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Labor Supply of Poor Residents in Metropolitan Miami, Florida: The Role of Depression and the Co-Morbid Effects of Substance Use

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Abstract

Background: Depression represents one of the most common behavioral health problems among the workforce in the United States, with about 1 in every 20 employees experiencing this condition. A recent study estimated that in 1990 the economic costs of depressive disorders in the American workplace amounted to as much as $43 billion, with absenteeism alone accounting for $12 billion. Recently, economists have been focusing attention on the relationship between mental health and labor supply, but a lack of quality data sets containing detailed information on mental health and labor market variables represents a significant barrier to rigorous research.

Aims of the Study: The primary aims of the present study were to (i) examine the relationship between depression and employment, (ii) conditional on being employed, estimate the effect of depression on annual weeks worked, and (iii) examine the stability of the model estimates to the co-morbid effects of substance use (illicit drugs and alcohol), which has been consistently found to be a correlate of depression.

Data: The study used a unique set of survey data collected between 1996 and 1997 in crime-ridden and low-income neighborhoods of Miami-Dade County, Florida. A targeted sampling strategy was used to recruit chronic drug users (including injection drug users) and non-drug users to examine local health care delivery system characteristics in relation to the population of substance users. The final analysis sample for the present study included 1,274 adults, aged 18 to 65. Depression status was measured from the 20-item Zung Self-Rating Depression Scale (SDS) that classified 384 individuals as depressed and 890 as non-depressed. According to the definition developed by the U.S. Office of National Drug Control Policy for chronic drug use (CDU), about 46 percent of the depressed individuals were found to be CDUs compared to 30 percent of the non-depressed sample. The survey instrument collected information on alcohol use and problem drinking as defined by the 10-item Michigan Alcoholism Screening Test (MAST-10). Based on criteria defined in the MAST-10, 26 percent of the depressed individuals were problematic alcohol users (PAUs) compared to about 16 percent of the non-depressed sample.

Methods: The labor supply measures included employment in the past 30 days and number of weeks worked in the past 12 months. The analysis estimated a univariate probit model of employment as well as a bivariate probit model of depression and employment, which accounted for the possible correlation between the unobserved determinants of depression and employment. The annual weeks worked specification was estimated by a standard Tobit model as well as an instrumental variable (IV) Tobit model, which, in addition to the censoring of the observations, accounted for the possible endogeneity of depression. The stability of the estimated effects of depression to comorbid illicit drug and alcohol use was assessed, by controlling for CDU and PAU in these models.

Results: Results from both the univariate probit and the bivariate probit models indicate that depression significantly decreased the probability of being employed. Specifically, depression reduced the probability of employment by an average of 19 percentage points in both models, from a sample average of 43 percent for the non-depressed to 24 percent for the depressed. Estimates from the Tobit models revealed that depression also significantly reduced the number of weeks worked. Conditional on being employed, depressed individuals worked an average of 7 fewer annual weeks than the non-depressed sample in the univariate Tobit model and 8 fewer weeks in the IV Tobit. The findings also showed that the effects of depression on employment and annual weeks worked may be over-estimated if the analysis does not account for the comorbid influence of substance use.

Implications for Health Care Provision and Use: The results suggest that prevention and/or treatment of mental health problems such as depression may yield economic benefits by promoting employment and enhancing labor supply. While expansion of public mental health services may not lead to overall increases in employment, it may be justified on social grounds given the high unemployment rate in low-income and crime-ridden neighborhoods. Further insights can be gained by estimating these models with national and international data if one applies appropriate econometric tools to account for complex sample designs.

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Introduction

The first White House Conference on Mental Health and the first Surgeon General's Report on Mental Health reported that in 1999 nearly 20 million Americans were clinically depressed.[1] Depression represents one of the most common behavioral health problems of adults in the workforce; about 1

in every 20 employees experience depression.[1] A recent study estimated that the annual economic costs of depressive disorders in the American workplace amounted to $43 billion, with absenteeism alone contributing $12 billion.[2] Additional costs accrued from decreased productivity due to diminished energy, poor work habits, and problems with concentration, memory, and decision-making.[1]

For many individuals, personal conditions such as mental health problems may be one of the most important factors in influencing labor market decisions.[3,4] Bartel and Taubman[5] examined the effect of several diseases, including mental disorders, and found that individuals diagnosed as either psychotic or neurotic had a lower probability of being in the labor force, received lower wages, and worked fewer weekly hours. Mitchell and Anderson[6] explored the relationship between mental health and the labor force status of older American workers, aged 50 to 64. The authors found that mental illness negatively affected the labor force participation of older men, but had no significant effect on the labor force participation of older women. A recent study by Hamilton *et al.*[7] based on a data set of Montreal residents concluded that better mental health improved the probability of being employed. Ettner *et al.*[8] examined the impact of psychiatric disorders on employment, conditional work hours, and income for 2,225 men and 2,401 women from the U.S. National Comorbidity Survey. They found that psychiatric disorders reduced employment and conditional earnings among men and women as well as conditional work hours for men. French and Zarkin[9] used data from a large manufacturing worksite and found that workers who reported symptoms of emotional/psychological problems had higher absenteeism and lower earnings than otherwise similar coworkers. Depression has also been linked to a variety of negative functional outcomes associated with the labor market (Berndt *et al.*,[10] Hays *et al.*,[11] Conti and Burton,[12] Mintz *et al.*[13]). With regard to absenteeism in the workplace, depressive disorders tend to surpass other common chronic medical conditions such as heart disease and low back pain in terms of the average length of the disability period.[12]

The present study used a unique set of data collected in high-risk neighborhoods of Miami-Dade County, Florida, to examine the connection between depression and employment, and, conditional on being employed, the effect of depression on annual weeks worked. Using geo-coding procedures, high-risk communities were identified based on standardized scores for crime, drug use, and poverty. Hence, the individuals included in this study were predominantly poor, lived in crime-ridden neighborhoods, and many had drug problems. Another important aspect of these data is that detailed measurements of depression status were available on all subjects in the study. Namely, our measure of depression did not depend on a respondent having had contact with the health care system and obtaining a diagnosis from a clinician, a potential source of measurement error,[14] since most individuals with symptoms of depression do not generally seek treatment.[15,16]

Attempts to understand the relationships between depression and labor market problems should also investigate other possible co-occurring and confounding factors. One possible factor is substance use, which has been found to be a consistent correlate of depression.[17-20] SAMHSA[1] reported that substance use disorders were present in 32 percent of individuals with depressive disorders, and co-occurred in 27 percent of those with major depression and 56 percent of those with bipolar disorder. To conduct a richer analysis of the depression/labor supply relationships, the present study examined the stability of the model estimates to the co-morbid effects of substance use, including both alcohol and illicit drugs.

Methods

Empirical Models and Estimation Issues

Health problems associated with mental illness may cause an exogenous decrease in the usable time available, leading to an increase in the individual's reservation wage. Thus, the probability of employment would be lower, and conditional on employment, individuals with health problems would work fewer weeks in any given period. Alternatively, stresses associated with unemployment may be important factors distinguishing the depressed from the non-depressed. This endogenous relationship may also work through an income effect in two ways.[7] First, reduced income associated with employment gaps and other labor supply problems may lead to increased mental distress. Second, employed individuals may have more disposable income to spend on mental health services as well as increased access to mental health care through employer-provided insurance coverage. To the extent that mental health and physical health are positively correlated, even health insurance that solely covers physical health may also improve mental health. Finally, depressed and non-depressed individuals may differ in unobserved ways that impact skills and ability and, thus, are likely to affect employment outcomes. For example, mental disorders may make skill acquisition more costly and thereby result in lower skill levels among the mentally ill. On the job, individuals with mental disorders may experience lower productivity as a result of impaired concentration, reduced cognitive abilities, or absenteeism.[1] To account for these unobservable factors, we estimate a univariate probit model in which depression is modeled as an exogenous explanatory variable and a bivariate probit model that allows for the possible correlation of unobserved factors that are related to both depression and labor supply.

Two important aspects of the empirical models are worth noting: (i) the first response variable of interest, employment,† is binary, and (ii) the potentially endogenous right-hand side variable (depression) is also binary. In this context, employment (*Emp*) and depression status (*Dep*) are latent

† To account for the possible effect of depression on employment, the analysis did not distinguish between individuals who were unemployed (actively looking for job) and those who were not in the labor force.

variables that can be expressed through the following reduced-form two-equation model: †

$$Emp^* = \beta_1 X + \beta_2 Dep + \varepsilon \quad (1)$$

$$Emp = 1 \text{ if } Emp^* > 0 \text{ and } Emp = 0 \text{ if } Emp^* \leq 0$$

$$Dep^* = \delta_1 X + \delta_2 Z + \eta \quad (2)$$

$$Dep = 1 \text{ if } Dep^* > 0 \text{ and } Dep = 0 \text{ if } Dep^* \leq 0$$

where X is a vector of exogenous socio-demographic characteristics, Z is a vector of variables that identify the depression equation, the β's and δ's are parameters to estimate, and ε and η are error terms, containing among other things, omitted and unobserved characteristics of the individuals, with $E[\varepsilon]=E[\eta]=0$ and $Var[\varepsilon]=Var[\eta]=1$.

A likelihood function for the single-equation specification of employment, in which depression is exogenous, is the univariate probit that can be expressed as follows:

$$\Pr(Emp = 1) = \Phi(\beta_1 X + \beta_2 Dep) \quad (3)$$

where ϕ is the cumulative normal distribution.

A likelihood function for the simultaneous specification of employment and depression is the bivariate probit, which can be written as (see Maddala,[21] Greene[22,23]):

$$\Pr(Emp = 1, Dep = 1) = \Phi_b(\beta_1 X + \beta_2 Dep,\ \delta_1 X + \delta_2 Z,\ \rho) \quad (4)$$

where ϕ_β is the bivariate cumulative distribution function and $\rho = \text{cov}[\varepsilon, \eta]$ is the correlation coefficient.Maximum likelihood estimates of the parameter vectors β_1, β_2, δ_1, δ_2 as well as ρ from the bivariate probit model were derived by maximizing the log-likelihood of the two jointly determined depression and employment variables.‡

Since ρ measures the correlation between the unobserved or omitted factors in both equations, it is roughly the correlation between the depression and employment outcomes after accounting for the influence of the included factors. If ρ is not significantly different from 0, it implies that maximum likelihood estimation of Equation (3) will be consistent. A statistically significant positive correlation implies that unobserved factors increase both the probability of depression and employment and, therefore, the univariate probit model will overestimate the impact of depression. A statistically significant negative correlation implies that the univariate probit specification will underestimate the impact of depression on employment.

The empirical analysis also estimated the effect of depression on the number of annual weeks worked. In addition to the potential endogeneity of depression, another estimation issue with the weeks worked specification was the censoring of the observations.[27] The weeks worked variable displayed a large number of zeros since a nonzero outcome (weeks worked > 0) was observed only if the individual was working. An appropriate approach to modeling censored dependent variables is the Tobit model, which can be formulated as:

$$Weeks^* = \gamma_1 X + \gamma_2 Dep + v \quad (5)$$

$$Weeks = Weeks^* \text{ if } Weeks^* > 0 \text{ and } Weeks = 0 \text{ if } Weeks^* \leq 0$$

where *Weeks**, denoting the number of weeks worked in the past 12 months, is a latent variable that is observed only when it is positive. The other variables are as previously defined, and v is the error term.

The Tobit model has been modified in many ways to deal with potential bias associated with unobserved or omitted variables.[25,26,28-33] This paper used a variation of a two-step instrumental variables (IV) technique suggested by Nelson and Olsen[28] and Newey,[32] which consists of substituting the predicted probability of depression from Equation (2) in the annual weeks worked equation (Equation (5))' and estimating a Tobit maximum likelihood specification. To correct for potential measurement error in the estimated standard errors,[21,34,35] the analysis used bootstrapping. While research has cast doubt on the Tobit model because of the strict assumption of normality,[36,37] the model has been extended in applied work to deal with such diverse topics as the number of hours worked by women in the labor force,[27] unemployment,[38] the expected wage at retirement,[39] the number of arrests following release from prison,[40] vacation expenditures,[41] or number of extramarital affairs.[42,43] Additionally, Newey *et al.*[33] argue that specification of the regression function and the set of instrumental variables are more important in the IV Tobit model than specification of the error distribution.

The core demographic variables (X) hypothesized to affect depression and labor supply included age, gender, race, marital status, and years of schooling. The analysis also included age squared to account for nonlinear effects of age. Dummy variables were used to identify whether there were children living in the household, whether the individual was born in a foreign country, and whether the individual had received unearned income during the last 12 months.

The vector Z in Equations (2) and (4) included two instrumental variables that were determined a priori as being significantly related to depression, but unrelated to either employment or annual weeks worked (see Staiger and Stock,[44] Norton *et al.*[45]). The first variable was a composite measure of religiosity. It is equal to 1 if the respondent "considered himself/herself to be very religious" and agreed that "beliefs of his/her religious group strongly influenced his/her behavior." Cross-sectional and longitudinal studies have consistently found significant associations between religious beliefs and mental and physical health.[46] Religious involvement appears to have significant protective effects for the emotional well being of individuals in crisis.[47-49]

† Equation (2) does not include employment as an explanatory variable, as the likelihood function for the symmetric specification does not, in general, integrate to one.[21] In addition, the primary interest of the paper is the labor market effect of depression (See Greene,[22,23] Ribar[24]). Notice also that the variable *Dep* has a direct impact on *Emp** but not on the observed variable *Emp* (see Heckman,[25] Smith and Blundell[26]).

‡ The likelihood function for the bivariate proibit model is given in Greene[23] (page 850). Greene[23] (pages 83 and 180) also discusses the standard method of reducing a bivariate normal to a function of a univariate normal and the correlation ρ.

The second instrumental variable was the number of workers at individual and family services agencies per 10,000 residents in a particular zip code area. This variable was developed using population data and employment statistics by zip code for individual and family services agencies (4-digit Standard Industrial Classification (SIC) code 8322).[50,51] These services comprise a wide variety of individual and family assistance, including family and marriage counseling, youth organizations and centers, senior citizens organizations, child abuse information and treatment centers, suicide prevention services, as well as refugee, disaster, and temporary relief services. The per-capita adjusted individual and family services jobs were a proxy for neighborhood "individual and family social support" availability. Social support variables have been used as instruments in previous studies and were found to strengthen mental health status.[7]

Although the choice of these identifying variables is grounded in epidemiological research, some qualifications should be noted and explained. First, the assumption regarding the effects of religious involvement on depression is well documented in the literature. But, given the lower socioeconomic class and the higher percentage of substances abusers among the subjects in the study, these groups are at higher risk for mental disorders, which may lead to a weak or insignificant association between religiosity and depression in the analysis. Second, it is plausible that religiosity is related to labor supply because strongly religious persons may allocate more time to market work. Third, some concern may also be present with the other instrument used in the analysis, the per-capita adjusted individual and family services jobs (SIC 8322). If these services included activities such as vocational services and job placement assistance, a significant relationship may be present between the services variable and the labor supply variables. However, the analysis used the detailed SIC code 8322, which excluded organizations delivering vocational services, job training, and related services that are part of SIC code 8331.[50] Thus, we have greater confidence in this narrowly-defined instrument relative to a broadly defined services variable. To empirically address these reliability issues, the analysis tested whether these instruments were significantly related to depression but not related to labor supply.

A final objective of the analysis was to examine the stability of the estimated effects of depression to the comorbid effects of substance use. In this regard, we created measures for chronic drug use and problematic alcohol use, re-estimated the models with these new measures included among the control variables, and calculated the marginal effects of depression on employment and annual weeks worked. These new marginal effects were then compared to the estimates from the previous models. However, this approach introduces other statistical challenges, as substance use is potentially endogenous in both the depression and labor supply equations. While consistent estimates can still be obtained if the endogenous nature of substance use is ignored in formulating the log-likelihood function of the bivariate model in Equation (4),[23] absent additional instruments, separate identifications of depression and substance use were not plausible. Thus, the estimates derived from the models with comorbid substance use should be interpreted in the context of these considerations.

Sample and Data

The empirical analysis used a unique set of data collected between April 1996 and September 1997 from a lengthy questionnaire developed by the Health Services Research Center (HSRC) at the University of Miami. Several researchers at the University of Miami have described the study implementation and data collection methods in earlier studies.[18,52-54] A targeted sampling strategy was used to recruit illegal drug users (including injection drug users) and non-drug users to examine local health care delivery system characteristics in relation to the population of substance users. Targeted sampling is a strategy to obtain systematic data when true random sampling techniques are not possible and convenience sampling is not rigorous enough to meet the demands of the research design. It is an adaptation of aspects of theoretical sampling, stratified survey sampling, and network sampling.[55,56] The primary goals were to identify a broad spectrum of study-eligible participants and to develop a trust level that would minimize potential selection bias resulting from a high rate of refusal to participate.

Using geo-coding procedures, high-risk areas within Miami-Dade County were identified based on indicator data from drug treatment, criminal justice, and street outreach databases.[57] A high-risk designation was based on above average scores for crime, drug use, and poverty indicators. Once high-risk communities were identified, the study conducted further ethnographic mapping to delineate the locations, and specific plans for recruiting in each community were developed.

Subjects were recruited from high-risk areas that spanned 78 zip codes. Non-drug users were recruited from the same areas as drug users. Three full-time outreach workers visited these neighborhoods and potential participants were screened in the community. The outreach workers recruited subjects at all times and days of the week to obtain a representative sample of both drug users and non-drug users. Consenting individuals who appeared to be eligible were provided round-trip transportation to a central assessment center for a more comprehensive screening. Eligibility at the center was determined through a brief screening prior to full administration of the instrument. Individuals were excluded from the study if they (i) were significantly impaired, (ii) had difficulty understanding the questions, (iii) were violent or abusive, or (iv) misreported their eligibility as revealed by laboratory reports of their specimens. The study purpose and confidentiality issues were explained to all potential participants and an informed consent document was signed. After passing the full eligibility criteria, the subjects were escorted to a private room to complete the questionnaire with the assistance of an experienced survey administrator. Total participant time (including transportation) generally ranged from 1.5 to 2.5 hours. Each participant was paid 25 dollars. Less than five percent of the participants who were transported to the assessment site were found to be study-ineligible or

refused to participate in the study.

The final data set offered a unique source of information to analyze depression and labor supply relationships. The labor supply variables were consistent with standard definitions of labor market status.[58] Information on the respondent's employment status was obtained from a question that contained ten mutually exclusive responses regarding work status during the past 30 days: (i) regular full-time work (at least 35 hours/week); (ii) regular part-time work (less than 35 hours/week); (iii) occasional work; (iv) not working, actively seeking employment; (v) not working, not actively seeking employment; (vi) retired; (vii) unable to work – disabled; (viii) full-time homemaker; (ix) full-time student; (x) other specified status. Responses to categories (i), (ii), and (iii) defined the employed individuals. To account for the possible effect of depression on employment, the analysis did not distinguish between individuals who were unemployed (actively looking for job) and those who were not in the labor force. The number of weeks worked at a job in the past 12 months, including paid vacation(s) and sick leave, was recorded as a categorical variable and then converted to a continuous measure by taking the midpoint of the intervals. The five mutually exclusive and collectively exhaustive categories—0 weeks, 1-13 weeks, 14-26 weeks, 27-39 weeks, and 40-52 weeks—contained 41 percent, 21 percent, 13 percent, 8 percent, and 17 percent of the respondents, respectively.

Depression status was measured from the 20-item Zung Self-Rating Depression Scale (SDS). The SDS was chosen because it is brief, reliable, and highly correlated with other depression scales.[59] It also uses simple language and spans a wider range of education levels than other scales.[18] The SDS rates depression as a syndrome and documents its severity levels. The developers classify four clusters: normal, minimum to mild, moderate to marked, and severe to extreme. Pharmacological interventions would likely be considered for individuals who were classified within moderate and severe categories.[18] For the present analysis, those who might require pharmacological intervention (moderately to severely depressed) were coded as depressed, and those not likely to require intervention (non- to mildly depressed) were coded as non-depressed. Of the 1,274 subjects, aged 18 to 65, included in the final sample, 384 were classified as depressed and 890 as non-depressed.

Drug-using status was based on criteria specified by the Office of National Drug Control Policy (ONDCP),[60] and comprised chronic drug users (CDUs) and non-drug users (NDUs). CDUs included individuals who used illicit drugs (including injection) once a week or more during the previous 12 months and tested positive for cocaine and/or opiates on a urine screen. NDUs included individuals who (i) never used cocaine or opiates, but (ii) may have used marijuana less than 13 times during the past 12 months. According to this definition, about 46 percent of the depressed individuals were also CDUs, compared to 30 percent of the non-depressed sample.

The survey instrument collected information on alcohol use and problem drinking from the 10-item brief Michigan Alcoholism Screening Test (MAST-10). Test content of the MAST-10 refers to the respondent's self-appraisal of his/her drinking habits and the eventual social, physical, and psychological complications associated with problematic alcohol use. Items were weighted based on severity rankings and summed to produce an overall diagnostic score. A score of six or more on the MAST-10 distinguished problematic alcohol users (PAUs) from non-problem users (NPAUs), with the latter group including light drinkers and non-drinkers.[61,62] Based on these criteria, 26 percent of the depressed individuals were PAUs compared to approximately 16 percent of the non-depressed sample.

Table 1 presents mean values for all variables used in the analysis, by depression status. A two-stage quota sampling design was used to insure inclusion of adequate numbers of women and ethnic groups. Subsamples by gender and race/ethnicity included 725 men, 549 women, 486 Blacks, 385 Hispanics, and 403 non-Hispanic Whites. Most of the variables displayed significant differences in mean values across depression status ($p<0.05$, Kruskal-Wallis equality of populations rank test). Depressed individuals were less likely to be employed and worked almost 10 fewer weeks relative to non-depressed individuals. More than 46 percent of the non-depressed individuals were employed within 30 days of the interview, compared to 22 percent of the depressed sample. About 28 percent of the non-depressed employed individuals were working full time, relative to 18 percent of the depressed employed individuals. Overall, only 26 percent of the employed individuals worked full time during the 30 days preceding the interview. Finally, non-depressed individuals who were employed at the time of the interview worked an average of 29 annual weeks during the past 12 months, compared to 22 weeks for the depressed individuals who were classified as employed. The conditional average number of annual weeks worked for the full sample was 28 weeks. The following section presents the results of the univarite probit, bivariate probit, and Tobit models.

Results

Determinants of Depression

Estimation results from both the univariate and bivariate models of depression and employment are presented in **Table 2**. It is interesting to note that the qualitative and quantitative findings were almost identical across models. The probability of being depressed was a concave function with age. Men were less likely to be depressed than women. African-Americans were less likely to be depressed relative to other ethnic groups. Being of Hispanic origin and marital status had no significant relationship with the probability of depression. Years of schooling, having children in the household, and foreign birth were all inversely related to the probability of depression, whereas receiving unearned income was positively related to depression. As expected, strong religious beliefs and per-capita adjusted number of social services jobs in a respondent's neighborhood significantly reduced the likelihood of being depressed.

Table 1. Variable means, by depression status

Variable	Depressed (N=384)	Non-Depressed (N=890)	Full Sample (N=1,274)
Labor Supply			
Employed**	0.2214	0.4618	0.3893
	(0.4157)	(0.4988)	(0.4878)
Employed Full Time	0.1765	0.2822	0.2641
	(0.3835)	(0.4506)	(0.4413)
Annual Weeks Worked**	7.64	17.39	14.45
	(13.12)	(17.97)	(17.24)
Conditional Annual Weeks Worked‡,**	22.04	28.78	27.63
	(16.35)	(16.44)	(16.60)
Substance Use Status			
Chronic Drug Users**	0.4609	0.3000	0.3485
	(0.4991)	(0.4585)	(0.4767)
Problematic Alcohol Users**	0.2604	0.1562	0.1876
	(0.4394)	(0.3632)	(0.3905)
Socio-Demographics			
Age	36.53	37.69	37.34
	(8.42)	(9.87)	(9.47)
Male	0.4766	0.6080	0.5270
	(0.5001)	(0.4883)	(0.4950)
African-American	0.2943	0.4191	0.3415
	(0.4563)	(0.4937)	(0.4859)
Hispanic	0.3411	0.2854	0.3022
	(0.4747)	(0.2854)	(0.4594)
White	0.3620	0.2955	0.3155
	(0.4812)	(0.4565)	(0.4649)
Married	0.2865	0.2506	0.2614
	(0.4527)	(0.4336)	(0.4396)
Highest Grade Completed**	10.74	11.44	11.23
	(2.58)	(2.52)	(2.56)
Any Children in Household	0.1088	0.1691	0.1510
	(0.3118)	(0.3750)	(0.3582)
Foreign Birth	0.1406	0.2056	0.1860
	(0.3481)	(0.4044)	(0.3893)
Any Unearned Income**	0.5938	0.3506	0.4239
	(0.4918)	(0.4774)	(0.4945)
Instrumental Variables			
Strongly Religious**	0.3359	0.4685	0.4286
	(0.4729)	(0.4993)	(0.4951)
Jobs in Individual and Family	46.90	58.04	54.70
Social Services Agencies†,**	(69.37)	(64.49)	(66.16)

Note: Standard deviations are in parentheses.
** Significant differences between the Depressed and the Non-Depressed samples, $p \leq 0.01$
* Significant differences between the Depressed and the Non-Depressed samples, $p \leq 0.05$
‡ Sample sizes for the conditional annual weeks worked as follows: Depressed (N=85), Non-Depressed (N=411), and Full Sample (N=496).
† Total number of jobs in individual and family social services agencies per 10,000 residents in a particular zip code.

Effects of Depression on Employment

Maximum likelihood estimates of the parameters from the univariate probit and bivariate probit models of employment are reported in the lower portion of **Table 2**. Most importantly, the results in both the univariate probit and the bivariate probit models indicate that depression significantly reduced the probability of employment. The marginal effects of depression on employment, evaluated at the mean values for the other variables, were calculated as the difference in

Table 2. Estimation results for depression and employment

Variable	Univariate Probit		Bivariate Probit	
	Coefficent Estimates	Standard Errors	Coefficent Estimates	Standard Errors
Depression Equation				
Age	0.0949**	0.0275	0.0987**	0.0273
Age Squared	-0.0013**	0.0004	-0.0013**	0.0004
Male	-0.4538**	0.0846	-0.4577**	0.0842
Black	-0.2631**	0.0979	-0.2605**	0.0961
Hispanic	0.0402	0.1020	0.0395	0.1012
Married	-0.0024	0.0888	-0.0075	0.0878
Highest Grade Completed	-0.0663**	0.0158	-0.0629**	0.0158
Any Children in Household	-0.3921**	0.1241	-0.3889**	0.1223
Foreign Birth	-0.4756**	0.1508	-0.5316**	0.1511
Any Unearned Income	0.0947**	0.0166	0.0935**	0.0165
Strongly Religious	-0.1876**	0.0863	-0.1828*	0.0791
Jobs in Individual and Family Social Services Agencies†	-0.0015**	0.0006	-0.0014**	0.0006
Constant	-1.4629**	0.5661	-1.6337**	0.5685
Employment Equation				
Depressed	-0.5345**	0.0901	-1.6217**	0.3196
Age	-0.0091	0.0238	0.0262	0.0268
Age Squared	-0.00002	0.0003	-0.0005	0.0003
Male	0.8546**	0.0866	0.5586**	0.1781
Black	-0.2454**	0.0938	-0.3222**	0.0884
Hispanic	-0.1976*	0.1009	-0.1528	0.0992
Married	0.0256	0.0883	0.0227	0.0824
Highest Grade Completed	0.0405**	0.0155	0.0090	0.0200
Any Children in Household	0.0787	0.1204	-0.0821	0.1297
Foreign Birth	0.3529**	0.1316	0.2952	0.1593
Any Unearned Income	-0.0595**	0.0184	-0.0089	0.0273
Constant	-0.2329	0.5010	-0.1933	0.4746
Marginal Effect of Depression on Employment	-0.1908**	0.0301	-0.1875**	0.0367
χ^2 for LR test of ρ=0 (H_0: Independent Equations)	—	—	2.96	—

** Statistically significant, $p \leq 0.01$
* Statistically significant, $p \leq 0.05$
† Total number of jobs in individual and family social services agencies per 10,000 residents in a particular zip code.

expected probabilities of employment between the depressed and the non-depressed samples.[22,23,63,64] The results from both the univariate probit and the bivariate probit models indicate that depression reduced the probability of being employed by about 19 percentage points, from a sample average prediction of 43 percent for the non-depressed to 24 percent for the depressed. The magnitude of this depression effect on employment is substantial, especially compared to earlier studies. For example, Ettner *et al.*[8] examined psychiatric disorders and employment in the United States and found a marginal effect of 11 percentage points for both men and women, aged 15 to 54.

In both the univariate and bivariate models, men were more likely to be employed than women, and African-Americans had a lower probability of employment relative to other racial groups. Although the univariate probit model indicates that being of Hispanic origin, years of schooling, foreign birth, and unearned income were significant predictors of employment, these control variables were not significant in the bivariate probit model.

We also conducted a likelihood ratio test of the null hypothesis that ρ=0. Under the null hypothesis, the log likelihood for the bivariate probit model is equal to the sum of the log likelihood of the two univariate probit models. The likelihood ratio statistic, distributed as chi-squared with one degree of freedom, failed to reject the null hypothesis that the depression and employment equations were independent ($\chi^2(1)=2.9627$; $p=0.0852$). This implies that the depression and employment equations can be consistently estimated by separate univariate probit specifications without being seriously affected by the correlation of unobserved factors across specifications.

Table 3. Estimation results for annual weeks worked

Variable	Univariate Tobit	Instrumental Variables Tobit
Depressed	-12.1894**	-13.7865**
	(1.7021)	(5.5387)
Age	-0.3808	0.6424
	(0.4545)	(0.7028)
Age Squared	0.0008	-0.0129
	(0.0058)	(0.0092)
Male	16.5111**	13.6100**
	(1.6294)	(2.4870)
Black	-5.0378**	-8.8681**
	(1.7569)	(2.6377)
Hispanic	-0.2851	-0.4484
	(1.8854)	(1.9208)
Married	-0.0807	-0.0228
	(1.6533)	(1.6866)
Highest Grade Completed	2.0316**	1.3909**
	(0.2913)	(0.4645)
Any Children in Household	0.9029	2.4736
	(2.2637)	(2.2992)
Foreign Birth	7.1313**	2.2403
	(2.4312)	(3.6207)
Any Unearned Income	-1.8068**	-0.8413
	(0.3494)	(0.6894)
Constant	1.2347	-27.4197*
	(9.4973)	(10.6507)
Marginal Effect of Depression	-7.2770**	-8.2170**
	(1.0161)	(3.3012)
F-value for Smith-Blundell Test (H_0: Depression is Exogenous)	—	3.3157

Notes: Standard errors reported in parentheses.
** Statistically significant, $p \leq 0.01$
* Statistically significant, $p \leq 0.05$

Effects of Depression on Annual Weeks Worked

Results from the standard Tobit as well as the IV Tobit of annual weeks worked are presented in **Table 3**. To test for the endogeneity of depression in the weeks worked equation, the analysis used the Smith-Blundell test of exogeneity.[26] This test is related to the Davidson and MacKinnon auxiliary test for exogeneity in a regression context, which in turn is a convenient alternative to the commonly used Hausman test.[65-67] It was conducted under the assumption that the IV Tobit estimates were consistent. Under the null hypothesis, the predicted depression variable in the weeks worked equation should have no explanatory power. The null hypothesis that depression was exogenous in the annual weeks worked equation was not rejected ($F(1,1262)=3.3157$; $p=0.0689$). Marginal effects, estimated as the difference in expected annual weeks worked between the non-depressed and the depressed samples, are presented at the bottom of **Table 3**. The results from the univariate Tobit and the IV Tobit models indicate that depressed individuals worked an average of 7 and 8 fewer weeks than the non-depressed sample during the past 12 months. Men worked more weeks than women. Blacks had fewer annual weeks of work than people of other racial groups. Years of education was positively related to annual weeks worked. Foreign birth and having received unearned income were related to annual weeks worked in the univariate Tobit model, but not in the IV Tobit model.

Table 4. Effects of depression on employment and annual weeks worked: alternative identification restrictions

Estimate or Statistic	Depression Modeled as Endogenous, Identified by:			
	Depression Modeled as Exogenous	Religious Beliefs and Social Services Jobs†	Religious Beliefs	Social Services Jobs†
Marginal Effect of Depression on Employment	-0.1908** (0.0301)	-0.1875** (0.0367)	-0.2026** (0.3014)	-0.1839** (0.0392)
χ^2 for LR test of ρ=0 (H_0: Independent Equations)	—	2.9627	3.0015	2.1321
Marginal Effect of Depression on Annual Weeks Worked	-7.2770** (1.0161)	-8.2170** (3.3012)	-8.4074 (5.0468)	-8.1380 (4.3368)
F-value for Smith-Blundell Test (H_0: Depression is Exogenous)	—	3.3157	1.4775	1.8850

** Statistically significant, $p \leq 0.01$
* Statistically significant, $p \leq 0.05$
† Total number of jobs in individual and family social services agencies per 10,000 residents in a particular zip code.

Sensitivity and Specification Tests of the Effects of Depression

The coefficient estimates for the effects of depression on employment and annual weeks worked in **Table 2** and **Table 3** were subjected to several sensitivity and specifications tests. To examine the sensitivity of the results to gender and ethnic differences, separate models were estimated for subsamples of men and women as well as for subsamples of individuals of African, non-African, Hispanic, and non-Hispanic origins. While most of the results for these subsamples confirm the negative effects of depression on employment and annual weeks worked obtained for the full sample, coefficient estimates for the male, African-American, and Hispanic subsamples were insignificant in both the bivariate probit and the IV Tobit models.† Small sample sizes and diminished outcome variability in these models may account for the insignificant results.

The analysis also paid particular attention to testing the instrumental variables criteria. First, the joint significance of the identifying variables (p<0.01), a necessary condition for the reliability of instruments, indicated that they were good predictors of depression. This also implied that the model estimates should be less sensitive to minor violations of the other assumptions of the model.[68] Second, we tested the overidentifying restrictions using a simple test described by Norton *et al.*[45] and Bollen *et al*.[69] The test compares the performance of the univariate labor supply specifications with and without the excluded exogenous variables. We used a Wald statistic to test the null hypothesis that the instruments were jointly equal to zero. We failed to reject the null hypothesis in both the employment equation ($\chi^2(2)$=0.04; p=0.9797) and the annual weeks worked equation (F(1,1262)=0.36; p=0.6972), supporting the assumption that the instruments were excludable from the labor supply equations.

The sensitivity of the estimated effects of depression on employment and annual weeks worked to alternative identification assumptions was also examined. For comparison purposes, the relevant estimates from **Table 2** and **Table 3** appear in the first and second columns of **Table 4**, and the last two columns list estimation results of models using each of the identifying variables (religious beliefs and jobs in social services agencies) independently. Again, these alternative specifications yielded coefficient estimates that were similar to the original specifications, but the marginal effects of depression on annual weeks worked were not significant for either the religiosity variable specification (p=0.09) or the per-capita adjusted individual and family social services jobs specification (p=0.06).

Comorbid Effects of Substance Use

As explained earlier, to assess the stability of the estimated effects of depression to the comorbid effects of substance use we controlled for chronic drug use and problematic alcohol use in the employment and annual weeks worked equations and re-estimated the models. **Table 5** and **Table 6** present the maximum likelihood estimates and the calculated marginal effects. As expected, CDU and PAU were positively related to depression, but were not significant in any of the labor supply specifications. When controlling for CDU and PAU, the coefficient estimates for depression remained significant in all of the labor supply specifications, but the marginal effects of depression generally decreased, suggesting that part of the estimated effects of depression reported in **Tables 2-4** was due to the co-occurring and confounding effect of substance use. Stated differently, the effects of depression on employment and annual weeks worked may be over-estimated if the analysis does not account for the comorbid influence of substance use.

† These gender- and ethnicity-specific estimates are available from the correspondig author.

Table 5. Estimation results for depression and employment with substance use co-morbidity

Variable	Univariate Probit		Bivariate Probit	
	Coefficent Estimates	Standard Errors	Coefficent Estimates	Standard Errors
Depression Equation				
Chronic Drug User	0.2211**	0.0833	0.2116**	0.0834
Problematic Alcohol User	0.3566**	0.0998	0.3471**	0.1005
Age	0.0780**	0.0277	0.0814**	0.0279
Age Squared	-0.0010**	0.0004	-0.0011**	0.0004
Male	-0.4808**	0.0866	-0.4834**	0.0862
Black	-0.2190*	0.0994	-0.2193**	0.0984
Hispanic	0.0933	0.1037	0.0906	0.1033
Married	-0.0076	0.0896	-0.0100	0.0891
Highest Grade Completed	-0.0596**	0.0160	-0.0579**	0.0160
Any Children in Household	-0.3283**	0.1256	-0.3258**	0.1246
Foreign Birth	-0.4896**	0.1535	-0.5318**	0.1563
Any Unearned Income	0.0904**	0.0166	0.0900**	0.0166
Strongly Religious	-0.1824*	0.0872	-0.1855*	0.0835
Jobs in Individual and Family Social Services Agencies†	-0.0016**	0.0006	-0.0016**	0.0006
Constant	-1.4428**	0.5673	-1.5482**	0.5748
Employment Equation				
Depressed	-0.5315**	0.0908	-1.3645**	0.4862
Chronic Drug User	0.0297	0.0836	0.0929	0.0895
Problematic Alcohol User	-0.0602	0.1003	0.0426	0.1178
Age	-0.0092	0.0241	0.0109	0.0274
Age Squared	-0.00001	0.0003	-0.0003	0.0003
Male	0.8625**	0.0874	0.6696**	0.1889
Black	-0.2519**	0.0944	-0.3050**	0.0934
Hispanic	-0.2029*	0.1016	-0.1665	0.1042
Married	0.0228	0.0884	0.0206	0.0854
Highest Grade Completed	0.0406**	0.0156	0.0208	0.0210
Any Children in Household	0.0784	0.1210	-0.0166	0.1347
Foreign Birth	0.3587**	0.1319	0.2085	0.1708
Any Unearned Income	-0.0595**	0.0184	-0.0257	0.0299
Constant	-0.2272	0.5011	-0.1750	0.4873
Marginal Effect of Depression on Employment	-0.1757**	0.0287	-0.1494**	0.0527
χ^2 for LR test of ρ=0 (H_0: Independent Equations)	—	—	1.3383	—

** Statistically significant, $p \leq 0.01$
* Statistically significant, $p \leq 0.05$
† Total number of jobs in individual and family social services agencies per 10,000 residents in a particular zip code.

Conclusions and Suggestions for Further Research

This study used a unique set of community-based information from low-income and high-crime neighborhoods to examine the relationships between depression and employment and, conditional on being employed, estimated the effect of depression on annual weeks worked. The employment analysis used a univariate probit model and a bivariate probit specification that accounted for possible unobserved heterogeneity between depression and employment. Coefficient estimates for the annual weeks worked model were derived using a standard Tobit as well as an IV Tobit method suggested by Nelson and Olsen[28] and Newey.[32] The Tobit models accounted for the censoring of the observations and the potential endogeneity of depression.

Results indicate that depression reduced the probability of being employed and the number of weeks a person worked during the last 12 months. These results were subjected to several sensitivity and specification analyses, and the findings were relatively stable. Most coefficient estimates maintained sign and magnitude, and significance level across specifications changed only slightly. To assess the stability of the estimated effects of depression to co-occurring substance use, the analysis included chronic drug use and problematic alcohol use in the employment and annual weeks worked specifications. The results suggest that, in addition to depression, co-morbid substance use contributed to the effects

Table 6. Estimation results for annual weeks worked with substance use co-morbidity

Variable	Univariate Tobit	Instrumental Variables Tobit
Depressed	-12.1964**	-13.0859**
	(1.7180)	(5.3654)
Chronic Drug User	-1.2630	1.1965
	(1.5700)	(2.0984)
Problematic Alcohol User	1.2675	4.7294
	(1.8694)	(2.7319)
Age	-0.3503	0.4272
	(0.4609)	(0.6236)
Age Squared	0.0003	-0.0100
	(0.0059)	(0.0081)
Male	16.3300**	13.1812**
	(1.6414)	(2.6194)
Black	-4.8940**	-7.9278**
	(1.7674)	(2.4005)
Hispanic	-0.1914	0.2674
	(1.8964)	(1.9564)
Married	0.0020	-0.0657
	(1.6553)	(1.6873)
Highest Grade Completed	2.0207**	1.4840**
	(0.2929)	(0.4296)
Any Children in Household	0.8369	2.1819
	(2.2751)	(2.3125)
Foreign Birth	6.9570**	2.1642
	(2.4366)	(3.6280)
Any Unearned Income	-1.7954**	-0.9436
	(0.3509)	(0.6469)
Constant	0.9155	-22.2250
	(9.5101)	(13.2573)
Marginal Effect of Depression	-7.2806**	-7.8010**
	(1.0255)	(3.1985)
F-value for Smith-Blundell Test (H_0: Depression is Exogenous)	—	3.1725

Notes: Standard errors reported in parentheses.
** Statistically significant, $p \leq 0.01$
* Statistically significant, $p \leq 0.05$

of depression on employment and annual weeks worked.

These findings offer support for the expansion of mental health services as a means to improve quality-of-life and promote economic benefits. Programs that prevent mental illness or improve mental health may sustain or even enhance work force productivity through avoided negative consequences of mental illness on employment and work time. Previous studies suggest that these programs were generally cost-effective, could substantially improve mental health, and increased employment and job retention.[70,71] While public health interventions may not lead to overall increases in employment, they may be justified on social welfare grounds given the high unemployment rate in low-income and crime-ridden communities. The findings reported here naturally have direct implications for certain neighborhoods in South Florida, but estimation of these models with national data would yield further insights to the role of depression in labor market outcomes.

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