay, retirement plan, and paid vacations), occupation and industry indicators,[10] number of children under 5 or 18 in

[9] Employed individuals who had missing hours or wage were dropped from the conditional sample. Those who reported working more than 120 hours per week were also excluded due to concerns over reporting error. When estimating the aggregate cost of worker absenteeism due to depression we imputed the wages of the self-employed and included them in our calculations.

[10] The industry indicators include: 1. natural resources/mining/construction/manufacturing; 2. wholesale and retail trade/transportation and utilities; 3. professional and business services/education, health, and social services; 4. other services/public administration/military/unclassifiable industry. We also included an indicator for whether the reported occupation required professional training.

the household, log of income earned by other family members (normalized by household size), and year dummies. In order to control for physical health status, we included the Physical Component Summary (PCS) score, which is derived from the questions in SF-12 Health Survey contained in the SAQ. Higher values of the PCS score indicate better physical health status. In the regressions where the dependent variable is weekly hours worked, we also included the log of hourly wages as a control to ensure our specification is consistent with the standard labor supply model. Table 1 contains descriptive statistics of all the variables we used in the analysis. Note that all means were weighted using the MEPS SAQ weight which adjusts for SAQ non-response. In our estimation sample, 75 percent of all the individuals aged 18-64 were employed and 9.1 percent suffered from major depression.

5. Results

5.1 Employment

We report complete estimation results for the CRE probit models of employment in columns (6) and (8), and the cross-sectional probit models for comparison purposes in columns (2) and (4), of Table A1 in the Appendix. In all of our models, the random effect capturing unobserved heterogeneity was specified to be correlated with marital status, log of family income (excluding the individual's own income), the PCS score, and the depression measure (index or indicator). Across all specifications, we found a negative and statistically significant association between depression and employment. However, the magnitude of the CRE estimates is substantially smaller than the cross-sectional estimates for both the continuous PHQ-2 depression index and the dichotomous indicator for index values ≥ 3.

The average marginal effects derived from these estimates are reported in Table 2. The cross-sectional estimates imply that depression is associated with a 17.6 percentage point reduction in the probability of employment, which is similar in magnitude to the effect found in previous studies (Ettner et al, 1997; Alexandre and French, 2001; Chatterji et al, 2011). In contrast, the CRE estimates imply depression lowers the probability of employment by only 2.6 percentage points, or 3.5 percent. This is similar to the marginal effect we obtain from a linear probability model containing individual fixed effects.

The sizeable and significant correlation parameters in Table A1 indicate that depression, along with marital status, physical health status, and income earned by other family members, are endogenous in the reduced form estimating equation. This endogeneity is presumably caused by the failure to fully measure worker productivity and health status, which are captured by the random effect in the CRE model. The downward bias on the effect of depression on employment in the cross sectional model is consistent with a positive correlation between unobserved productivity (or good health) and employment, and a negative correlation between productivity and depression.

5.2 Hourly wage and weekly hours worked

Panel A of Table 3 contains marginal effects of depression on weekly work hours and the hourly wage rate estimated using the conditional sample of workers. The cross-sectional estimates imply that depression is associated with an 8.3 percent reduction in the hourly wage, but this effect is small and imprecisely estimated using both CRE and individual fixed effects to control for unmeasured productivity. We failed to find a relationship between depression and weekly hours worked using either the cross-sectional or panel data specifications. The correlation parameters from the CRE models reported in appendix Table A2 indicate that the random effect is not correlated with the depression measure in the work hours model, but that it is significantly correlated with depression in the wage equation.[11] The latter is consistent with the downward bias of depression on wages due to unmeasured worker productivity in the cross sectional model. The marginal effects from both cross-sectional and CRE ordered probit models for part-time versus full-time employment are reported in panel B of Table 3. In the cross section, depression reduces the probability of working full time by 1.5 percentage points while the CRE estimates again suggest that depression has no effect on full-time work status.

5.3 Absenteeism and aggregate productivity costs of depression

Unlike wages or hours, which are relatively rigid due to labor contracts, work loss days are potentially more responsive to the presence or onset of contemporaneous depression. We report the coefficient estimates of the ZIOP model in Table A4. Note that the inflation part of the model captures the effect of depression on the propensity to be sick enough to take days off, while the ordered probit part of the model captures the effect of depression on the length of sick leave. The coefficient estimates from the inflation equation indicate that the depressed are more likely to take days off from work in general than are the non-depressed, although this effect is not precisely estimated. For both the continuous and dichotomous measure, the coefficient estimates of the PHQ-2 indexes are

[11] Note that the wage rate in the CRE work hours models is assumed to be endogenous, and as a result, is specified to be correlated with the random effect.

positive and statistically significant in the ordered probit equation, indicating that conditional on taking days off from work, depression increases the length of sick leave.

Marginal effects constructed from these coefficients are reported in Table 4. The treatment effect specification suggests that depression increases work loss days by 1.4 days per year. This represents a one-third increase in work loss days relative to the mean in the conditional sample of workers. Likewise, the marginal effect for the continuous PHQ-2 index indicates that a one unit change in the index value increases work loss days by 0.6 days per year. Although these are relatively large effects, the estimate from the cross-sectional treatment effects model that fails to account for productivity differences across workers is two and half times larger, while the estimate based on the continuous index is nearly twice as large.

In addition, we examined whether depression has a differential impact on absenteeism across worker groups. We stratified the sample by whether the individual had a retirement plan as a proxy for salaried versus hourly paid jobs, and found that depression is associated with a 43.3 percent increase in work loss days by workers without retirement plans (hourly paid), and a 29.3 percent increase among workers with retirement plans (salaried). Given that we controlled for whether the employer provided sick leave or paid time off to visit medical care professionals, these estimates suggest that the cost of depression is greater for lower paid workers.

Using our CRE estimates of the impact of depression on work loss days and information on the weekly work hours and wage rates, we were able to calculate annual estimates of the aggregate cost of depression due to workplace absenteeism for the U.S.

working population.[12] In Table 5 we report the aggregate cost from 2005-2008 using our CRE estimates. Since the MEPS asks the respondents to report whether they missed work for a half day or more due to sickness or injury, we calculated two different estimates: Our upper bound estimate assumes individuals always missed a full day of work, while our lower bound estimate assumes they always missed a half day. We found that the annual total cost of workplace absenteeism due to depression is relatively constant over time, and ranges from 0.7 to 1.4 billion in 2009 dollars.

6. Sensitivity Analyses

We performed several sensitivity checks of our main results. First, we re-estimated all of our models after excluding control variables for union status, industry, occupation, employer size, and employer benefits (and wages). These variables could be endogenous if those with depression seek employment only at firms with certain characteristics. While the cross-sectional estimates of the impact of depression are sensitive to the exclusion of these variables, the CRE estimates are not. Second, we tested whether the differences between the cross-sectional and CRE estimates could be due to functional form misspecification rather than unobservables. To address this, we re-estimated cross-sectional models after including quadratic and cubic terms of all continuous variables, a full set of pairwise interaction terms, and lags of all the variables that were specified to be

[12] For individuals who worked less than 70 hours per week, we assumed that they worked 5 days a week; for those who worked more than 70 hours per week, we assumed that they worked 6 days a week. We then calculated the daily wage by (weekly hours worked*hourly wage/number of days worked per week). The total annual cost of depression is therefore the weighted sum of (daily wage*overall marginal effect) among the depressed individuals. We imputed wages for the self-employed and included them in the aggregate cost estimates. Since the 2003-2004 and 2009-2010 cohorts are excluded from the estimation sample, we did not calculate the aggregate costs for 2004 and 2009.

correlated with unobserved heterogeneity in the CRE model.[13] In the models of employment and log hourly wage, the estimated effects of depression decreased after we added the interaction and lag terms (see Table 6). However, the cross-sectional marginal effects are still sizeable and precisely estimated even using this highly flexible specification.

Third, we used a broader measure of mental illness, the Kessler-6 (K-6) index, to investigate whether our results are sensitive to the scale we use to measure depression. The K-6 index is a standardized and validated measure of non-specific psychological distress, and reflects a diagnosis of anxiety disorder, or mood disorder, or non-affective psychosis (Kessler et al, 2002). Individuals who scored greater or equal to 13 (out of 24) are considered to have serious mental illness.[14] We re-estimated all models using the K-6 index and report all the results in the Appendix. These estimates are consistent with those from our primary specifications using the PHQ-2, and maintain the pattern of CRE estimates of depression that are smaller than those from the cross-sectional models.

Unfortunately, there is no direct way of assessing the robustness of panel data techniques designed to account for unobserved heterogeneity without a confirmatory randomized experiment or valid instrumental variables. However, one can assess how sensitive the cross-sectional estimates are to selection on unobservables. If the cross-sectional estimates are very sensitive to unobservables, this provides strong motivation for the CRE approach and suggests the estimates are likely to be more reliable. Using the

[13] Since $T = 2$ for our panel, we only used the observations from the second year to include lags of time-varying controls. As a result, point estimates from baseline models differed from the full sample estimates.
[14] In the MEPS, the K6 index was calculated based on questions that asked whether the respondent felt "nervous", "hopeless", "fidget or restless"," worthless", "so sad that nothing could cheer the person up", and "everything is an effort" during the past 30 days.

framework proposed by Altonji et al (2005) we determined whether a modest degree of negative selection into depression on unobservables could account for the whole effect of depression in the cross-sectional models. Other studies that have applied the same framework include Altonji et al. (2008), Millimet et al. (2010), and Chatterji et al. (2011). For example, Chatterji et al. (2011) demonstrated the utility of this method in measuring associations between recent psychiatric disorders and the probability of employment; a case where identifying instruments are not generally available.

Intuitively, the degree of selection on observables can be used as a guide to the degree of selection on unobservables. In the case of binary outcome variable, consider the following bivariate probit model:

$$Y = 1(X'\gamma + \alpha \cdot D + \varepsilon > 0), \tag{17}$$

$$D = 1(X'\beta + u > 0), \tag{18}$$

where $1(\cdot)$ is an indicator function, and it is assumed that u and ε follow a standard bivariate normal distribution with correlation ρ. In the absence of valid exclusion restrictions, identification of the bivariate probit model is achieved through the bivariate normality assumption. Let Y^* be a latent variable underlying outcome Y such that

$$Y^* = \alpha \cdot D + W'\Gamma, \tag{19}$$

where W is the full set of variables that determine Y^* and D is a binary indicator for depression. In practice, we only observe a subset X of W, so we rewrite (19) as

$$Y^* = \alpha \cdot D + X'\gamma + \varepsilon. \tag{20}$$

Note that in (20) γ and ε are defined so that $\text{cov}(X, \varepsilon) = 0$. Similarly, let D^* be the latent variable underlying D and the linear projection of D^* onto $X'\gamma$ and ε is

$$E(D^* \mid X'\gamma, \varepsilon) = \varphi_0 + \varphi_1 X'\gamma + \varphi_2 \varepsilon. \tag{21}$$

Then the assumption that selection on unobservables is the same as selection on observables can be re-expressed as $\varphi_1 = \varphi_2$. In the bivariate probit framework, this condition can be replaced by

$$\rho^* = \frac{\text{cov}(X'\beta, X'\gamma)}{\text{var}(X'\gamma)}. \tag{22}$$

We provide a proof of this result in section 1 of the appendix. Setting $\rho = 0$ generates the cross-sectional estimate of α, and setting $\rho = \rho^*$ generates the lower bound of α (Altonji et al, 2005). We followed a two-step procedure to approximate the value of ρ that satisfies equation (22). First, β and γ are estimated from an unconstrained bivariate probit model, and then α is estimated from a constrained bivariate probit model imposing the estimated value of ρ^* from the first step.

We set ρ from 0 to -0.4, ρ^* (-0.52 for our application) and $\rho^* / 2$ (-0.26), and estimated the constrained bivariate probit models on employment. The coefficient estimates and marginal effects of the dichotomous PHQ-2 index are reported in Table 7. The negative effect of depression on employment decreases dramatically as negative selection on the unobservables gets stronger. When ρ is set to -0.3, the coefficient estimate becomes positive and the negative effect of depression goes away. This provides evidence that the cross-sectional estimate is very sensitive to selection on unobservables, and that even a modest level of negative selection on unobservables can reverse the direction of the estimated effect. Under the assumption that selection along unmeasured factors is equal to selection along measured factors ($\rho = \rho^*$), the coefficient estimate is positive and statistically significant. Under this condition the elements of X are just a random subset of W, and are no more useful than the unobserved elements of W in terms of reducing the bias in $\hat{\alpha}$ (Altonji et al, 2005). However, this assumption is likely to be too strong given that our models contain a large number of socio-demographic controls, some of which (such as education and age) are known to be strong determinants of employment.

Given the significant predictive power of the observables on employment, it is reasonable to assume in our application that selection on unobservables is weaker than selection on observables. The last column of table 7 contains the marginal effect of depression on employment under the constraint: $\rho = 0.5\rho^*$. In this case the marginal effect is slightly smaller than that from our CRE model. Although it is impossible to know the true value of ρ, this suggests that the CRE specification generates estimates that are consistent with a moderate degree of selection on unobservables.

In the case of continuous outcomes such as wages and hours worked, Altonji et al (2005) provide a different method for assessing the role of unobservables. Here, the relevant question is: Relative to the degree of selection on observables, how large should the selection on unobservables be, to explain away the whole effect of depression? We provide a detailed derivation of statistic we used to determine this in section 2 of the appendix. We conducted this sensitivity analysis only for the hourly wage outcome because depression is not associated with hours worked in either the cross-sectional or panel data model. Our estimates indicate that the normalized shift in the distribution of unobservables only needs to be around 30 percent of the normalized shift in the observables to explain away the entire effect of depression.

As a result, the OLS estimate suggesting that depression decreases wages is likely less reliable than the CRE estimate indicating no effect. Although this exercise is not a direct check of our CRE estimates, it is consistent with the significant differences we observe between the cross-sectional and CRE models when worker productivity and health status are not fully observable. If unobserved low productivity is positively correlated with depression and negatively correlated with employment and wages, we should find a smaller negative impact of depression on employment and wages in the CRE models than the naïve cross-sectional models.

7. Discussion and Conclusions

It is difficult to empirically evaluate the disabling effects of mental health conditions like depression. The main challenge in estimation is the endogeneity of mental health measures in the structural model. In this paper, we achieved identification by accounting for time-invariant unobserved differences in productivity and health that are potentially correlated with both labor market outcomes and depression. We found that depression has a modest negative effect on employment and a large effect on absenteeism. However, we did not find any causal effect of depression on wage or hours worked conditional on employment.

There are several limitations of our method. Although our identification strategy is not dependent on exclusion restrictions, it hinges on the assumption that the way we model unobserved heterogeneity fully accounts for the unobserved confounders of depression. In all of our models, we specified the random effect in the structural model to be correlated with marital status, income earned by other family members, physical health status, and depression. This is reasonable if the main confounding factors are time-invariant unobserved productivity and unobserved dimensions of physical and mental health status. We feel this is plausible in the case of health status since variation in the PHQ-2 and PCS scores will capture time-varying dimensions of mental and physical health, while age (conditional on educational attainment) should capture changes in labor market experience, and as a result, time-varying productivity. Nonetheless, if the error term has a time-varying component that is also correlated with depression, our estimates will be biased.

Another limitation is that individuals with the most severe forms of mental illnesses residing in institutions are not in the scope of the MEPS. One would expect the effect of depression on employment to be larger for the full population. Finally, our structural model captures the contemporaneous rather than the life-cycle effect of depression. While a comprehensive assessment of the impact of depression on labor market outcomes would consider both effects, the MEPS lacks information on the onset and duration of depression necessary to estimate the latter.

We found that depression has a smaller negative impact on employment than previous studies. For example, Alexander and French (2001) reported a 19 percentage point reduction in the probability of employment due to depression. Our cross-sectional models produced a very similar estimate of 17.6 percentage points, but the CRE estimate is only 2.6 percentage points. This could be due to the fact that we used data from 2004-2009, a time period during which the use of mental health care increased substantially compared to the 1990s when the NCS was administered. Soni (2012) reported that between 1999 and 2009, the number of adults treated for depression increased by 74 percent, and the total health care expenditures for depression increased from 18 to 22.8 billion in 2009 dollars. Given the effectiveness of depression treatment, this increase in the use of mental health services might have dampened the disabling effects of depression (Simon, 2002; Gibbons et al, 2012). Also, despite the fact that we found no evidence of a causal relationship of depression on wage or hours, our aggregate estimates of workplace productivity loss from short-term disability are not trivial.

In the aggregate, we found that the productivity loss in the U.S. economy due to depression-induced absenteeism was between 700 million and 1.4 billion 2009 USD annually, which is less than estimates from most previous studies. For example, Greenberg et al. (2003) reported that the cost of depression from workplace absenteeism totaled 36.2 billion in 2000 (current dollars). Birnbaum et al. (2010) estimated that *monthly* depression-related productivity loss from both absenteeism and presenteeism was 2 billion, also in 2000 dollars. Due to methodological differences, caution is needed when comparing our estimates of aggregate costs with those from these studies. In particular, we did not attempt to quantify the impact of depression on presenteeism, which cannot be calculated using the MEPS without making an untestable assumption about how depression lowers productivity at work. Previous studies may also overestimate the workplace productivity loss due to absenteeism as a result of failure to address the endogeneity of depression.

Our findings have implications, in particular, for the substantial expansions of mental health coverage under the Affordable Care Act (ACA). Garfield et al (2011) estimated that 2.0 million previously uninsured Americans with severe mental disorders would gain coverage under the individual and small group exchange provisions of the

ACA.[15] Mental health and substance use services are considered essential benefits and must be covered at parity with other health services in the exchanges. In defining the services as part of the essential benefit package, the government extends mental health and substance abuse coverage well beyond the newly insured. The U.S. Department of Health and Human Services estimates that 3.9 million Americans currently covered in the individual market and 1.2 million currently in small group plans would gain mental health coverage under the essential benefit requirement (Beronio et al, 2013). A further 7.1 million currently insured Americans in the individual market and 23.3 million in the small group market with some form of mental health coverage would now be guaranteed parity coverage (Beronio et al, 2013). Our estimates suggest that some of these coverage expansions may be offset through less productivity loss.

[15] Garfield et al (2011) estimated that another 1.7 million Americans with severe mental disorders would gain coverage under the Medicaid expansions if implemented in every state.

References

Alexandre, P.K., French, M.T., 2001. Labor supply of poor residents in metropolitan Miami, Florida: The role of depression and the co-morbid effects of substance use. Journal of Mental Health Policy and Economics 4, 161-173.

Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. Journal of Political Economy 113, 151-184.

Altonji, J.G., Elder, T.E., Taber, C.R., 2008. Using selection on observed variables to assess bias from unobservables when evaluating Swan-Ganz catheterization. The American Economic Review: Papers & Proceedings 98, 345-350.

Beronio, K., Po, R., Skopec, L., Glied, S., 2013. Affordable Care Act Will Expand Mental Health and Substance Use Disorder Benefits and Parity Protections for 62 Million Americans. ASPE Research Brief, February 2013.

Birnbaum, H.G., Kessler, R.C., Kelley, D., Ben-Hamadi, R., Joish, V.N., Greenberg, P.E., 2010. Employer burden of mild, moderate, and severe major depressive disorder: Mental health services utilization and costs, and work performance. Depression and Anxiety 27, 78-89.

Cameron, A.C., Trivedi, P.K., Microeconometrics: Methods and Applications. Cambridge University Press: Cambridge and New York; 2005.

Chamberlain, G., 1980. Analysis of covariance with qualitative data. Review of Economic Studies 47, 225-238.

Chatterji, P., Alegria, M., Lu, M., Takeuchi, D., 2007. Psychiatric disorders and labor market outcomes: Evidence from the national Latino and Asian American study. Health Economics 16, 1069-1090.

Chatterji, P., Alegria, M., Takeuchi, D., 2011. Psychiatric disorders and labor market outcomes: Evidence from the national comorbidity survey-replication. Journal of Health Economics 30, 858-868.

Cseh, A., 2008. The effects of depressive symptoms on earnings. Southern Economic Journal 75, 383-409.

Currie, J., Madrian, B.C., 1999. Health, health insurance, and the labor market. In: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics, Vol.3, pp.3309-3415.

Ettner, S.L., Frank, R.G., Kessler, R.C., 1997. The impact of psychiatric disorders on labor market outcomes. Industrial and Labor Relations Review 51, 64-81.

Farahati, F., Marcotte, D.E., Wilcox-Gok, V., 2003. The effects of parents' psychiatric disorders on children's high school dropout. Economics of Education Review 22, 167-178.

Fletcher, J.M., 2010. Adolescent depression and educational attainment: Results using sibling fixed effects. Health Economics 19, 855-871.

Garfield, R.L., Zuvekas, S.H., Lave, J.R., Donohue, J.M., 2011. The impact of national health care reform on adults with severe mental disorders. The American Journal of Psychiatry 168, 486-94.

Gibbons, R.D., Hur, K., Brown, C.H., Davis, J.M., Mann, J.J., 2012. Benefits from antidepressants: Synthesis of 6-week patient-level outcomes from double-blind placebo-controlled randomized trials of fluoxetine and venlafaxine. Archives of General Psychiatry 69, 572-579.

Government Accountability Office (GAO), 2011. Mental Health and Substance Use: Employers' Insurance Coverage Maintained or Enhanced Since Parity Act, but Effect of Coverage on Enrollees Varied. Accessed at http://www.gao.gov/new.items/d1263.pdf.

Greenberg, P.E., Kessler, R.C., Birnbaum, H.G., Leong, S.A., Lowe, S.W., Berglund, P.A., et al., 2003. The economic burden of depression in the United States: how did it change between 1990 and 2000. Journal of Clinical Psychiatry 64(12), 1465-1475.

Harris, M.N., Zhao, X., 2007. A zero-inflated ordered probit model, with an application to modelling tobacco consumption. Journal of Econometrics 141, 1073-1099.

Jakubson, G., 1988. The Sensitivity of Labor Supply Parameter Estimates to Unobserved Individual Effects: Fixed and Random Effects Estimates in a Non-Linear Model Using Panel Data. Journal of Labor Economics. 6(3), 302-329.

Kessler, R.C., Andrews, G., Colpe, L.J., Hiripi, E., Mroczek, D.K., Normand, S.T., et al., 2002. Short screening scales to monitor population prevalences and trends in non-specific psychological distress. Psychological Medicine 32, 959-976.

Kessler, R.C., Barber, C., Birnbaum, H.G., Frank, R.G., et al., 1999. Depression in the workplace: Effects on short-term disability. Health Affairs 18, 163-71.

Kessler, R.C., Chiu, W.T., Demler, O.,Walters, E.E., 2005. Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication. Archives of General Psychiatry 62, 617-627.

Kroenke, K., Spitzer, R.L., Williams, J.B.W., 2003. The patient health questionnaire-2: Validity of a two-item depression screener. Medical Care 41, 1284-1292.

Lim, D., Sanderson, K., Andrews, G., 2000. Lost productivity among full-time workers with mental disorders. Journal of Mental Health Policy and Economics 3, 139-146.

Meyerhoefer, C.D., Zuvekas, S.H., 2010. New estimates of the demand for physical and mental health treatment. Health Economics 19, 297-315.

Millimet, D.L., Tchernis, R., Husain, M., 2010. School nutrition programs and the incidence of childhood obesity. Journal of Human Resources 45, 640-654.

National Institute of Mental Health (NIMH), 2002. Annual total direct and indirect costs of serious mental illness (2002). Accessed at http://www.nimh.nih.gov/statistics/4COST_TOTAN.shtml.

National Institute of Mental Health (NIMH), 2011. Depression. Accessed at http://www.nimh.nih.gov/health/publications/depression/depression-booklet.pdf.

National Survey on Drug Use and Health, 2011. Results from the 2011 National Survey on Drug Use and Health: Mental Health Findings. Accessed at http://www.samhsa.gov/data/NSDUH/2k11MH_FindingsandDetTables/2K11MHFR/NSDUHmhfr2011.pdf.

Ojeda, V.D., Frank, R.G., McGuire, T.G., Gilmer, T.P., 2010. Mental illness, nativity, gender and labor supply. Health Economics 19, 396-421.

Simon, G.E., 2002. Evidence review: efficacy and effectiveness of antidepressant treatment in primary care. General Hospital Psychiatry 24, 213-224.

Soni, A., 2012. Trends in Use and Expenditures for Depression among U.S. Adults Age 18 and Older, Civilian Noninstitutionalized Population, *1999 and 2009*. Statistical Brief #377, Agency for Healthcare Research and Quality. Rockville, MD.

World Health Organization (WHO), 2008. The global burden of disease: 2004 update. Accessed at http://www.who.int/healthinfo/global_burden_disease/GBD_report_2004update_full.pdf.

Tables

Table 1. Descriptive statistics (*N*= 76,132; *T* = 2)

Variable	Mean	Standard deviation	Min	Max
Age	41.878	12.181	18	64
Age squared/100	19.021	10.259	3.24	40.96
Female	0.527	0.499	0	1
Married	0.583	0.493	0	1
White	0.672	0.469	0	1
Hispanic	0.148	0.355	0	1
Black	0.125	0.331	0	1
Other race	0.055	0.227	0	1
Urban	0.837	0.369	0	1
West	0.231	0.421	0	1
Midwest	0.224	0.417	0	1
South	0.367	0.482	0	1
Northeast	0.178	0.383	0	1
Education(years)	13.154	2.952	0	17
Number of children under 5	0.273	0.608	0	5
Number of children between 6 and17	0.573	0.941	0	9
Log family income (2009 USD)	6.953	4.448	0	12.965
Union	0.106	0.307	0	1
Employer size <25	0.226	0.418	0	1
Employer size 25-99	0.178	0.383	0	1
Employer size 100-500	0.162	0.368	0	1
Employer size >500	0.138	0.345	0	1
Sick pay	0.508	0.500	0	1
Retirement plan	0.444	0.497	0	1
Paid vacation	0.575	0.494	0	1
Industry construction & manufacturing	0.158	0.365	0	1
Industry professional & education	0.381	0.486	0	1
Industry transportation & utility	0.137	0.344	0	1
White collar occupation	0.564	0.496	0	1
PCS score	50.746	9.754	4.56	73.09
PHQ2	0.748	1.322	0	6
PHQ2 $\geq$ 3	0.091	0.287	0	1
Employed	0.750	0.433	0	1
Hourly wage (2009 USD)	15.463	14.909	0	84.632
Weekly hours worked	30.192	19.666	0	112
Annual work loss days	3.548	19.708	0	365

Notes: Means are weighted to be nationally representative.

Table 2. Marginal effects of depression on employment

	Cross-section	Fixed-effects	CRE
PHQ-2 index	-0.042***	-0.012***	-0.011***
	(0.001)	(0.002)	(0.002)
Depression (PHQ-2 $\geq$ 3)	-0.176***	-0.033***	-0.026***
	(0.008)	(0.007)	(0.007)

Notes: Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Models include cross-sectional and CRE probit regressions and linear fixed-effects regressions. Control variables include age and its square, gender, race and ethnicity, marital status, years of education completed before entering the survey, region, urban residence, number of children under 5 or 18 in the household, log of income earned by other family members (normalized by household size), PCS score, and year dummies.

Table 3. Marginal effects of depression on work hours and wages

Panel A

	Weekly work hours			Log wage		
	Cross-section	Fixed-effects	CRE	Cross-section	Fixed-effects	CRE
PHQ-2 index	-0.031	0.007	0.006	-0.021***	-0.002	-0.004
	(0.055)	(0.034)	(0.033)	(0.003)	(0.002)	(0.003)
Depression	0.053	-0.023	-0.053	-0.083***	-0.006	-0.004
(PHQ-2 ≥ 3)	(0.259)	(0.155)	(0.163)	(0.012)	(0.008)	(0.012)

Panel B: Weekly work hours

	Cross-section			CRE		
	Less than 30 hours	Between 30 and 40 hours	More than 40 hours	Less than 30 hours	Between 30 and 40 hours	More than 40 hours
Depression	0.010***	0.005***	-0.015***	0.004	0.003	-0.006
(PHQ-2 ≥ 3)	(0.003)	(0.001)	(0.005)	(0.002)	(0.002)	(0.004)

Notes: Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Models include cross-sectional and CRE OLS and ordered probit regressions as well as linear fixed-effects regressions. Control variables include age and its square, gender, race and ethnicity, marital status, years of education completed before entering the survey, region, urban residence, union status, employer size (less than 25 employees, between 25-99 employees, between 100-500 employees, more than 500 employees), benefits provided by the employer (sick pay, retirement plan, and paid vacations), occupation and industry indicators, number of children under 5 or 18 in the household, log of income earned by other family members (normalized by household size), PCS score, and year dummies.

Table 4. Marginal effect of depression on work loss days

	Cross-section	CRE
PHQ-2 index	0.926***	0.567***
	(0.081)	(0.083)
Depression (PHQ-2$\geq$3)	3.359***	1.382***
	(0.498)	(0.433)

Note: Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Models include cross-sectional and CRE zero-inflated ordered probit regressions. Control variables include age and its square, gender, race and ethnicity, marital status, years of education completed before entering the survey, region, urban residence, union status, employer size (less than 25 employees, between 25-99 employees, between 100-500 employees, more than 500 employees), benefits provided by the employer (sick pay, retirement plan, and paid vacations), occupation and industry indicators, number of children under 5 or 18 in the household, log of income earned by other family members (normalized by household size), and year dummies.

Table 5. Annual cost of depression-induced absenteeism for employed adults aged 18-64 (Billions of 2009 USD; 90% C.I. in brackets)

Year	Total employed population aged 18-64 (millions)	Total Population (full day estimate)	Total population (half day estimate)
2005	135.3	1.41	0.70
		[0.66, 2.15]	[0.33, 1.07]
2006	136.5	1.35	0.67
		[0.63, 2.06]	[0.32, 1.03]
2007	139.5	1.38	0.69
		[0.63, 2.12]	[0.32, 1.06]
2008	138.7	1.43	0.71
		[0.67, 2.19]	[0.33, 1.09]
2005-2008 average	137.6	1.39	0.69
		[0.67, 2.11]	[0.33, 1.06]

Notes: All confidence intervals are adjusted for the complex survey design of the MEPS. The population estimates are obtained using the MEPS sampling weights. In order to obtain national representative estimates, we adjusted the sampling weights to account for sample attrition of the panel.

Table 6. Marginal effects from cross-sectional models using more flexible specifications

	(1)	(2)	(3)
Employment	-0.183***	-0.155***	-0.107***
	(0.010)	(0.010)	(0.010)
Hour	-0.189	-0.241	-0.397
	(0.355)	(0.362)	(0.368)
Log wage	-0.075***	-0.062***	-0.041**
	(0.015)	(0.014)	(0.015)
Higher order and interactions terms	No	Yes	Yes
Lags of correlated variables	No	No	Yes

Notes: Significance level: ***p<0.01, **p<0.05, *p<0.1; Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Models include cross-sectional probit and OLS regressions. Control variables include age and its square, gender, race and ethnicity, marital status, years of education completed before entering the survey, region, urban residence, union status, employer size (less than 25 employees, between 25-99 employees, between 100-500 employees, more than 500 employees), benefits provided by the employer (sick pay, retirement plan, and paid vacations), occupation and industry indicators, number of children under 5 or 18 in the household, log of income earned by other family members (normalized by household size), and year dummies

Table 7. Sensitivity analysis of coefficient on depression in the bivariate probit model of employment

	ρ = -0.4	ρ = -0.3	ρ = -0.2	ρ = -0.1	ρ = 0	ρ =ρ*= -0.52	ρ = ρ*/2= -0.26	CRE
Depression (PHQ-2 ≥ 3)	0.205***	0.009	-0.187***	-0.381***	-0.574***	0.432***	-0.074***	-0.091***
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)	(0.023)	(0.022)
	[0.053***]	[0.002]	[-0.053***]	[-0.113***]	[-0.176***]	[0.104***]	[-0.020***]	[-0.026***]

Note: Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses; Marginal effects in brackets; All standard errors are adjusted for the complex survey design of the MEPS. Models include cross-sectional bivariate probit regressions. Control variables include age and its square, gender, race and ethnicity, marital status, years of education completed before entering the survey, region, urban residence, number of children under 5 or 18 in the household, log of income earned by other family members (normalized by household size), and year dummies.

Appendix

1. Proof of equation (22):

Note that

$$\begin{aligned} \varphi_1 &\equiv \frac{\mathrm{cov}(D^*, X'\gamma)}{\mathrm{var}(X'\gamma)}, \\ \varphi_2 &\equiv \frac{\mathrm{cov}(D^*, \varepsilon)}{\mathrm{var}(\varepsilon)}. \end{aligned} \tag{23}$$

It follows that $\varphi_1 = \varphi_2$ is equivalent to

$$\begin{aligned} & \frac{\mathrm{cov}(D^*, X'\gamma)}{\mathrm{var}(X'\gamma)} = \frac{\mathrm{cov}(D^*, \varepsilon)}{\mathrm{var}(\varepsilon)} \\ \Rightarrow \quad & \frac{\mathrm{cov}(X'\beta + u, X'\gamma)}{\mathrm{var}(X'\gamma)} = \frac{\mathrm{cov}(D^*, \varepsilon)}{\mathrm{var}(\varepsilon)} \\ \Rightarrow \quad & \frac{\mathrm{cov}(X'\beta, X'\gamma)}{\mathrm{var}(X'\gamma)} = \frac{\mathrm{cov}(D^*, \varepsilon)}{\mathrm{var}(\varepsilon)} \end{aligned} \tag{24}$$

In the bivariate probit framework, $\mathrm{var}(\varepsilon) = 1$, and also

$$\rho = \mathrm{cov}(\varepsilon, u) = \mathrm{cov}(\varepsilon, D^* - X'\beta) = \mathrm{cov}(\varepsilon, D^*). \tag{25}$$

Therefore, imposing $\varphi_1 = \varphi_2$ is equivalent to imposing $\rho^* = \dfrac{\mathrm{cov}(X'\beta, X'\gamma)}{\mathrm{var}(X'\gamma)}$.

2. Derivation of statistic used to assess impact of unobservables for continuous outcomes:

Write the linear projection of D onto X as

$$D = X'\beta + \tilde{D}. \tag{26}$$

By substituting (26) into (20), we have

$$Y^* = \alpha\tilde{D} + X'(\alpha\beta + \gamma) + \varepsilon. \tag{27}$$

Since $\tilde{D}$ is orthogonal to X by construction, the probability limit of the OLS estimator of α can be written as

$$\begin{aligned}\text{plim}\,\hat{\alpha} &= \alpha + \frac{\text{cov}(\tilde{D},\varepsilon)}{\text{var}(\tilde{D})} \\ &= \alpha + \frac{\text{var}(D)}{\text{var}(\tilde{D})}\left[E(\varepsilon \mid D=1) - E(\varepsilon \mid D=0)\right].\end{aligned} \tag{28}$$

The bias term in (28) is estimated under the assumption that the normalized degree of selection on observables is equal to the normalized degree of selection on unobservables. More formally, this is equivalent to

$$\frac{E(\varepsilon \mid D=1) - E(\varepsilon \mid D=0)}{\text{var}(\varepsilon)} = \frac{E(X'\gamma \mid D=1) - E(X'\gamma \mid D=0)}{\text{var}(X'\gamma)}. \tag{29}$$

Under the null hypothesis that depression has no effect ($\alpha = 0$), it is possible to obtain a consistent estimate of γ in (27). In this case, the term $E(\varepsilon \mid D=1) - E(\varepsilon \mid D=0)$ can be estimated using the variance of residual $\hat{\varepsilon}$ under (29). With the sample analog of $\text{var}(D)$ and $\text{var}(\tilde{D})$ we can consistently estimate the bias term in (28). The ratio between the unconstrained estimate of $\hat{\alpha}$ and the bias term

$$\frac{\hat{\alpha}}{\left[\text{var}(D)/\text{var}(\tilde{D})\right]\left[E(\varepsilon \mid D=1) - E(\varepsilon \mid D=0)\right]} \tag{30}$$

is used to gauge how large selection on unobservables must be relative to selection on observables to fully account for the effect of depression. If the ratio is less than 1, then the effect of depression in the OLS model is likely to be biased because it suggests the observed effect of depression could result from a relatively small degree of selection along unobservable dimensions.

Table A1. Correlated random effect probit models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	K-6 index	PHQ-2 index	K-6 ≥ 13	PHQ-2 ≥ 3	K-6 index	PHQ-2 index	K-6 ≥ 13	PHQ-2 ≥ 3
Constant	-3.111***	-3.242***	-3.448***	-3.396***	-3.296***	-3.420***	-3.674***	-3.588***
	(0.127)	(0.128)	(0.126)	(0.126)	(0.131)	(0.129)	(0.129)	(0.127)
Age	0.131***	0.131***	0.128***	0.127***	0.132***	0.133***	0.130***	0.129***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age squared/100	-0.167***	-0.167***	-0.163***	-0.162***	-0.168***	-0.168***	-0.164***	-0.163***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female	-0.418***	-0.422***	-0.431***	-0.430***	-0.409***	-0.413***	-0.423***	-0.422***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
Hispanic	-0.047*	-0.043*	-0.038	-0.040	-0.057**	-0.052**	-0.046*	-0.049*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Black	-0.107***	-0.088***	-0.088***	-0.077***	-0.106***	-0.084***	-0.085***	-0.072***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)
Other race	-0.100**	-0.089**	-0.092**	-0.081**	-0.101***	-0.089**	-0.093**	-0.078**
	(0.040)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)
Urban	0.050*	0.049*	0.049*	0.049*	0.043*	0.041*	0.041*	0.041*
	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
West	-0.033	-0.037	-0.040	-0.038	-0.031	-0.035	-0.038	-0.036
	(0.030)	(0.030)	(0.030)	(0.030)	(0.035)	(0.035)	(0.035)	(0.035)
Midwest	0.069**	0.063**	0.064**	0.064**	0.070**	0.062*	0.064*	0.065*
	(0.032)	(0.031)	(0.031)	(0.031)	(0.035)	(0.035)	(0.034)	(0.035)
South	0.005	0.005	0.002	0.002	0.011	0.012	0.009	0.009
	(0.027)	(0.027)	(0.026)	(0.026)	(0.032)	(0.032)	(0.033)	(0.032)
Education(years)	0.051***	0.051***	0.053***	0.052***	0.047***	0.047***	0.049***	0.048***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of children under 5	-0.232***	-0.228***	-0.228***	-0.226***	-0.240***	-0.236***	-0.237***	-0.234***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Number of children between 6-17	-0.080***	-0.079***	-0.078***	-0.078***	-0.083***	-0.082***	-0.081***	-0.080***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Married	0.152***	0.151***	0.167***	0.166***	0.026	0.025	0.027	0.026
	(0.022)	(0.022)	(0.022)	(0.022)	(0.049)	(0.049)	(0.050)	(0.050)
Log family income	-0.028***	-0.027***	-0.026***	-0.026***	-0.006*	-0.006*	-0.006*	-0.006*

	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
PCS score	0.029***	0.030***	0.032***	0.032***	0.002*	0.002*	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Depression measure	-0.050***	-0.160***	-0.720***	-0.574***	-0.012***	-0.037***	-0.119***	-0.091***
	(0.002)	(0.006)	(0.029)	(0.024)	(0.002)	(0.005)	(0.029)	(0.022)
Correlation Parameters								
Married period 1					-0.055	-0.051	-0.048	-0.046
					(0.048)	(0.048)	(0.050)	(0.048)
Married period 2					0.191***	0.187***	0.198***	0.196***
					(0.051)	(0.050)	(0.051)	(0.050)
Log family income period 1					-0.008**	-0.008**	-0.008**	-0.008**
					(0.003)	(0.003)	(0.003)	(0.003)
Log family income period 2					-0.018***	-0.018***	-0.017***	-0.017***
					(0.004)	(0.004)	(0.004)	(0.004)
PCS score period 1					0.018***	0.019***	0.020***	0.020***
					(0.001)	(0.001)	(0.001)	(0.001)
PCS score period 2					0.014***	0.014***	0.016***	0.015***
					(0.001)	(0.001)	(0.001)	(0.001)
Depression measure period 1					-0.024***	-0.080***	-0.448***	-0.346***
					(0.003)	(0.008)	(0.037)	(0.032)
Depression measure period 2					-0.022***	-0.072***	-0.353***	-0.320***
					(0.003)	(0.008)	(0.044)	(0.033)

Notes: The coefficients of the year dummies are omitted. Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Base categories are white and northeast.

Table A2. CRE linear regression models of weekly work hours and hourly wages

	Weekly hours worked				Log hourly wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	K-6 index	PHQ-2 index	K-6 ≥ 13	PHQ-2 ≥ 3	K-6 index	PHQ-2 index	K-6 ≥ 13	PHQ-2 ≥ 3
Constant	25.345***	25.553***	25.486***	25.459***	0.470***	0.439***	0.401***	0.422***
	(1.298)	(1.312)	(1.304)	(1.308)	(0.071)	(0.069)	(0.068)	(0.068)
Age	0.238***	0.239***	0.238***	0.238***	0.040***	0.040***	0.040***	0.040***
	(0.050)	(0.051)	(0.051)	(0.050)	(0.003)	(0.003)	(0.003)	(0.003)
Age squared/100	-0.320***	-0.321***	-0.321***	-0.320***	-0.042***	-0.041***	-0.041***	-0.041***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.003)	(0.003)	(0.003)	(0.003)
Female	-3.402***	-3.397***	-3.399***	-3.400***	-0.198***	-0.200***	-0.202***	-0.201***
	(0.160)	(0.161)	(0.160)	(0.161)	(0.009)	(0.009)	(0.009)	(0.009)
Hispanic	1.084***	1.072***	1.074***	1.073***	-0.062***	-0.061***	-0.059***	-0.060***
	(0.194)	(0.195)	(0.195)	(0.196)	(0.015)	(0.015)	(0.015)	(0.015)
Black	-0.208	-0.225	-0.222	-0.227	-0.120***	-0.115***	-0.114***	-0.114***
	(0.193)	(0.194)	(0.195)	(0.195)	(0.010)	(0.010)	(0.010)	(0.010)
Other race	0.151	0.148	0.148	0.141	-0.024	-0.022	-0.022	-0.021
	(0.341)	(0.313)	(0.312)	(0.313)	(0.018)	(0.018)	(0.018)	(0.018)
Urban	-0.694***	-0.691**	-0.693***	-0.690**	0.157***	0.156***	0.156***	0.156***
	(0.244)	(0.245)	(0.244)	(0.246)	(0.015)	(0.015)	(0.015)	(0.015)
Union	-0.762***	-0.764***	-0.763***	-0.759***	0.087***	0.087***	0.087***	0.087***
	(0.255)	(0.255)	(0.255)	(0.256)	(0.014)	(0.014)	(0.014)	(0.014)
West	0.530**	0.534**	0.534**	0.533**	0.022	0.022	0.022	0.022
	(0.246)	(0.247)	(0.247)	(0.247)	(0.016)	(0.016)	(0.016)	(0.016)
Midwest	0.705***	0.708***	0.706***	0.709***	-0.057***	-0.059***	-0.058***	-0.058***
	(0.226)	(0.226)	(0.226)	(0.266)	(0.014)	(0.014)	(0.014)	(0.014)
South	1.675***	1.677***	1.676***	1.674***	-0.063***	-0.063***	-0.063***	-0.063***
	(0.220)	(0.220)	(0.221)	(0.220)	(0.014)	(0.014)	(0.014)	(0.014)
Education(years)	-0.068**	-0.069**	-0.068**	-0.069**	0.071***	0.071***	0.071***	0.071***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.002)	(0.002)	(0.002)	(0.002)
Number of children under 5	-0.044	-0.045	-0.046	-0.046	0.020**	0.020**	0.021**	0.021**
	(0.121)	(0.121)	(0.121)	(0.121)	(0.009)	(0.009)	(0.009)	(0.009)
Number of children between 6-17	-0.261***	-0.262***	-0.262***	-0.262***	-0.005	-0.005	-0.005	-0.005
	(0.084)	(0.084)	(0.084)	(0.084)	(0.004)	(0.004)	(0.004)	(0.004)

Employer size < 25	0.188	0.191	0.189	0.191	-0.120***	-0.121***	-0.119***	-0.121***
	(0.231)	(0.232)	(0.231)	(0.231)	(0.011)	(0.011)	(0.011)	(0.011)
Employer size 25-99	0.921***	0.920***	0.922***	0.919***	-0.118***	-0.119***	-0.118***	-0.119***
	(0.210)	(0.210)	(0.210)	(0.209)	(0.012)	(0.012)	(0.012)	(0.012)
Employer size 100-500	0.293	0.296	0.298	0.294	-0.071***	-0.072***	-0.072***	-0.072***
	(0.220)	(0.200)	(0.200)	(0.201)	(0.011)	(0.011)	(0.011)	(0.011)
Sick pay	2.113***	2.116***	2.107***	2.114***	0.142***	0.143***	0.144***	0.144***
	(0.203)	(0.202)	(0.203)	(0.203)	(0.012)	(0.012)	(0.012)	(0.012)
Retirement plan	2.011***	2.012***	2.010***	2.021***	0.214***	0.214***	0.215***	0.214***
	(0.188)	(0.188)	(0.188)	(0.188)	(0.010)	(0.010)	(0.010)	(0.010)
Paid vacation	3.909***	3.898***	3.909***	3.895***	0.064***	0.065***	0.065***	0.065***
	(0.248)	(0.248)	(0.248)	(0.249)	(0.013)	(0.013)	(0.013)	(0.013)
Industry construction & manufacturing	1.974***	1.975***	1.978***	1.978***	0.121***	0.121***	0.121***	0.122***
	(0.260)	(0.260)	(0.259)	(0.262)	(0.015)	(0.015)	(0.015)	(0.015)
Industry professional & education	-0.103	-0.098	-0.101	-0.097	0.003	0.002	0.001	0.002
	(0.222)	(0.221)	(0.222)	(0.222)	(0.014)	(0.014)	(0.014)	(0.014)
Industry transportation & utility	0.995***	0.997***	0.997***	0.999***	-0.033**	-0.033**	-0.034**	-0.033**
	(0.268)	(0.267)	(0.267)	(0.267)	(0.014)	(0.014)	(0.014)	(0.013)
White collar occupations	-0.942***	-0.938***	-0.937***	-0.934***	0.067***	0.066***	0.066***	0.066***
	(0.222)	(0.221)	(0.220)	(0.222)	(0.012)	(0.012)	(0.012)	(0.012)
Log wage	0.761*	0.763*	0.762*	0.725*				
	(0.427)	(0.434)	(0.429)	(0.432)				
Married	0.164	0.156	0.164	0.130	-0.009	-0.008	-0.008	-0.009
	(0.223)	(0.228)	(0.223)	(0.238)	(0.014)	(0.014)	(0.014)	(0.014)
Log family income	-0.013	-0.013	-0.013	-0.012	0.000	0.000	-0.001	0.000
	(0.014)	(0.014)	(0.014)	(0.014)	(0.002)	(0.002)	(0.002)	(0.002)
PCS score	-0.010	-0.010	-0.010*	-0.010	0.000	0.000	0.000	0.000
	(0.006)	(0.006)	(0.006)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Depression index	-0.009	0.006	-0.148	-0.053	0.000	-0.004	-0.003	-0.004
	(0.012)	(0.033)	(0.185)	(0.163)	(0.001)	(0.003)	(0.014)	(0.012)
Correlation parameters								
Log wage period 1	-0.021	-0.027	-0.016	-0.001				
	(0.398)	(0.402)	(0.398)	(0.400)				
Log wage period 2	1.802***	1.799***	1.793***	1.813***				

	(0.522)	(0.522)	(0.521)	(0.525)				
Married period 1	-0.746**	-0.744**	-0.745**	-0.739**	0.024	0.024	0.023	0.024
	(0.338)	(0.338)	(0.337)	(0.338)	(0.025)	(0.025)	(0.025)	(0.025)
Married period 2	0.800**	0.796**	0.794**	0.823**	0.079***	0.078***	0.081***	0.080***
	(0.364)	(0.361)	(0.364)	(0.365)	(0.024)	(0.025)	(0.025)	(0.025)
Log family income period 1	-0.104***	-0.103***	-0.103***	-0.104***	-0.002	-0.002	-0.002	-0.002
	(0.029)	(0.029)	(0.029)	(0.029)	(0.002)	(0.002)	(0.002)	(0.002)
Log family income period 2	-0.004	-0.005	-0.005	-0.005	0.000	0.000	0.000	0.000
	(0.027)	(0.026)	(0.027)	(0.027)	(0.002)	(0.002)	(0.002)	(0.002)
PCS score period 1	0.005	0.005	0.005	0.005	0.003***	0.003***	0.003***	0.003***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.001)	(0.001)	(0.001)	(0.001)
PCS score period 2	0.027**	0.025**	0.025**	0.026**	0.002**	0.002**	0.002***	0.002***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.001)	(0.001)	(0.001)	(0.001)
Depression index period 1	-0.003	0.038	0.221	0.460	-0.006***	-0.014***	-0.068***	-0.069***
	(0.024)	(0.074)	(0.495)	(0.343)	(0.001)	(0.004)	(0.024)	(0.019)
Depression index period 2	0.037	-0.034	0.392	-0.006	-0.004***	-0.011**	-0.070***	-0.055***
	(0.031)	(0.099)	(0.643)	(0.413)	(0.001)	(0.004)	(0.025)	(0.017)

Notes: The coefficients of the year dummies are omitted. Significance level: ***p<0.01, **p<0.05, *p<0.1. Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Base categories are white, northeast, employer size > 500, and other services/public administration/military/unclassifiable industry.

Table A3. CRE ordered probit model models of work hour categories

	(1)	(2)	(3)	(4)
	K-6 index	PHQ-2 index	K-6 ≥ 13	PHQ-2 ≥ 3
Constant	-0.248	-0.244	-0.258	-0.237
	(0.208)	(0.205)	(0.206)	(0.203)
Age	0.043***	0.043***	0.042***	0.043***
	(0.007)	(0.008)	(0.007)	(0.007)
Age squared/100	-0.054***	-0.054***	-0.054***	-0.055***
	(0.009)	(0.009)	(0.009)	(0.009)
Female	-0.576***	-0.577***	-0.577***	-0.576***
	(0.026)	(0.027)	(0.026)	(0.026)
Hispanic	0.264***	0.264***	0.263***	0.264***
	(0.039)	(0.039)	(0.039)	(0.039)
Black	0.017	0.016	0.017	0.016
	(0.035)	(0.035)	(0.035)	(0.035)
Other race	0.239***	0.239***	0.239***	0.239***
	(0.058)	(0.058)	(0.058)	(0.058)
Urban	-0.030	-0.030	-0.031	-0.030
	(0.038)	(0.037)	(0.037)	(0.037)
Union	-0.140***	-0.140***	-0.140***	-0.140***
	(0.040)	(0.040)	(0.040)	(0.040)
West	0.150***	0.150***	0.151***	0.150***
	(0.039)	(0.039)	(0.039)	(0.039)
Midwest	0.129***	0.129***	0.129***	0.129***
	(0.036)	(0.036)	(0.036)	(0.036)
South	0.336***	0.336***	0.336***	0.336***
	(0.036)	(0.036)	(0.036)	(0.036)
Education(years)	-0.022***	-0.022***	-0.022***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.005)
Number of children under 5	0.004	0.004	0.004	0.004
	(0.022)	(0.022)	(0.022)	(0.022)
Number of children between 6-17	-0.028**	-0.028**	-0.028**	-0.028**
	(0.012)	(0.012)	(0.012)	(0.012)
Employer size < 25	-0.067**	-0.067**	-0.067**	-0.067**
	(0.031)	(0.031)	(0.031)	(0.031)

Employer size 25-99	0.074**	0.073**	0.074**	0.073**
	(0.032)	(0.032)	(0.032)	(0.032)
Employer size 100-500	0.045	0.045	0.045	0.046
	(0.031)	(0.031)	(0.031)	(0.032)
Sick pay	0.396***	0.395***	0.396***	0.396***
	(0.036)	(0.036)	(0.036)	(0.036)
Retirement plan	0.318***	0.318***	0.318***	0.318***
	(0.029)	(0.029)	(0.029)	(0.029)
Paid vacation	0.626***	0.625***	0.625***	0.625***
	(0.032)	(0.032)	(0.032)	(0.031)
Industry construction & manufacturing	0.519***	0.518***	0.520***	0.518***
	(0.054)	(0.055)	(0.054)	(0.055)
Industry professional & education	-0.183***	-0.183***	-0.182***	-0.183***
	(0.040)	(0.040)	(0.040)	(0.040)
Industry transportation & utility	-0.072	-0.072	-0.072	-0.072
	(0.045)	(0.045)	(0.045)	(0.045)
White collar occupation	-0.163***	-0.163***	-0.162***	-0.163***
	(0.039)	(0.039)	(0.039)	(0.039)
Log wage	0.161**	0.161**	0.161**	0.162**
	(0.066)	(0.067)	(0.067)	(0.067)
Married	0.065*	0.065*	0.065*	0.064*
	(0.036)	(0.036)	(0.036)	(0.036)
Log family income	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
PCS score	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Depression measure	-0.002	-0.001	-0.032	-0.027
	(0.002)	(0.005)	(0.032)	(0.022)
Cutoff				
µ1	0.723***	0.723***	0.723***	0.723***
	(0.015)	(0.015)	(0.015)	(0.015)
Correlation parameters				
Log wage period 1	-0.044	-0.044	-0.044	-0.044
	(0.050)	(0.050)	(0.050)	(0.050)

Log wage period 2	0.159**	0.159**	0.161**	0.158**
	(0.068)	(0.069)	(0.068)	(0.068)
Married period 1	-0.140**	-0.141**	-0.142**	-0.141**
	(0.071)	(0.071)	(0.071)	(0.071)
Married period 2	0.056	0.057	0.058	0.057
	(0.072)	(0.072)	(0.072)	(0.072)
Log family income period 1	-0.010**	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Log family income period 2	0.008*	0.008*	0.008*	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
PCS score period 1	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
PCS score period 2	0.003	0.003*	0.003*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Depression measure period 1	-0.002	-0.007	0.083	-0.030
	(0.003)	(0.010)	(0.066)	(0.041)
Depression measure period 2	0.004	0.007	0.005	0.031
	(0.004)	(0.014)	(0.087)	(0.059)

Notes: The coefficients of the year dummies are omitted. Significance level: ***p<0.01, **p<0.05, *p<0.1; Standard errors in parentheses are adjusted for the complex survey design of the MEPS using balanced repeated replication. Base categories are white, northeast, employer size > 500, and other services/public administration/military/unclassifiable industry.

Table A4. CRE zero-inflated ordered probit models of work loss days

	K-6 index		PHQ-2 index		K-6 ≥ 13		PHQ-2 ≥ 3	
	Inflation	Ordered probit	Inflation	Ordered probit	Inflation	Ordered probit	Inflation	Ordered probit
Constant	0.006	3.230***	0.112	3.335***	0.440	3.562***	0.207	3.497***
	(0.500)	(0.599)	(0.465)	(0.523)	(0.535)	(0.531)	(0.464)	(0.507)
Age	0.010	-0.022	0.010	-0.024	0.011	-0.022	0.013	-0.022
	(0.012)	(0.016)	(0.012)	(0.016)	(0.011)	(0.016)	(0.012)	(0.016)
Age squared/100	-0.025	0.029*	-0.026*	0.031*	-0.025*	0.028	-0.029**	0.029
	(0.015)	(0.018)	(0.014)	(0.018)	(0.014)	(0.017)	(0.014)	(0.018)
Female	0.182***	0.175***	0.191***	0.168***	0.209***	0.168**	0.197***	0.175***
	(0.059)	(0.067)	(0.053)	(0.060)	(0.052)	(0.066)	(0.048)	(0.056)
Hispanic	-0.247***	-0.006	-0.248***	-0.021	-0.250***	-0.025	-0.254***	-0.018
	(0.053)	(0.059)	(0.055)	(0.062)	(0.046)	(0.059)	(0.051)	(0.063)
Black	-0.224***	0.108	-0.239***	0.090	-0.223***	0.086	-0.238***	0.070
	(0.073)	(0.078)	(0.064)	(0.085)	(0.064)	(0.079)	(0.061)	(0.085)
Other race	-0.216*	-0.088	-0.217*	-0.102	-0.223	-0.080	-0.213*	-0.097
	(0.111)	(0.152)	(0.121)	(0.147)	(0.111)	(0.151)	(0.113)	(0.141)
Union	-0.044	0.160	-0.043	0.161	-0.028	0.163**	-0.040	0.158
	(0.074)	(0.102)	(0.073)	(0.107)	(0.071)	(0.080)	(0.067)	(0.098)
Urban	0.083	0.007	0.082	0.013	0.074	0.015	0.080	0.021
	(0.061)	(0.064)	(0.059)	(0.061)	(0.054)	(0.060)	(0.060)	(0.060)
Education(years)	0.035**	-0.036***	0.033**	-0.036***	0.027	-0.036***	0.033*	-0.039***
	(0.015)	(0.010)	(0.017)	(0.010)	(0.018)	(0.011)	(0.017)	(0.010)
Number of children under 5	-0.086	0.212***	-0.092	0.210***	-0.059	0.188***	-0.088	0.207***
	(0.101)	(0.071)	(0.096)	(0.060)	(0.093)	(0.069)	(0.093)	(0.059)
Number of children between 6-17	-0.027	-0.016	-0.026	-0.020	-0.026	-0.016	-0.025	-0.021
	(0.022)	(0.028)	(0.025)	(0.027)	(0.020)	(0.026)	(0.024)	(0.028)
West	0.116**	-0.028	0.115**	-0.026	0.103*	-0.025	0.123**	-0.033
	(0.058)	(0.074)	(0.056)	(0.069)	(0.056)	(0.065)	(0.056)	(0.068)
Midwest	0.089	-0.038	0.098	-0.038	0.087	-0.038	0.102	-0.045
	(0.069)	(0.066)	(0.066)	(0.062)	(0.065)	(0.063)	(0.068)	(0.064)
South	0.113	-0.066	0.116*	-0.071	0.097	-0.062	0.119*	-0.070
	(0.070)	(0.056)	(0.065)	(0.055)	(0.072)	(0.056)	(0.067)	(0.057)
Employer size < 25	-0.024	-0.126**	-0.029	-0.115*	-0.043	-0.113**	-0.032	-0.110*

	(0.059)	(0.063)	(0.055)	(0.065)	(0.052)	(0.056)	(0.053)	(0.060)
Employer size 25-99	-0.022	-0.071	-0.027	-0.055	-0.026	-0.070	-0.032	-0.050
	(0.047)	(0.056)	(0.051)	(0.059)	(0.044)	(0.056)	(0.050)	(0.061)
Employer size 100-500	0.080	-0.003	0.074	0.013	0.074	0.006	0.075	0.014
	(0.056)	(0.057)	(0.060)	(0.060)	(0.053)	(0.058)	(0.057)	(0.058)
Sick pay	0.142*	0.025	0.128*	0.037	0.109	0.027	0.120*	0.030
	(0.075)	(0.109)	(0.068)	(0.110)	(0.067)	(0.093)	(0.063)	(0.100)
Retirement plan	0.057	-0.004	0.066	-0.010	0.051	-0.013	0.061	-0.014
	(0.049)	(0.072)	(0.054)	(0.073)	(0.045)	(0.067)	(0.054)	(0.072)
Paid vacation	0.146***	0.040	0.139**	0.038	0.141***	0.030	0.143**	0.031
	(0.055)	(0.093)	(0.059)	(0.092)	(0.049)	(0.083)	(0.058)	(0.086)
Industry construction & manufacturing	-0.073	-0.193	-0.066	-0.188	-0.096	-0.168	-0.057	-0.210*
	(0.153)	(0.158)	(0.147)	(0.153)	(0.153)	(0.155)	(0.148)	(0.143)
Industry professional & education	-0.077	-0.108	-0.070	-0.105	-0.087	-0.092	-0.058	-0.123
	(0.098)	(0.117)	(0.102)	(0.117)	(0.103)	(0.126)	(0.103)	(0.110)
Industry transportation & utility	-0.184***	-0.024	-0.179**	-0.025	-0.166***	-0.029	-0.164**	-0.041
	(0.069)	(0.095)	(0.070)	(0.100)	(0.060)	(0.093)	(0.065)	(0.093)
White collar occupation	0.172	-0.204***	0.175*	-0.196***	0.147	-0.190***	0.177*	-0.197***
	(0.121)	(0.067)	(0.104)	(0.061)	(0.117)	(0.063)	(0.099)	(0.059)
Married	0.094	0.119	0.099	0.113	0.078	0.114	0.108	0.103
	(0.121)	(0.082)	(0.124)	(0.078)	(0.115)	(0.074)	(0.116)	(0.079)
Log family income	-0.007	0.004	-0.007	0.004	-0.005	0.003	-0.007	0.004
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
PCS score	-0.018**	-0.035***	-0.018**	-0.035***	-0.021**	-0.033***	-0.019**	-0.035***
	(0.006)	(0.005)	(0.008)	(0.005)	(0.008)	(0.006)	(0.007)	(0.005)
Depression measure	0.018	0.028***	0.040	0.090***	0.109	0.325***	0.043	0.222**
	(0.013)	(0.009)	(0.036)	(0.030)	(0.116)	(0.093)	(0.120)	(0.092)
Cutoffs								
$\mu 1$	0.609**		0.600**		0.674*		0.603***	
	(0.298)		(0.240)		(0.345)		(0.226)	
$\mu 2$	0.926**		0.914***		1.008**		0.917***	
	(0.369)		(0.302)		(0.421)		(0.284)	
$\mu 3$	1.142***		1.128***		1.231***		1.131***	
	(0.403)		(0.333)		(0.457)		(0.314)	

μ4	1.309***	1.294***	1.403***	1.298***
	(0.424)	(0.352)	(0.478)	(0.332)
μ5	1.443***	1.427***	1.539***	1.430***
	(0.437)	(0.364)	(0.491)	(0.343)
Correlation parameters				
Married period 1	-0.083	-0.082	-0.071	-0.083
	(0.076)	(0.075)	(0.065)	(0.065)
Married period 2	-0.055	-0.054	-0.065	-0.063
	(0.060)	(0.059)	(0.059)	(0.060)
Log family income period 1	-0.003	-0.004	-0.004	-0.003
	(0.005)	(0.005)	(0.004)	(0.005)
Log family income period 2	0.000	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
PCS score period 1	0.001	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
PCS score period 2	-0.005***	-0.005***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Depression measure period 1	0.010***	0.032***	0.144***	0.146***
	(0.003)	(0.009)	(0.049)	(0.046)
Depression measure period 2	0.009	0.025**	0.146**	0.128***
	(0.005)	(0.010)	(0.057)	(0.040)

Notes: The coefficients of the year dummies are omitted. Significance level: ***p<0.01, **p<0.05, *p<0.1; Standard errors are adjusted for the complex survey design of the MEPS using balanced repeated replication. Base categories are white, northeast, employer size > 500, and other services/public administration/military/unclassifiable industry.