Mental Health Disability and Labor Market Participation: A Comparative Analysis of Reservation Wage Estimation Methods

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Abstract

This paper presents the first application of stochastic frontier regression and bivariate probit selection methods to estimate reservation wages for individuals with psychiatric disabilities. Using Employment Intervention Demonstration Program data ($n = 1.648$), we compare these methods among Supported Employment participants. The stochastic frontier approach yields an average reservation wage of $5.25 per hour, while bivariate probit produces $4.50 per hour. Reliability tests indicate that bivariate probit shows greater consistency with labor search theory predictions. Because the sample consists of Supported Employment participants, the findings should not be generalized to all people with psychiatric disabilities. Our findings suggest that disability benefits may facilitate rather than hinder labor market participation until wealth reaches higher levels, with important implications for employment policy.

Keywords: Reservation wage; mental health disability; labor market participation; stochastic frontier; bivariate probit.
JEL Classification: C25, J21, J24, I14

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Discapacidad de salud mental y participación en el mercado laboral: un análisis comparativo de métodos de estimación de salarios de reserva

Resumen

Este artículo presenta la primera aplicación de regresión de frontera estocástica y métodos probit bivariado para estimar salarios de reserva en individuos con discapacidades psiquiátricas. Utilizando datos del Proyecto de Demostración de Intervención de Empleo ($n = 1.648$), comparamos estos métodos entre participantes de Empleo Apoyado. La frontera estocástica produce un salario de reserva promedio de $5.25 por hora, mientras que probit bivariado produce $4.50 por hora. Las pruebas demuestran que probit bivariado muestra mayor consistencia con predicciones de teoría de búsqueda laboral. Debido a que la muestra está compuesta por participantes de programas de Empleo Apoyado, los resultados no deben generalizarse a todas las personas con discapacidades psiquiátricas. Nuestros hallazgos sugieren que beneficios de discapacidad pueden facilitar participación en mercado laboral hasta niveles superiores de riqueza, con implicaciones importantes para política de empleo.

Palabras clave: salario de reserva; discapacidad de salud mental; participación en mercado laboral; frontera estocástica; probit bivariado.
Clasificación JEL: C25, J21, J24, I14

Deficiência relacionada à saúde mental e participação no mercado de trabalho: uma análise comparativa de métodos de estimativa de salários de reserva

Resumo

Este artigo apresenta a primeira aplicação da regressão de fronteira estocástica e dos métodos de probit bivariado com seleção amostral para estimar salários de reserva de pessoas com deficiências psiquiátricas. Utilizando dados do Employment Intervention Demonstration Program (n = 1.648), são comparados esses métodos entre participantes de programas de Empleo Apoyado. A abordagem de fronteira estocástica produz um salário de reserva médio de US$ 5,25 por hora, enquanto o modelo de probit bivariado com seleção amostral estima um valor de US$ 4,50 por hora. Os testes de confiabilidade indicam que o modelo probit bivariado com seleção apresenta maior consistência com as previsões da teoria da busca por emprego. Como a amostra é composta por participantes de programas de Empleo Apoyado, os resultados não devem ser generalizados para todas as pessoas com deficiências psiquiátricas. Os achados sugerem que os benefícios por incapacidade podem facilitar a participação no mercado de trabalho até níveis mais elevados de riqueza, com importantes implicações para as políticas de emprego.

Palavras-chave: salário de reserva; deficiência relacionada à saúde mental; participação no mercado de trabalho; fronteira estocástica; probit bivariado com seleção amostral
Classificação JEL: C25, J21, J24, I14

Introduction

Individuals with mental health disabilities face serious challenges in labor market participation. For example, approximately one in five people with schizophrenia works in competitive employment settings, and fewer than 50 % engage in any kind of employment at all (Gioia & Brekke, 2003). The unemployment rates for individuals with psychiatric disabilities have been estimated to be three to five times higher than for those without (Cook, 2006). In large-scale epidemiological surveys such as the Centers for Disease Control and Prevention's (CDC) National Health Interview Survey, one study estimates that 61 % of working-age adults with psychiatric disabilities, compared with 20 % of adults without, are not even in the labor force (Cook et al., 2006).

Barriers to labor market participation among people with mental health disabilities stem from several factors. Workers with psychiatric disabilities may have difficulty remaining employed. Impairments associated with psychiatric disability, such as those affecting concentration and certain cognitive processes, can lead to functional limitations in the workplace, which can be exacerbated by increased interpersonal and social alienation (Ettner et al., 1997; MacDonald-Wilson et al., 2003). These factors contribute to adverse labor market outcomes, including higher rates of absenteeism and disability-related work leaves, reduced work hours, lower perceived productivity, and, ultimately, lower earnings (Chatterji et al., 2009). The labor force participation decisions of workers with mental health disabilities may also be affected by sensitivity to the benefit structures of the Social Security Disability Insurance (SSDI) or the Supplemental Security Income (SSI), which influence decisions to enter or exit the labor market.[1]

One of the earliest studies of the labor force participation decision comes from the Epidemiological Catchment Area (ECA) study, a large-scale research project based on structured diagnostic interviews of adults in five communities. Designed to capture the prevalence of mental health disabilities, the ECA study provided the first opportunity for researchers to evaluate the relationship between psychiatric disability and labor supply. For example, analysts using ECA data found that among older men aged 50 to 64, mental health symptoms reduced their probability of labor force participation, but

1 Numerous studies document the effects of Social Security benefit programs on labor market participation among individuals with psychiatric disabilities. Examples include Averett et al. (1999), Bond et al. (2007), Drake et al. (2009), and MacDonald-Wilson et al. (2003).

this finding did not extend to older women (Alexandre et al., 2004). Others found that mental health significantly predicted employment among both men and women, though the effects varied by gender (Ettner et al., 1997). Both studies corroborated findings from earlier studies based on smaller samples in select communities,[2] yet those earlier studies suffered from methodological weaknesses, the most important of which was that they were based on data from one or at most three of the five sites in the study.

Other researchers who have examined non-diagnostic or symptom-related barriers to labor force participation have highlighted the challenges individuals with mental health disabilities face in accessing appropriate, integrated, and recovery-oriented mental health services. They also document the frustration these individuals experience when the vocational services they receive do not lead to employment satisfaction (Cook, 2006). Other barriers to employment, such as labor market volatility (employment rates) and socioeconomic status, were not included in these analyses. These gaps indicate that our understanding of workers' decisions to participate in the labor market remains incomplete. More recent systematic reviews and meta-analyses continue to document the effectiveness and labor-market context of supported employment for this population (Modini et al., 2016; Metcalfe et al., 2018; Frederick & Vander Weele, 2019).

Employer decisions may also contribute to low labor market participation among individuals with psychiatric disabilities. Policy analysts have argued that people with disabilities, in general, possess characteristics that set them apart from people without disabilities, subjecting them to discrimination (Burkhauser et al., 1995; Burkhauser & Stapleton, 2003; Jones, 2008). Research on employer hiring decisions for individuals with psychiatric disabilities has uncovered an association between disability-related characteristics and patterns of prejudicial hiring attitudes. Studies based on a 2000 survey reported that only 33 % of employers made an effort to hire individuals with psychiatric disabilities, fewer than those who made similar attempts to hire workers with other disabilities (41 %) or those among race/ethnic minority (68 %) populations (Baldwin & Marcus, 2006; Scheid, 1999). However, this evidence, though important for policy considerations, is impressionistic. From a labor policy

2 Ettner et al. (1997) cite nine community-based studies documenting adverse labor market outcomes and conclude that earlier empirical findings presented selection problems and reverse causality. The authors also describe selection bias in earlier utilization-based studies, leading to conclusions that tend to underestimate the impact of mental health on employment earnings.

perspective, it suggests we have a long path ahead toward achieving full employment for individuals with serious psychiatric disabilities.

Reservation Wage

One factor that influences labor market participation is the individual's willingness to work, as represented by the reservation wage, the lowest wage rate at which a worker would accept a particular type of job. Static labor supply theory models the decisions individuals make about labor force participation at a point in time (Borjas, 2008). Individuals choose to supply labor to maximize well-being or utility, balancing hours of leisure and work while taking into account constraints on their economic situation. Leisure is defined as non-labor market activity. Economists typically consider leisure to include household management and pleasurable or restful activities (Blundell & Macurdy, 1999; Cahuc & Zylberberg, 2004). A critical factor that induces labor force participation, besides preferences for work and financial circumstances, is the reservation wage. The reservation wage is positively correlated with a person's preference for leisure, so the more someone enjoys time not performing work activities, the higher that individual's reservation wage. For individuals with disabilities, the reservation wage can also be increased by non-labor income, such as income from other household members and entitlements. In static labor supply theory, the reservation wage plays an important role in determining how long one searches for employment. Job search duration is also governed by the rate of incoming wage offers. Empirical evidence suggests that many accept the first wage offer (Cahuc & Zylberberg, 2004). It is not yet established whether this finding extends to job-seekers who are individuals with mental health disabilities.

The reservation wage is an unobserved concept in labor economics search theory. It refers to the minimum wage necessary to entice an unemployed individual to enter the labor market or accept a wage offer. It presumes that every individual has a wage rate that reflects their willingness to work. If a wage offer comes to the individual and is higher than the reservation wage, the offer is accepted. The reservation wage represents the monetary value the person places on being at home and engaging in leisure activities, and as such, it serves as a shadow price for labor outside the labor market (Heckman, 1974; Mohanty, 2005).

Economists have identified two aspects of the reservation wage that are important in the decision to participate in the labor market. The first is that it is based on individual tastes, which is an important reason it is unobservable (Hofler & Murphy, 1994; Voeks, 2000). The second is that it is affected by the job search process, the duration of unemployment, and benefits such as unemployment insurance, Social Security disability payments, and family endowment. Individual preferences for work and the likelihood of obtaining gainful employment are important factors in determining the reservation wage. For individuals with psychiatric disabilities, public policies governing employment practices, access to social programs such as supported employment, and the social safety net against cyclical downturns also determine their reservation wage. The reservation wage may be considered exogenous and static, a rate that each unemployed person holds and that remains consistent until the job search ends. It could also be dynamic, as it can change over the course of the job search and be influenced by policy changes. In the present study, we consider the reservation wage to be static and exogenous. Demographic factors such as entitlements, family support, and social policies such as supported employment programs could alter the shape of the reservation wage function across individuals, but once formed, the reservation wage remains consistent until a job offer is accepted.[3] Accordingly, the higher the reservation wage, the less likely a person with psychiatric disabilities is to participate in the labor market.

There are essentially two approaches to capturing information on the reservation wage. The traditional approach is to ask the unemployed person directly in a survey, for example, "What is the lowest wage you would be willing to accept?" (Voeks, 2000). However, direct surveys have methodological limitations. Individuals may not be fully informed about the wage distribution in the labor market and, consequently, may inflate their responses. Hofler and Murphy (1994) refer to this as wishful thinking, whereby individuals report amounts higher than what they would actually accept. Another source of bias may be a survey's inability to accurately control for job characteristics that could affect an individual's reservation wage, leading an individual to accept a wage offer lower than indicated in the survey. Finally, if the surveyor is from a government agency, individuals may be more likely to report a lower rate for fear of repercussions if they perceive that their unemployment insurance or disability benefit might be terminated if a higher amount was offered. Nonetheless, despite these shortcomings, direct responses have been used to evaluate the reliability and validity of capturing reservation wage information through the second approach, alternative empirically driven methods (Mohanty, 2005; Voeks, 2000).

3 For more on the dynamic aspect of the reservation wage, see Kiefer and Neumann (1995).

Econometricians have proposed empirical methods as a viable alternative to the direct survey method for estimating the reservation wage. Despite these advances, to date the direct survey method has been the only approach used to capture the reservation wage of individuals with psychiatric disabilities (Warner & Polak, 1996). Therefore, this paper is the first attempt to apply two empirical methods to estimate the reservation wage for this population. These methods are the stochastic frontier approach and the bivariate probit/selection approach (Hofler & Murphy, 1994; Mohanty, 2005). We apply these methods to a national dataset from a federally funded multisite study. Both econometric techniques derive the reservation wage from the individual's actual behavior by subtracting a quasi-rent (earnings in excess of the individual's opportunity cost) from the observed wage.

In labor economics, the opportunity cost is the value of not participating in the labor market; that is, the value placed on leisure, or, as Mohanty (2005) puts it, the "value of home time." By implication, the observed wage is an offer that at least covers, and frequently exceeds, a person's value of being at home; thus, estimation techniques center on measuring the excess value above the level that keeps the individual at home. The reservation wage has also been defined as the level that equates the marginal benefit and the marginal cost of continuing the job search process, where the unemployed person is indifferent between extending the search or accepting an offer. The benefit of continuing would be the possible arrival of job offers at higher rates of income, and the cost would be the prolonged exhaustion of one's personal and familial resources while waiting for that "perfect job offer" (Hofler & Murphy, 1994; Kiefer & Neumann, 1989). Although the objectives are the same, the approach to finding that excess value above the minimum asking wage differs between the two methods.

Methodology

3.1 Stochastic Frontier with Heteroscedasticity-Adjustment Approach

The stochastic frontier method estimates the quasi-rent, using the wage function, by decomposing the disturbance term in the wage equation. The simple wage equation is written as

$$w_i = \boldsymbol{X}'\boldsymbol{\beta} + \varepsilon_i \qquad (1)$$

where w_i is the observed wage on the prior job; $\boldsymbol{X}'\boldsymbol{\beta}$ is the row and column vector of the wage determining factors estimated in the equation; and ε_i is the disturbance. Since the reservation wage is embedded in the observed wage, it may be decoupled from the observed wage by decomposing ε_i, so that $\varepsilon_i = v_i + u_i$. The v_i term is the random disturbance that is specific to an individual, and it is normally and identically distributed. However, the u_i term—also an individual-specific random disturbance—is ≥ 0. This component of the disturbance is non-negative by necessity because it demarcates the magnitude of the observed wage above the individual's reservation wage.

The decomposition of the disturbance is achieved through stochastic frontier estimation. This technique was developed to determine efficiency levels in the production function across firms with similar inputs but different levels of output.[4] It estimates efficiency or inefficiency by decomposing the disturbance into two parts: a normally-distributed stochastic frontier (v_i) and a one-sided disturbance typically called inefficiency (u_i) to which one of several distributions could be assumed.[5] This method is applicable to reservation wage estimation because the dependent variable, the natural logarithm of a prior wage, is constrained from below, since we only observe the prior wages of participants with a given human capital formation, work motivation, and employment functional limitation distributed above their reservation wage levels. Therefore, the ability of stochastic frontier regression to estimate the one-sided inefficiency disturbance term is its chief advantage. In this setting, that term is critical to the estimation of the quasi-rent, the difference between the observed wage and the reservation wage. The final parametric model we selected for reservation wage estimation is the cost model with a normal-exponential disturbance assumption,[6] written as

4 A useful review of the theoretical basis of stochastic frontier analysis is provided by Kumbhakar and Lovell (2000). Greene (1993) also provides a substantial overview of the econometric techniques used in firm efficiency analysis, including the method used in this approach to address heteroscedasticity in the disturbance terms.

5 Usually truncated-normal, half-normal, or exponential. For this analysis, the final model is based on the exponential distribution assumption for u_i. Both the half-normal and the exponential were implemented, and although the half-normal resulted in a lower -2Log Likelihood (-872.48 vs. -850.10 for exponential), the standard errors were generally lower in the exponential model. The final reservation wage estimate did not differ significantly between the two assumptions for u_i.

6 The cost function implies a non-negative one-sided disturbance, and its density function is specified as $E(u_i | \varepsilon_i) = \theta \exp(-\theta u_i)$, $\theta > 0$, $u_i \geq 0$. This model specification is adapted from (Greene, 1993).

$$Ln(w_i) = X'\beta + v_i + u_i \quad (2)$$

$$w_{reservation} = w_{prior\ employment} - \hat{u}_i \quad (3)$$

We carried out the estimation in two steps. First, we used the prior wage equation in a natural logarithm to estimate the one-sided disturbance via maximum likelihood, denoted as the quasi-rent, u_i. Second, we subtracted the quasi-rent from the observed prior wage to obtain the reservation wage estimate.

We modified the stochastic frontier model as delineated by Hofler and Murphy (1994) by using an estimation technique that corrects for heteroscedasticity in stochastic frontier models. Left uncorrected, our estimate would be vulnerable to a downward bias in the intercept and an upward bias in the coefficients (Voeks, 2000). To address this problem, we added a heteroscedasticity correction for both the normal (v_i) or two-sided disturbance term and the one-sided (u_i) inefficiency term.[7] The correction parameterizes both disturbance variance terms by a multiplicative function to constrain the variance terms (σ_v, σ_u) to be >0. The correction we implemented was $\sigma_u = e^{(ZT\,\zeta)}$ and $\sigma_v = e^{(WT\,\delta)}$, where Z is the vector of factors that are likely to contribute to the heteroscedasticity in σ_u and W the vector of factors likely to contribute to the heteroscedasticity of σ_v. The literature has not settled on which factors are likely to determine the disturbance variances.[8] Rather than specifying *a priori* the demographic variables that may be responsible for heteroscedasticity in the variance terms, we performed an LR-test [$2(L_R$-$L_U)$] proposed by Voeks (2000) to test the H_0 that the restricted model with no heteroscedasticity is true. If the χ^2 statistic was found to be greater than the critical value, the unrestricted model with heteroscedasticity corrections would be favored. For the ln(wage) function used in the LR-test, we included terms that we hypothesized as common sources of heteroscedasticity, such as age, marital status, education, employment experience, gender, and an interaction term (male*married). We tested the unrestricted models with these variables specified in the one-sided and two-sided error terms, in sequence, against the restricted model. The results suggested that four terms be included in the correction for σ_v (two-sided) and three terms

7 Greene (1993) also suggested a similar method.

8 Schmidt (1986) suggests interpreting v_i as factors external to the individual's control, and u_i as factors internal to the individual's control. Both categories of demographic factors were considered in the LR-test.

in the correction for σ_u (one-sided), respectively.[9] For model identification, only one term appeared in both the disturbance variance parametrizations.

3.2 Bivariate Probit with Selection Correction Approach

The second econometric approach we used to estimate the reservation wage empirically from the observed wage is based on an extension of the Heckman selection model. In the conventional Heckman model typically employed to estimate employment outcomes such as wages or work hours, the only source of selection considered is the individual's decision to participate in the labor market. However, the literature points to the need to account for a second source of selection bias, namely the employer's decision to hire the same individual. This approach then calls for adjusting the ordinary least squares (OLS) wage regression model with two selection parameters, one for the factors that influence the worker's decision to participate and another for those that determine whether the employer will likely hire that individual. Recently, this approach was used to estimate the wage difference between black and white workers using data from the National Longitudinal Study of Youth survey (Baffoe-Bonnie, 2009).

The chief difference between the conventional Heckman and the extended Heckman procedure lies in the first step of wage estimation, where we replaced the conventional probit equation with a bivariate probit equation. Formally, an individual chooses to participate in the labor market if their preference for work is positive,

$$Participate\ in\ Labor\ Market_i = \begin{cases} 1\ if\ y_{1i} \geq 0 \\ 0\ if\ y_{1i} < 0 \end{cases}$$

And is hired if the employer's preference for that individual is also positive,

$$Hired\ by\ employer_i = \begin{cases} 1\ if\ y_{2i} \geq 0 \\ 0\ if\ y_{2i} < 0 \end{cases}$$

Where y_{1i} represents the person's preference for work, and y_{2i} the employer's preference for the candidate. Since the two preference functions are related,

9 Z = age, male, white; W = age, male*married, education, and employment experience.

$$y_{1i} = x_{1i}\beta_1 + u_{1i}, \tag{4}$$

$$y_{2i} = x_{2i}\beta_2 + u_{2i} \tag{5}$$

Equations (4) and (5) can be estimated jointly using a bivariate probit with partial observability on the entire sample (Mohanty, 2005). Theoretically, the vector x_{1i} contains variables that determine the worker's decision such as, socio-demographic, clinical and work experience, and education and work motivation factors, while x_{2i} contains variables identical to those in the first equation, plus additional factors not in the labor market participation equation that might be important to the employer's hiring decision, such as the person's propensity to abuse substances or a history of criminal justice involvement.

To calculate the reservation wage, we subtracted the predicted values (i.e., the quasi-rent) from the labor force participation equation in the bivariate probit model $\widehat{y_{1i}} = x_{1i}\widehat{\beta_1}$ from the predicted values of the wage equation. We used the estimates from the bivariate probit for both the labor force participation and the hiring equations to build the selection variables. As in the stochastic frontier approach, we estimated the reservation wage model using the wage recorded in a prior employment through OLS, formally represented as

$$\ln(w_{prior\ employment}) = x_{3i}\beta_3 + \sigma_{13}\lambda_{1i} + \sigma_{23}\lambda_{2i} + u_i \tag{6}$$

Where the selection parameters for labor force participation (λ_{1i}) and for being hired (λ_{2i}) are estimated by

$$\lambda_{1i} = \frac{\phi(x_{1i}\beta_1)\Phi(\mathrm{x_{2i}b_2 - \rho x_{1i}b_1} \ / \ \sqrt{(1-\rho^2)})}{F(x_{1i}b_1, x_{2i}b_2, \rho)} \tag{7}$$ and

$$\lambda_{2i} = \frac{\phi(x_{2i}\beta_2)\Phi(\mathrm{x_{1i}b_1 - \rho x_{2i}b_2} \ / \ \sqrt{(1-\rho^2)})}{F(x_{1i}b_1, x_{2i}b_2, \rho)} \tag{8}$$

with ϕ and Φ representing the standard normal and cumulative distribution function, and ρ (rho) the correlation of the two disturbance terms in the bivariate probit. The expected prior wage offer computed from Equation (6) is $\widehat{w^0} = e(\widehat{^{lnw^p}})$. Finally, we computed the reservation wage $w_i^{\widehat{reservation}} = w_i^{\widehat{expected}} - \widehat{y_{1i}}$ for all individuals in the sample.

Data Source

The data in this investigation come from a federally funded multisite implementation effectiveness study known as the Employment Intervention Demonstration Program (EIDP), which evaluated the impact of an evidence-based approach to delivering employment services, named Supported Employment, to individuals with serious psychiatric disabilities between 1996 and 2000 (Cook et al., 2005). Please refer to Cook et al. (2005) for more details on the EIDP design, recruitment, and eligibility criteria. The total eligibility pool for the EIDP study was 10.653, of which 2.883 were invited to join the study. Of the 2.883 who were approached, 1.648 underwent random assignment. We used data from those who underwent random assignment as the sample for estimating the reservation wage.

Individuals were followed for 24 months at six-month intervals to record changes in demographic and clinical information using a standard protocol instrument. They were interviewed between February 1996 and May 2000 and received compensation ranging from $10 to $20 per person, as determined by each study site. However, for this paper, we used only baseline information in the analysis.

Cook et al. (2005) described in detail the data quality measures their team implemented at the program level. They took extensive steps to ensure that the interview protocol met the strongest psychometric requirements. After we received the dataset from the program staff, we also conducted quality assurance at the study level by purging the dataset of input and calculation errors. We generated descriptive statistics for all study variables to detect and correct for illegal values. For the most part, the dataset we received from the program staff was already cleaned before it was transferred to the lead author. Illegal values were minimal. We subjected all variables we created for the analysis to the same scrutiny as those we received in the original format from the program coordinating center.

Results

We performed all analyses using Stata v.12. All variables used to estimate the reservation wage and for the subsequent reliability are listed in Table 1, which summarizes the descriptive statistics and the definitions of the variables. We ensured that most variables in the analysis matched as closely as possible those identified by Hofler and Murphy (1994) and by Mohanty (2005) as critical to their respective estimation methods. The variables we chose were consistent with factors from labor economics search theory known to determine the reservation wage. The observed wage used to estimate the reservation wage was the hourly rate of the participant's previous job prior to enrolling in the program as reported directly through the baseline interview protocol.[10]

Table 1. Descriptive Definitions and Statistics on Variables in the Reservation Wage Estimation Equations

Variable	N	%	Mean (SD)	Definition
Arizona	337	20.5	—	Located in the Arizona study site
Connecticut	139	8.4	—	Located in the Connecticut study site
Maryland	220	13.4	—	Located in the Maryland study site
Massachusetts	175	10.6	—	Located in the Massachusetts study site
Maine	139	8.4	—	Located in the Maine study site
Pennsylvania	182	11.0	—	Located in the Pennsylvania study site
Occupational group 1	52	3.4	—	Previous occupational classification category 1: Managerial, executive, or administrative positions
Occupational group 2	60	3.9	—	Previous occupational classification category 2: Health diagnosis or assessment positions
Occupational group 3	31	2.0	—	Previous occupational classification category 3: Education, social science, and social work positions
Occupational group 7	58	3.7	—	Previous occupational classification category 7: Farming, forestry, and fishing-related positions
Male	872	52.9	—	Male gender
White	802	48.5	—	Caucasian
Bilingual	214	13.0	—	Bilingual or multilingual
Married	166	10.1	—	Married or living as married
Independently housed	1.319	79.7	—	Respondent lives in the community independently or with family

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10 Kiefer and Neumann (1989, 1995) have shown theoretically that prior wage could be a reliable estimator of the reservation wage.

Variable	N	%	Mean (SD)	Definition
Children under 18 living at home	393	23.8	—	Respondent has children under age 18 living at home over the 5 interview periods
Criminal justice involvement past 2 months	50	3.1	—	Respondent has been arrested or picked up for a crime in the past two months
Functioning	757	45.8	—	Good to excellent overall level of mental health functioning reported
Labor force participation	1.259	79.1	—	Labor force participation for individuals working, temporarily on leave, or looking for work (including sheltered employment)
Hire	1.437	90.3	—	Positive response on the hourly wage of a job prior to participating in EIDP
Prior vocational training	1.654	57.5	—	Respondent received vocational training prior to joining the study
Good overall health	1.074	65.0	—	Respondent reported good to excellent overall physical health
Positive work motivation	1.541	93.2	—	Respondent believes more dignity and self-respect come with working
Education completed				Education completed from 1 (some elementary) to 10 (doctoral)
Elementary through high school	1.055	64.1	—	
Some college	414	25.2	—	
College graduate (AA-PhD)	176	10.7	—	
Gross hourly wage past job (current USD)	1.437	—	6.34 (13.66)	Self-reported gross hourly wage of the previous employment
Age in 2000	1.647	—	41.70 (9.43)	Respondent's age on January 1, 2000
Number of children	1.647	—	1.19 (1.64)	Total number of children given birth to
Employment experience	1.549	—	45.03 (53.09)	Total number of months at the longest-held job
Employment experience^2	1.549	—	4844.93 (13210.02)	Employment experience squared

Continúa

Variable	N	%	Mean (SD)	Definition
Male*married	1.648	—	.04 (.19)	Interaction between male and married or living as married
Educ*age	1.644	—	173.10 (82.40)	Interaction between education level at baseline and age as of January 1, 2000
Social Security retirement	1.643	—	9.17 (71.85)	Respondent received Social Security Retirement (SSA) benefits past month.
Retirement income (current USD)	1.640	—	9.91 (81.83)	Retirement, investment, or savings income if received regularly
Amount SSI past month (current USD)	1.619	—	182.24 (226.02)	Amount received in SSI previous month (current USD)
Amount SSDI past month (current USD)	1.629	—	203.48 (477.37)	Amount received in SSDI previous month (current USD)
Unemployment compensation (current USD)	1.643	—	3.78 (46.64)	Amount received in unemployment compensation previous month
Household wealth (current USD)	1.654	—	1636.99 (1594.63)	Sum of entitlements and income (personal + household)
Local unemployment rate (%)	1.649	—	4.4 (1.16)	Monthly local prevailing unemployment rate
Days recipient used alcohol past 30 days	1.642	—	1.55 (4.41)	Total number of days recipient used alcohol past month
Days recipient used drugs past 30 days	1.638	—	.94 (4.24)	Total number of days recipient used non-prescribed drugs past month

Note: All tabulations are based on results from baseline interview. AA: Associate of Arts; SSA: Social Security Administration; SSDI: Social Security Disability Insurance; SSI: Supplemental Security Income.

We present the coefficients from both methods, along with the resulting reservation wage derived from those estimates, in Table 2. In the first column, we report coefficients estimated from the uncorrected stochastic frontier model, and in the second column, those from the heteroscedasticity-corrected model. In the third column, we present coefficient estimates from the extended Heckman/bivariate probit model. The dependent variable is the natural log of the previous hourly wage. As Table 2 shows, with minor exceptions, the results are consistent across the two models in the direction and magnitude of effect.

Table 2. Comparison of Frontier Regression (Normal/Exponential Model) with Extended Heckman/Bivariate Probit Results (Statistically Significant Variables Only)

	Unadjusted	**Heteroscedasticity-adjusted**	**Extended Heckman/ bivariate probit**
Variable	**Coefficient**	**Coefficient**	**Coefficient**
	(Standard error)	**(Standard error)**	**(Standard error)**
Age in 2000	0.404 (0.349)	0.265 (0.330)	-0.009* (0.004)
Education completed (baseline)	0.909* (0.476)	0.708 (0.453)	-0.023 (0.444)
Educ*age	-0.626* (0.351)	-0.473 (0.330)	0.001 (0.001)
Employment experience	0.077*** (0.012)	0.077*** (0.012)	0.002*** (0.001)
Prior vocational training	-0.131*** (0.038)	-0.112*** (0.038)	-0.101*** (0.028)
White	-0.001 (0.044)	0.192** (0.088)	0.012 (0.031)
Independently housed (baseline)	0.182*** (0.038)	0.169*** (0.037)	0.113** (0.036)
Unemployment Compensation (current USD)	0.037 (0.022)	0.039* (0.022)	0.001* (0.001)
Amount SSI past month (current USD)	-0.025*** (0.005)	-0.024*** (0.004)	-0.0002*** (0.001)
Retirement Income (current USD)	0.021 (0.014)	0.024 (0.015)	0.0003* (0.001)
Massachusetts	0.147** (0.061)	0.140** (0.058)	0.079 (0.050)
Pennsylvania	0.191*** (0.061)	0.189*** (0.061)	0.130** (0.047)
Occupational group 1	0.529*** (0.100)	0.518*** (0.102)	0.368*** (0.072)
Occupational group 2	0.392*** (0.104)	0.284*** (0.109)	0.301*** (0.081)
Occupational group 3	0.507*** (0.124)	0.467*** (0.130)	0.332*** (0.090)
Occupational group 7	-0.193* (0.099)	-0.177* (0.097)	-0.124* (0.072)

Continúa

	Unadjusted	Heteroscedasticity-adjusted	Extended Heckman/ bivariate probit
Variable	**Coefficient**	**Coefficient**	**Coefficient**
	(Standard error)	**(Standard error)**	**(Standard error)**
Local unemployment rate (%)	-0.137** (0.057)	-0.125** (0.055)	-0.031** (0.014)
Intercept	1.514* (0.777)	1.684*** (0.364)	1.916*** (0.205)
N	1.343	1.343	1.333
-2Log Likelihood	-877.53	-850.10	
σ_v (normal error term variance)	.432*** (.010)	—	—
σ_u (exponential error term variance)	.165*** (.017)	—	—
λ	.382		—
Variables adjusting for σ_v term	—	—	—
Age in 2000	—	0.871*** (0.225)	—
Male*married	—	-0.572* (0.315)	—
Education completed (baseline)	—	0.338** (0.148)	—
Employment experience	—	0.032 (0.040)	—
Intercept	—	-5.521 (0.809)	—
Variables adjusting for σ_u term	—	—	—
Age in 2000	—	0.284 (0.938)	—
Male	—	-1.982** (0.842)	—
White	—	-4.699 (4.144)	—
Intercept	—	-3.926 (3.501)	—

Continúa

	Unadjusted	**Heteroscedasticity-adjusted**	**Extended Heckman/ bivariate probit**
Variable	**Coefficient**	**Coefficient**	**Coefficient**
	(Standard error)	**(Standard error)**	**(Standard error)**
IMR 1	—	—	.087 (.071)
IMR 2	—	—	.073 (.273)
	Reservation wage (Stochastic frontier with het. correction)	Actual Wage (Prior)	Reservation wage (Extended Heckman/bivariate probit)
Overall sample (mean)	$5.25	$6.34	$4.50

Note: *Significant at the .10 level. **Significant at the .05 level. ***Significant at the .01 level. Dependent variable is ln(hourly wage) from the previous employment prior to the study period. All regressors are in natural log form. Normal-exponential specification for the disturbances. het.: heteroscedasticity; IMR: inverse Mills ratio; SSI: Supplemental Security Income.

Earnings increased with experience, being bilingual, having established independent housing, and being a married man. Belonging to the occupational groups associated with professional, managerial, or other positions that typically required post-secondary education also increased a person's earnings. Consistent with other wage models, the marginal increase in Supplemental Security Income (SSI) reduced earnings, as did a rise in the local prevailing unemployment rate. Most statistically significant terms in one model were also significant in the other, except for race and age. Curiously, prior vocational training lowered workers' earnings in both the stochastic frontier and the extended Heckman models. Perhaps those with psychiatric disability who participated in vocational training were among individuals with the least work experience. For the stochastic frontier model, the estimated coefficients on the variables affecting σ_u and σ_v were statistically different from 0 on four of the seven terms. The inverse Mills ratio (IMR) for labor force participation was marginally significant in the extended Heckman model, indicating evidence of selection.

The calculated reservation wages from both models appear in the bottom two rows of Table 2. The mean estimated reservation wage from the stochastic frontier model indicates that the average person earned 20.8 % more than their $5.25-per-hour reservation wage. In the extended Heckman model, the average worker earned 40.9 % more than their $4.50-per-hour reservation wage.

We summarize the bivariate probit results in Table 3. The first column of coefficients shows the results of the labor force participation model, and the second column presents the results of the hire model. The variables in the model are equivalent to those employed by Mohanty (2005).[11] Factors hypothesized to affect the individual's reservation wage and labor force participation included personal characteristics such as gender, race/ethnicity, age, marital status, whether or not the person was bilingual or multilingual, and work motivation. Human capital variables hypothesized to influence labor force participation included the completed level of education, prior vocational training, and employment experience, measured by the duration of the longest-held job. In addition to personal and human capital variables were what Mohanty (2005) called family variables, such as the number of children in the household and whether or not the individual was living independently. Also included were variables such as health status and receipt of Social Security retirement benefits.

Factors hypothesized to affect the employer's hiring decision included those in the labor force participation equation, along with variables on substance use in the past 30 days, criminal justice involvement, the local unemployment rate, five of the program sites, and one occupational group. Receipt of SSI and Social Security Disability Insurance (SSDI) benefits is typically included in labor force equations. We placed these variables in the hiring equation for two reasons. Among those with psychiatric disabilities, employers sometimes preferred to hire individuals receiving SSI or SSDI benefits because of available tax incentives for hiring from this population. Employment specialists affiliated with a vocational service agency who typically negotiated with employers often raised this possibility as an incentive. Second, qualitative comments recorded in the dataset and found in program documentation suggest that employers were sometimes asked to keep wages below a certain level for the client to continue receiving benefits. Therefore, SSI and SSDI were likely factors in the hiring decision mechanism. The EIDP data do not include a variable measuring employer knowledge of a candidate's benefit status or eligibility for a hiring tax incentive; this explanation is therefore treated as contextual rather than as evidence directly observed in the dataset.

11 Mohanty (2005) included some variables not available in the EIDP dataset, such as parents' education, family size, unemployment duration, and beliefs about the traditional role of women.

Table 3. Bivariate Probit Model Predicting Labor Force Participation and Hire (Statistically Significant Variables Only

	Labor force participation	**Hired by a previous employer**
Variable	**Coefficient**	**Coefficient**
	(Standard error)	**(Standard error)**
Age in 2000	-0.005 (0.005)	-0.013** (0.007)
Good overall health	0.310*** (0.087)	0.312*** (0.109)
Education completed	0.074** (0.030)	0.042 (0.038)
Bilingual	0.476*** (0.145)	0.216 (0.180)
Number of children	-0.084*** (0.027)	—
Days recipient used alcohol past 30 days	0.018* (0.010)	0.001 (0.013)
Arizona	-1.030*** (0.105)	—
Maryland	-0.672*** (0.122)	—
Massachusetts	-1.128*** (0.136)	—
Functioning	0.312*** (0.089)	—
Positive work motivation	0.442*** (0.160)	—
Amount SSI past month (current USD)	—	-0.001*** (0.0003)
Employment experience^2	—	0.0002** (0.0001)
Maine	—	0.885** (0.393)
Connecticut	—	0.503** (0.207)
Occupational group 2	—	-0.554** (0.217)
Local unemployment rate (%)	—	0.010 (0.058)

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	Labor force participation	Hired by a previous employer
Variable	**Coefficient**	**Coefficient**
	(Standard error)	**(Standard error)**
Intercept	0.507* (0.297)	1.752*** (0.443)
N	1.435	1.435
-2Log Likelihood	-929.65	-929.65
ρ (Correlation between disturbances)	0.146* (0.076)	0.146* (0.076)

Note: *Significant at the .10 level. **Significant at the .05 level. ***Significant at the .01 level. Heteroscedasticity robust standard errors in parentheses. SSI: Supplemental Security Income.

The bivariate probit results in Table 3 indicated that, as expected, education, good overall health, being bilingual or multilingual, positive work motivation, and high functioning significantly predicted labor force participation. Having an additional child reduced labor force participation. All site variables were negative, suggesting higher labor force participation among the omitted reference sites. Unexpectedly, both substance use variables predicted labor force participation, even though alcohol use was only marginally significant. This suggests that substance use was not a severe detriment to employment, perhaps because it did not reflect dependence. The hiring estimates showed that good overall health positively predicted the probability of being hired, while older age and higher SSI benefits reduced the likelihood of being hired. Given that the average age of participants was over 40, this finding likely reflected age discrimination.

Reliability Findings of Reservation Wage Estimates

We conducted separate reliability assessments of the reservation wage estimates derived from both the stochastic frontier and the bivariate probit selection methods. We evaluated the consistency of the reservation wage estimates with respect to five hypotheses drawn from labor search theory. According to labor economists, a worker sets the reservation wage to equate the marginal benefit of the search with the marginal cost of depleting personal and financial resources and of foregoing wages during the unemployment spell. Workers with characteristics of human capital formation and access to resources such as unemployment benefits or SSI/SSDI that would enable a higher incremental reservation wage, without reducing net benefit, will continue to increase their reservation wage to a higher level. Because workers differ in the location at which their marginal benefit and marginal cost of the job search intersect, the reliability of the empirical reservation wages can be determined by testing their differences across several groups of workers. We summarize the results of the reliability analyses in Table 4. The table is organized by testable labor search theory hypothesis, comparing the reservation wage averages across multiple groups. We regard the reservation wage as reliable for a given hypothesis if the average wage was higher for the expected group and the test statistics exceeded the critical value at the .05 level.

Table 4. Reliability Test Results Comparing Reservation Wage Under the Stochastic Frontier and Bivariate Probit/OLS Methods

Category	N	Mean RW SF (SE)	Test statistics for H_0	Mean RW BP/Sel (SE)	Test statistics for H_0
Labor Search Theory Hypothesis 1: The demographic group with higher rates of time preference will set lower reservation wage rates than the group with lower rates.					
Married males	53	\$5.66 (0.401)		\$5.23 (0.239)	
Single females (with no children)	205	\$5.11 (0.2787)	0.946	\$4.55 (0.125)	2.511**
Married males aged 44 or younger	23	\$4.91 (0.470)		\$5.02 (0.422)	
Single females (with no children) aged 44 or younger	145	\$4.83 (0.306)	0.10	\$4.39 (0.129)	1.73*
Labor Search Theory Hypothesis 2: Individuals collecting unemployment benefits will set higher reservation wage rates than those not receiving unemployment benefits.					
Individuals who collected unemployment benefits at baseline	16	\$7.36 (0.655)		\$7.14 (0.495)	
Individuals who did not collect unemployment benefits at baseline	1,421	\$5.23 (0.325)	0.69	\$4.48 (0.044)	5.81***
Labor Search Theory Hypothesis 3: More educated individuals will set higher reservation wage rates.					
<12 years	458	\$4.50 (0.222)		\$4.06 (0.060)	
12 years (high school grad/GED)	438	\$4.81 (0.127)		\$4.43 (0.073)	
13-14 years (some college–AA degree)	434	\$5.98 (1.017)		\$4.75 (0.082)	

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Category	N	Mean RW SF (SE)	Test statistics for H_0	Mean RW BP/Sel (SE)	Test statistics for H_0
16 years (completed BA/BS)	65	\$6.01 (0.653)		\$4.95 (0.223)	
>16 years (some grad–doctorate)	40	\$9.75 (1.368)	2.35+**	\$7.00 (0.229)	33.69+***
Labor Search Theory Hypothesis 4: Individuals in urban areas will set higher reservation wage rates than those in rural areas.					
Urban areas	1,321	\$5.34 (0.349)		\$4.56 (0.047)	
Rural (SC only)	116	\$4.24 (0.276)	.93	\$3.82 (0.094)	4.70***
Urban area (dropping TX)	1,104	\$5.52 (0.417)		\$4.71 (0.052)	
Rural (SC & TX)	333	\$4.36 (0.127)	1.52	\$3.83 (0.062)	8.73***
Labor Search Theory Hypothesis 5: Individuals with greater wealth will set higher reservation wage rates.					
Financial profile (entitlements + income)					
Category 1: < \$968	289	\$6.31 (1.524)		\$4.41 (0.081)	
Category 2: \$968 - \$1,451	356	\$4.58 (0.141)		\$4.35 (0.089)	
Category 3: \$1,452- \$2,084	370	\$4.67 (0.280)		\$4.30 (0.077)	
Category 4: > \$2,084	373	\$5.66 (0.215)	1.45+	\$4.84 (0.100)	8.32+***

Note: All tabulations are based on results from the baseline interview.

H_0: Group means for reservation wage estimates are not statistically different from 0.

**Significant* at the .10 level. **Significant at the .05 level. ***Significant at the .01 level. All test statistics are based on inferences from the t-distribution except for + which are based on inferences from the F-distribution. AA: Associate of Arts; BA: Bachelor of Arts; BP: bivariate probit; BS: Bachelor of Science; GED: General Equivalency Diploma; RW: reservation wage; SC: South Carolina; SE: standard error; SF: stochastic frontier; TX: Texas.

The first hypothesis we tested was that the demographic group with higher time-preference rates would set lower reservation rates than groups with lower time-preference rates. Time preference is related to the marginal cost and marginal benefit of increasing the value individuals place on "home time." Married men have lower time preference than single women, who are presumed to have weaker labor force attachment and, therefore, are expected to have a higher marginal benefit from setting higher reservation wage rates. As the results in Table 4 show, Hypothesis 1 was strongly confirmed for the bivariate probit reservation wage but not for the stochastic frontier estimate. Several of these reliability subgroups have fewer than 100 observations. Appendix Table A1 reports nonparametric bootstrap confidence intervals for the subgroup mean reservation-wage estimates.

The second hypothesis we tested was that individuals receiving unemployment benefits will set higher reservation wages than those not receiving unemployment insurance. Unemployment insurance reduces the marginal cost of job searching. Therefore, those who receive unemployment insurance will likely hold out longer for a higher-paying job, setting higher reservation wages than people who do not receive those benefits or whose benefits have expired. While both reservation wage estimates appeared to confirm this hypothesis, the bivariate probit estimate was statistically significant.

The third hypothesis we tested was that more educated people will set higher reservation wage estimates. Highly educated individuals exhibit lower marginal job search costs because they tend to be more efficient at job search due to better training and access to job information. Hence, they tend to set higher reservation wage estimates. Hofler and Murphy (1994) report that college-educated workers have higher reservation wage rates than those without a college education. This is the only labor search theory hypothesis that was strongly confirmed across both reservation estimate procedures.

The fourth hypothesis we tested was that individuals in urban areas would set higher reservation wage rates than those in rural areas. Because there are generally more job vacancies in urban areas and better transportation infrastructure, these two factors reduce the marginal cost of job searching and the cost of setting higher reservation wages, thereby raising reservation wages. In the EIDP dataset, only one site out of 8 was confirmed to be rural (South Carolina). However, there was speculation that the Texas program may have included a sufficient number of individuals in rural areas between Austin and San Antonio to warrant placing it in the rural category. Because we could not verify this speculation, we conducted comparisons with Texas in both the urban and rural categories. In both cases, the hypothesis was strongly confirmed using the bivariate probit method.

The final hypothesis we tested was that individuals with greater wealth will set higher reservation wages. High levels of wealth reduce the marginal cost of job searching, thereby raising reservation wages. Mohanty (2005) reports findings from a study demonstrating the positive impact of wealth on reservation wage estimates. We calculated wealth in our dataset by aggregating all reported monthly entitlement benefits and all household and individual income (legal and extra-legal) provided during the baseline interview. We defined categories based on 25th-percentile increments in the distribution. Notably, reservation wages fell in the first two tiers using the stochastic frontier method and in the first three tiers using the bivariate probit method, only to rise afterward in the highest wealth category. This pattern may be explained by the financial instability that often accompanies severe psychiatric disabilities, which may have prompted individuals to feel insufficiently stable financially to reduce their marginal cost of job searching until they reached a monthly estimated income (including entitlements) of close to $2.000,00. This hypothesis is partially confirmed by the statistically significant finding in the comparison of the mean reservation wage estimates under the bivariate probit selection method.

Conclusion

This paper compares two empirical methods for estimating the reservation wage, drawn from the labor economics literature: stochastic frontier regression and bivariate probit. Both were used for the first time to estimate the reservation wage for individuals with psychiatric disabilities participating in Supported Employment programs. The two models were generally comparable in the variables they identified as having a significant influence on the reservation wage. We also found these variables to be generally in the expected direction and consistent with research on reservation wage for other populations. The two models differed in their estimates of the reservation wage derived from prior earnings. In the stochastic frontier model, earnings exceeded the average reservation wage of $5.25 per hour by 20.8 percent, whereas the bivariate probit model produced an average reservation wage estimate of $4.50 per hour, 40.9 percent below the observed hourly earnings. We compared the reliability of the two approaches by testing them separately against five hypotheses derived from labor search theory.

Although our paper focused on evaluating the merits of two empirical approaches to estimating the reservation wage among individuals with psychiatric disabilities, our findings also have an important policy implication. Results from both approaches indicate that as wealth, including benefits, increased, the reservation wage decreased until wealth reached a relatively high level, suggesting that benefits such as SSI or SSDI may facilitate rather than hinder participation in the labor force. The interaction between SSI and SSDI benefits and other sources of wealth warrants further investigation.

We present these results with two important limitations. The reliability checks must be interpreted with caution, as they are not generalizable to the population of individuals with psychiatric disabilities. The low sample sizes across five of the categories ($n < 100$) suggest that many of the reliability tests may have inadequate statistical power. Appendix Table A1 reports nonparametric bootstrap confidence intervals (5,000 resamples) for these subgroup mean estimates. Although we estimated the reservation wages using very similar techniques developed by Hofler and Murphy (1994) and Mohanty (2005), we were unable to match all variables they used. Appendix Table A2 documents the available EIDP variables/proxies and the remaining limitations. Because the observed wage was self-reported for the participant's most recent prior job through the baseline interview, it may be subject to recall (memory) bias; and because it reflects earnings from a job the person no longer held, it may also reflect selection into that prior employment. Both sources of bias should be considered when interpreting the reservation wage estimates derived from this measure. Despite these reservations, our pattern of findings demonstrates that the bivariate probit reservation wage estimate applied to the dataset provided by the EIDP study is more consistent with the factors that job search theory postulates as determinants of the reservation wage for this particular sample of individuals. Further work is needed to establish whether the consistency observed in the reliability checks remains robust when using the bivariate probit technique, or whether recent conditions in the labor market might favor the stochastic frontier approach.

Authorship Statement – CRediT taxonomy

Clifton M. Chow: conceptualization, methodology, formal analysis, investigation, writing (original draft and review & editing).
Jose Ordaz: data curation, formal analysis, software, validation, visualization, writing (review & editing).

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Conflict of interest

The authors declare no conflict of interest.

Ethical considerations

This article presents a secondary analysis of de-identified data from the EIDP multisite study; no additional ethical approval was needed.

Data availability

The EIDP data used in this study are not publicly available. Replication materials and aggregated results are available from the corresponding author upon reasonable request.

Use of AI

The authors used an AI assistant (Claude, Anthropic) under their direction and review to support the preparation of the revised manuscript, including reference and DOI verification, formatting, and the implementation of the bootstrap confidence-interval computations reported in Appendix Table A1. All conceptual, methodological, and interpretive decisions are the authors' own, and the authors take full responsibility for the article's content.

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Appendix Table A1. Bootstrap Confidence Intervals for Reservation-Wage Reliability Subgroup Means (5.000 Resamples; Seed 20260624)

Hypothesis	Category	N (SF)	SF mean [95% CI]	N (BP/ Sel)	BP/Sel mean [95% CI]
H1	Married males	53	$5.66 [4.92, 6.45]	48	$5.23 [4.80, 5.69]
H1	Single females (with no children)	205	$5.11 [4.60, 5.70]	184	$4.55 [4.32, 4.79]
H1 age ≤44	Married males aged 44 or younger	23	$4.91 [4.04, 5.86]	20	$5.02 [4.23, 5.82]
H1 age ≤44	Single females (with no children) aged 44 or younger	145	$4.83 [4.31, 5.49]	130	$4.39 [4.15, 4.64]
H2	Collected unemployment benefits at baseline	16	$7.36 [6.14, 8.68]	12	$7.14 [6.24, 8.10]
H2	Did not collect unemployment benefits at baseline	1,421	$5.23 [4.77, 5.97]	1321	$4.48 [4.39, 4.57]
H3	<12 years	458	$4.50 [4.13, 5.02]	427	$4.07 [3.95, 4.19]
H3	12 years (high school grad/GED)	438	$4.81 [4.57, 5.07]	396	$4.43 [4.29, 4.58]
H3	13-14 years (some college-AA degree)	434	$5.98 [4.78, 8.18]	414	$4.75 [4.58, 4.91]
H3	16 years (completed BA/BS)	65	$6.01 [4.95, 7.40]	59	$4.95 [4.50, 5.41]
H3	>16 years (some grad–doctorate)	39	$9.75 [7.38, 12.59]	37	$6.80 [5.97, 7.74]
H4 SC only	Urban areas	1,321	$5.34 [4.86, 6.14]	1224	$4.56 [4.47, 4.65]
H4 SC only	Rural (SC only)	116	$4.24 [3.74, 4.82]	109	$3.82 [3.64, 4.00]
H4 SC+TX	Urban area (dropping TX)	1,104	$5.52 [4.95, 6.47]	1018	$4.71 [4.61, 4.81]
H4 SC+TX	Rural (SC & TX)	333	$4.36 [4.12, 4.62]	315	$3.83 [3.71, 3.96]
H5	Category 1: < $968	289	$6.31 [4.55, 9.54]	270	$4.41 [4.25, 4.58]
H5	Category 2: $968-$1,451	356	$4.58 [4.32, 4.87]	319	$4.35 [4.18, 4.53]
H5	Category 3: $1,452-$2,084	370	$4.67 [4.21, 5.28]	349	$4.30 [4.16, 4.46]
H5	Category 4: > $2,084	373	$5.66 [5.26, 6.08]	356	$4.84 [4.65, 5.04]

Note: AA: Associate of Arts; BA: Bachelor of Arts; BP: bivariate probit; BS: Bachelor of Science; CI: confidence interval; GED: General Equivalency Diploma; RW: reservation wage; SC: South Carolina; SE: standard error; SF: stochastic frontier; TX: Texas.

Appendix Table A2. Variable Comparability Across Source Methods and the EIDP Implementation

Construct/ variable family	Hofler and Murphy (1994) source	Mohanty (2005) source	EIDP variable/ proxy used	Status/note
Observed wage	Wage in frontier equation	Predicted nominal wage (nomwage)	hourlyt0; LNSalary1Rev	Available in both
Age	AGE, AGESQ	age2000	age2000; age2000sq; lnage2000	Available in both
Education	EDATTEND, EDAGE	gradet0	gradet0; edgrade; educ	Available in both
Experience/ tenure	TEN, TENSQ (job tenure)	Employment experience/ longest job held	lgmont0; lgmontsq0; lnsflgmont	Available proxy in both
Sex	SEX	male	male; femalebase	Available in both
Marital status	MARSTAT	married0	married0; malemar; malemarbin	Available in both
Race/ethnicity	Not confirmed in the published Table I specification	White/race controls	white; whitebase	Available in EIDP and Mohanty (2005); not confirmed as included in the Hofler and Murphy (1994) model
Vocational training/ human capital	Not included in the published specification	voctrain	voctrain and derived vocational-rehabilitation items	Available for the Mohanty-style specification only
Language/ bilingual status	Not included in the published specification	lang2	lang2	Available for the Mohanty-style specification only
Household/ family context	NRKIDS	childt0; corest0; cokidt0; indhouse0	childt0; cokidt0; kidu18; corest0; indhouse0	Available in both; mapping differs across methods
Physical/ functional health	Not included in the published specification	phyhealth0; function0	phyhealth0; function0	Available for the Mohanty-style specification only

Continúa

Construct/ variable family	Hofler and Murphy (1994) source	Mohanty (2005) source	EIDP variable/ proxy used	Status/note
Unemployment insurance/ benefit receipt	UI83, included directly in the frontier wage equation	SSI/SSDI and other income in the participation/ hiring equations	ssdit0; ssit0; unempt0; alimont0; familyt0	Available; directly modeled in both source papers
Wealth	OWN (homeownership), included directly in the frontier wage equation	Family income (FAMINC) in the hiring equation	wealthcatall; familyt0	Available; directly modeled in both source papers
Local unemployment rate	URATE83	Local unemployment rate in the hiring decision	unemprate	Available in both
Rural/urban labor market	SMSAYN, CENCITY, LANDUSE	Reliability-hypothesis/ labor-market context	rural; rural2	Available in both
Occupation controls	OCCMP, OCCSTCH, OCCCRFT, OCCOPER, OCCUNSK	Not central in the Mohanty model	Occg1-Occg13 subset; some dropped for convergence	Partially available; the EIDP model drops several occupation categories for convergence
Industry controls	INDMIN, INDCON, INDDUR, INDNON, INDTPU, INDTRD, INDFIRE, INDSERV (8 categories)	Not included	Not available	Omitted; the EIDP dataset does not include an equivalent industry classification
Employer-specific hiring information	Generally unavailable	Hiring-decision equation uses observable proxies	Substance use, criminal-justice history, site, occupation, and benefit indicators; local unemployment rate	Direct employer knowledge of benefit status, tax-incentive use, and wage-negotiation content are not observed in the EIDP data
Direct reservation-wage survey answer	Not required by the method	Not required by the method	Not used	Deliberate: both methods estimate reservation wage from observed behavior rather than a direct survey response