2015 Mental Health Statistics Improvement Program:
2015 Adult Consumer Employment Survey Results

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Overview

The Office of Quality, Planning and Research in the Ohio Department of Mental Health and Addiction Services (OhioMHAS) administered its fifth annual mail survey in 2015, to adult consumers with serious mental illnesses (SMI) on their perception of care and treatment outcomes. Adults were queried between March 1 and May 31, 2015, using the Mental Health Statistics Improvement Program (MHSIP) instrument. In this administration of the consumer survey, additional questions were included that asked about employment status and incentives and barriers to employment. A study concerning consumer employment and predictors of labor force status was designed to provide policy and program planners with information about the general population of adult consumers with SMI.

Methodology

The 2015 survey administration drew a random sample stratified by race from the MACSIS/MITS billing database. A sample of 8,000 adults aged 18+ who met criteria for serious mental illness was drawn from a universe of 107,500 adults with SMI who received services in last two quarters of State Fiscal Year (SFY) 2014. The time frame for sample selection provided a degree of immediacy for subject recall during the survey period. The sample size for the adult service population was based on an estimated return sample of 1,060, with a power analysis for confidence intervals of +/-3%. Racial minorities were over-sampled in an effort to obtain adequate representation.

Surveys were mailed out in a two waves, with reminder postcards issued four weeks after the mailing and a second resurvey of the sample at eight weeks. Survey participants were given the option of responding by mail with a pre-paid business envelope, by phone over the department's toll-free line, or via an Internet survey website.

Sampling Results

In the adult return sample, 15% ($n = 1{,}201$) of the survey packets were returned as undeliverable mail. One percent ($n = 69$) of surveyed consumers declined participation, and 84.8% ($n = 5{,}766$) survey recipients did not respond by the survey deadline. A completed or partially completed survey was returned by 964 consumers, or 14.2% of the sample that received a mail packet. A valid employment survey was returned by 917 consumers, or 13.5% of the sample.

Of the 917 employment survey respondents, 65.4% (*n* = 600) were female, and 34.6% (*n* = 317) were male. The employment sample over-represented females in the general service population (60%) and under-represented males (40%). The mean age of the sample was 47.6 (*SD* = 11.993), which is five years older than the population's mean age of 42.3 (*SD* = 13.8). The sample was 26.6% African-American (*n* = 244), 65.8% White (*n* = 603), 3.8% (*n* = 35) Other Race, and 3.8% Unknown Race (*n* = 35). The racial stratification of the sample was similar to the stratification of the population. The geographic representation of the sample was 13.3% Appalachian board areas (*n* = 122), 6.7% Rural (*n* = 62), 15.8% Small Cities (*n* = 145), 13.7% Suburban (*n* = 126), and 50.4% Major Metro (*n* = 462). The geographic stratification of the return sample was similar to that of the population. The payment coverage was 91.9% Medicaid (*n* = 843) and 8.1% (*n* = 74) Non-Medicaid (NonMDC). The distribution of Medicaid coverage in the sample was disproportionately higher than the 81% with Medicaid coverage in the general service population who received publicly funded community-based mental health services during SFY 2014.

Measures and Instrumentation

Respondents to the Employment Questionnaire were asked to choose one of five conditions that best described their employment situation: Full-time competitive employment (35 or more hours a week at a job for which anyone can apply); Part-time (less than 35 hours a week or year-round); Sheltered Employment (SE: must have disability to apply for job); Unemployed, but actively looking for work; and, Not in Labor Force (NLF: retired, disabled, homemaker, volunteer, student without a job). The employment status measure used on the questionnaire is a state variant of MDS (Minimum Data Set) 13 used in the combined substance abuse and mental health Treatment Episode Data Set (TEDS).[1] MDS 13 is based on measurement methodology developed by the Bureau of Labor Statistics for use in the Current Population Survey (CPS) to ask about job holding, job seeking and non-labor force status.[2]

Additional questions about employment status asked those who were employed to indicate the length of their employment (less than a year; more than a year, but less than five years; more than five years, but less than ten years; more than ten years). Those who were unemployed were asked to indicate the length of their unemployment (less than a year; more than a year but less than five years; more than five years, but less than ten years; more than ten years; and, doesn't apply—I've never had a job).

The Employment Questionnaire used for the survey included ten Likert-style statements based on the Employment Commitment Measure (ECM) by Larson et al (2011). The modified version of the ECM is referred as the Adapted Employment Commitment Measure (A-ECM).[3] Like the ECM, the modified questionnaire used a five-point Likert measure that ranged from Strongly Agree (5) to Strongly Disagree (1). The A-ECM version also dropped one item concerning criminal record disclosure from the six-item barriers subscale employed in the original ECM. The decision to drop the item concerning disclosure of criminal history was based on a need to minimize measurement burden, the inclusion of a self-report question concerning 12-month arrest history, and the historically low percentage of respondents who report arrests in the annual consumer survey.

Factor analysis of the A-ECM resulted in a two-factor solution that accounted for 39.5% of the variance. Five items from the A-ECM loaded on incentives to employment, and five loaded on barriers. (See Table 1 for item-factor loadings.) "Having a job makes me a more responsible person" is an example of an incentive subscale item. "Having a job causes me to experience discrimination because of my mental illness" is an example of a barriers subscale item. The internal consistency reliability (Cronbach's alpha) for the 10-item A-ECM was 0.68. Cronbach's alpha for the subscale related to incentives for employment was 0.82, and the score was 0.61 for the subscale related to barriers to employment. These subscale reliability results were lower than those reported by Larson et al. on the original ECM.

Table 1. Factor Loadings for the Adapted Employment Commitment Measure (A-ECM) (*N* = 796)

Item	Factor	
	1	2
Incentives to employment		
Having a job reduces my depression.	.859	
Having a job reduces my anxiety.	.746	
Having a job show people that I can handle work stress.	.720	
Having a job makes me a more responsible person.	.618	
Having a job increases my problem solving.	.488	
Barriers to employment		
Having a job increases my stress.	-.323	.612
Having a job causes me to experience discrimination because of my mental illness.		.534
Having a job causes me to lose my free time.		.493
Having a job causes me to lose government benefits.		.433
Having a job causes me to be tested for illegal drugs.		.394

Measures from the MHSIP included in this study were mean scores on the six-item functioning scale, self-reported arrest status for the past 12 months, and whether the respondent was receiving services at the time of the survey. The functioning scale measures items such as "My symptoms are not bothering me as much" and "I am better able to take care of my needs."

In addition to age, race, gender, and county geographic category, other measures from administrative databases were diagnostic group, service system longevity (less than a year or more than a year), county unemployment rates, Medicaid program enrollment, and whether the primary provider was certified to provide employment services. Determination of diagnostic group was based on most frequent diagnosis during the study period. Determination of Medicaid groups was based on greatest number of member months during the study period.

Research Question

What predicts employment status in a general population sample of mental health consumers receiving services through providers certified by the Ohio Department of Mental Health and Addiction Services (OhioMHAS)?

Analysis

Data were analyzed using SPSS22. Variable frequencies were run, and the A-ECM mean subscales were calculated. Descriptive and inferential statistics were used to explore relationships among the dependent and independent variables.

Dependent Variable. Nine percent of respondents ($n = 82$; 8.9%) left the question about employment status blank. Analysis of survey responses to questions about history of any employment and length of current employment permitted blank responses in 56 cases to be recoded as "inferred employed." Based on the same approach, the remaining 26 cases were recoded as "inferred unemployed." For the purpose of the study, six of the seven resulting categories of self-reported or inferred labor force status were grouped as Employed/Unemployed-Looking/Not in Labor Force (E/UL/NLF; $n = 891$). See Table 2 for the original and regrouped distributions. The inclusion of sheltered employment in "not in the labor force" follows the SAMHSA and Bureau of Labor Statistics classification scheme for that group. The inferred unemployed group was dropped from the E/UL/NLF classification because it was not possible to infer whether the unemployed individual was "unemployed, but looking" or unemployed, not looking and therefore "not in the labor force." The opportunity to understand how the "unemployed, but looking" respondents might be similar to or different than the employed and those not in the labor force also influenced the decision not to the "inferred unemployed" in a singled group classified as "unemployed."

Table 2. Employment Status (*N* = 917)

Status					
Item	**N**	**%**	**N**	**%**	
Full-time	29	3.2%			
Part-time	55	6.0%	140	15.7%	E
Inferred-employed	56	6.1%			
Unemployed-looking	101	11%	101	11.3%	UL
Sheltered Employment	31	3.4%	650	73%	NLF
Not in Labor Force (NLF)	619	67.5%			
Inferred Not Employed	26	2.8%			
Total	917	100%	891	100%	

Results

One hundred forty respondents (15.1%) reported some form of employment, which included the full-, part-, and inferred-employment. One hundred one (11.3%) were unemployed, but actively looking, and 73% (*n* = 650) of the sample were not in the labor force or in sheltered employment. The 15.1% employment rate estimated on the sample is a few points lower than national data reported by SAMHSA[4] in which 17.9% of consumers reported employment in Federal Fiscal Year (FFY) 2014. SAMHSA's national data estimates 28.1% of publicly funded mental health consumers are unemployed while 53.9% are not in the labor force—much different proportions than the respective 11% and 69% found in the study sample.

County unemployment rate, geographic classification, race, arrest history, provider certification, and diagnostic group did not associate significantly with E/UL/NLF status.

Age was significantly associated with employment status ($F = 14.48$, $df = 2, 310.2$; $p < .001$). See Table 3 for mean age by E/UL/NLF category. While there was no statistical difference between the mean ages for the E and UL groups, the NLF group had a higher mean age of 48.9 years ($SD = 11.43$) compared to the other two groups.

Table 3. Mean Age for Employment, Unemployed-looking/Not in Labor Force (E/U/NLF) Classification (*N* = 891)

Status	*N*	$\bar{x}$	*SD*
Employed (E)	140	43.9	12.41
Unemployed-looking (U)	101	42.4	12.85
Not in Labor Force (NLF)	650	48.9	11.43
Total	891	47.36	11.98

Gender and labor force status approached significance (X^2= .081; p > .05). A higher proportion of individuals in the NLF category were women. Conversely, higher proportions of those in the employed and unemployed-looking categories were men.

Length of time in services (longevity) and labor force status were significantly associated (X^2 = .106, p < .01). Some 30.2% (n = 269) of the study sample were short-term consumers with a year or less in services, while 69.8% (n = 622) were long-term consumers with a year or more in services. A higher percentage of short-term consumers than long-term were in the employed group, and a lower percentage of short-term consumers than long-term were in the NLF group. The percentages of short- and long-term consumers who were unemployed-looking was about equal.

Functioning subscale means for the unemployed-looking and NLF groups were not statistically different, but the two groups differed significantly from the employed (F = 10.4, df = 2, 265.28; p < .001). Mean functioning for the employed (n = 130; x = 3.83; SD = .847) was substantially higher than that of the unemployed-looking (n = 95; x = 3.43; SD = 1.03) and NLF (n = 627; x = 3.42; SD = 1.01).

The study sample was covered primarily by Medicaid (n = 807; 90.6%). Services delivered to those in the NonMDC (n = 84; 9.4%) group were covered by other sources of public funding. With regard to service coverage, the sample was not representative of the general service population of adults with serious mental illnesses in SFY 2014, where approximately 15% were covered by NonMDC funding.

Table 4 shows that about a third of those in the study sample's NonMDC group (n = 26; 32.4%) were employed, while only 15.7% (n = 140) of those with Medicaid coverage were employed. A statistical test on this distribution was significant (X^2 = .145, p < .001). An odds ratio (OR) was run to determine the probability of employed status if not covered by Medicaid. The OR was significant, with β = 1.068; SE = .255; β(exp) = 2.909; p = .000. In other words, if the service coverage was NonMDC, the probability of employed status was increased by a factor of 2.91.

Table 4. Medicaid Coverage and Labor Force Status (*N* = 891)

Medicaid Coverage		Labor Force (LF) Status			Total
		Employed	Unemployed-L	NLF	
No	N	27	9	48	84
	% within Medicaid	32.4%	10.7%	57.1%	100.0%
	% within LF Status	19.3%	8.9%	7.4%	9.4%
Yes	N	113	92	602	807
	% within Medicaid	14.0%	11.4%	74.6%	100.0%
	% within LF Status	80.7%	91.1%	92.6%	90.6%
Total	N	140	101	650	891
	% within Medicaid	15.7%	11.3%	73.0%	100.0%
	% within LF Status	100.0%	100.0%	100.0%	100.0%

The portion of the study sample covered by Medicaid (n = 807) was further classified into five eligibility programs. See Table 5 for Medicaid program distributions.

The distribution of Medicaid programs in the sample were not representative of the program distributions in the general service population that received mental health services through providers licensed by OhioMHAS. The Aged, Blind and Disabled (ABD) group made up 59.6% (n = 481) of the study sample. The ABD group was over-represented, as the state's adult service population estimate for the group in the SFY 2014 Medicaid database was about 46%. The Covered Children and Families (CFC) group made up 13.8% (n = 111) of the sample, a substantial under-representation of the estimated 35% of the state's adult behavioral health service population covered by Medicaid in SFY 2014. The Buy-in category (n = 35; 4.3%) was over-represented compared to the general population estimate of 1.6%, as was the All Other Programs category (*n* = 48; 5.9%) compared to a state service population estimate of 2.4%. At 15.4% (n = 132), the Medicaid Adjusted Gross Income Expansion (MAGI) portion of the sample was roughly equal to the estimated 15.5% (*n* = 41,900) of the Medicaid general service population that received services through OhioMHAS-certified providers. The MAGI group are newly covered, low-income Ohioans who became eligible through the Affordable Care Act under the state's Medicaid expansion.

Among the five Medicaid programs, the Buy-in category had the highest percentage of sampled respondents in the employed group (*n* = 16; 45.7%). A statistical test of this distribution was significant, with X^2 = .326, $p < .002$.

Functioning was not associated with type of coverage.

The Buy-In and CFC groups had significantly lower mean agreement than the ABD group on the A-ECM item statement that "Having a job causes me to loose government benefits." The ABD group (*n* = 463) mean was 3.46 (*SD* = 1.154) compared to the Buy-In group (*n* = 34) mean of 3.03 (*SD*=1.167) and CFC group (*n* = 109) mean of 3.10 (*SD* = 1.146). A statistical test of the item means by coverage distribution was significant ($F = 3.160$, $df = 5, 773$; $p < .01$).

Means tests of the A-ECM incentives subscale by labor force status was significant ($F = 62.253$, $df = 2, 864$; $p < .001$). The incentives subscale mean score for the employed (*n* = 138; = 3.82; *SD* = .756) and unemployed-looking (*n* = 100; = 3.77; *SD* = .736) were significantly higher than the NLF (*n* = 629) subscale mean of = 3.10 (*SD* = .852).

A similar test of the A-ECM barriers subscale mean scores by labor force status was not significant.

Regression Model. Multinomial logistic regression was used to predict labor force status (Employed, Unemployed-Looking, NLF) with age, gender, longevity, Medicaid coverage, functioning, and the incentive and barrier subscales. A significant model emerged, with $X^2 = 250.102$, $df = 24$, $p = .000$. Table 6 shows the results of the model.

Results indicated similarities and differences between variables thought to predict employed or unemployed status versus NLF. For both employed and unemployed, incentives to employment are the strongest of the predictors. For every one point increase in the incentives subscale, the likelihood the person is employed versus NLF increased by a factor of 2.66. The likelihood the person is unemployed, but looking increased by a factor of 3.21 compared to NLF. The barriers subscale is also a significant predictor for both employed and unemployed, but it is a weak estimator compared to incentives. For every one point decrease in the barriers subscale, the likelihood of employed status increases by a factor of .58 while the likelihood of unemployed-looking status increases by a factor .68 compared to NLF.

Medicaid program coverage of ABD, CFC and All Other MDC significantly predicts the likelihood of NLF over employed, but not NLF over unemployed-looking status. Though significant, the Medicaid program predictors are weak estimators. The strongest—ABD—indicates that for every person in the sample covered by the program, the likelihood of being employed decreases by 90%. Although Buy-in is the strongest predictor of employed and unemployed-looking versus NLF status, it is not significant. Another non-significant, but strong predictor of unemployed-looking versus NLF status was MAGI coverage.

Table 5. Medicaid Program by Labor Force Status (*N* = 807)

Medicaid Program			Labor Force Status: Employed	Unemployed-L	NLF	Total
	ABD	*N*	29	44	408	481
		% within Program	6.0%	9.1%	84.8%	100.0%
		% within Labor Force	25.7%	47.8%	67.8%	59.6%
	Buy-In	*N*	16	6	13	35
		% within Program	45.7%	17.1%	37.1%	100.0%
		% within Labor Force	14.2%	6.5%	2.2%	4.3%
	CFC	*N*	26	18	67	111
		% within Program	23.4%	16.2%	60.4%	100.0%
		% within Labor Force	23.0%	19.6%	11.1%	13.8%
	MAGI	*N*	33	21	78	132
		% within Program	25.0%	15.9%	59.1%	100.0%
		% within Labor Force	29.2%	22.8%	13.0%	16.4%
	All Other Programs	*N*	11	3	36	48
		% within Program	18.8%	6.3%	75.0%	100.0%
		% within Labor Force	8.0%	3.3%	6.0%	5.9%
Total		*N*	113	92	602	807
		% within Program	14.0%	11.4%	74.6%	100.0%
		% within Labor Force	100.0%	100.0%	100.0%	100.0%

Notes: ABD = Aged, Blind and Disabled
Buy-in = Medicaid Buy-in for Workers with Disabilities
CFC = Covered Families and Children
MAGI Expansio*n* = Modified Adjusted Gross Income Expansion (Eligible under Affordable Care Act)
All Other Programs = Medicare Premium Assistance Program (*n* = 41); Breast & Cervical Cancer (*n* = 7)

Table 6. Summary of Regression for Variables Thought to Predict Employment (*N* = 850)

Variable	Employed‡ β	SE	Exp(β)	Unemployed-looking† β	SE	Exp(β)
Intercept	-1.284	1.004		-1.160	1.059	
Age	-.038**	.010	.963	-.046**	.011	.955
Functioning	.281*	.130	1.324	-.232	.128	.793
Incentives	.982**	.151	2.659	1.165**	.167	3.207
Barriers	-.542**	.174	.581	-.386*	.191	.679
Gender (Female)	-.035	.238	.883	-.187	.251	.829
Longevity (Short)	.299	.277	1.348	- .139	.316	.871
Medicaid‡						
ABD	-2.324**	.358	.098	-.788	.454	.455
Buy-In	.147	.507	1.158	.263	.676	1.301
CFC	-.887*	.435	.412	-.152	.537	.859
MAGI	-.753	.404	.471	.211	.522	1.234
All Other MDC	-1.236*	.521	.291	-.818	.759	.441

Notes: †Referent: NLF
‡Referent: NonMedicaid
**Significant at $p < .01$; *$p < .05$;
$X^2 = 249.469$, $df = 22$, p = .000

Limitations and Discussion

Results can be interpreted as they apply to the study sample, but should not be broadly inferred to the general service population due to disproportionate representation of important variables of interest. The sample under-estimates employment and over-estimates NLF status. That said, much can be learned from the sample about the relationship of incentives and barriers to employment, functional impairment, and payment program coverage to labor force status.

The study's adapted ECM produced a two factor incentives and barriers solution comparable to that of the original ECM developed by Larson et al (2011). Based on results of that study, it was hypothesized that the incentives to employment subscale would predict of labor force status in a statewide sample of mental health consumers. Results of the current study support that hypothesis. For every one point increase on the incentives subscale, the probability of an employed status increased by about 266% and the probability of an unemployed-looking status increased by about 321%. Incentives are an even stronger predictor of employment seeking than actual employment.

While A-ECM's barriers subscale also significantly predicted labor force status, this measure produced a lower probability estimate for an NLF over an employed or unemployed-looking status. Results suggest that for every one point increase in the barriers subscale, the probability of an employed status decreased by about 58% and the probability of unemployed-looking status decreased by about 68%.

According to the statistician George Box, "all models are wrong, but some are useful."[5] What is most useful about the current study's regression model is the finding that incentives to employment have more predictive strength regarding labor force participation than barriers. A cursory review of the five Incentive subscale items – depression reduction, anxiety reduction, greater responsibility, managing work stress, and increased problem solving—suggests intrinsic motivation is a hugely important factor for individuals with serious mental illnesses in the labor force. This has implications for encouraging greater interest in employment in the target population.

Another useful aspect of the study's regression model is the finding that the predictive importance of Medicaid program varies by program and labor force status when NonMDC coverage is held constant. It is no surprise to see that ABD coverage increased the likelihood of NLF status by 90%. A more promising finding is that coverage under MAGI expansion did not have a significant negative effect on labor force status. In addition, the unemployed-looking group does not appear to be significantly influenced by Medicaid coverage. Even within the employed group, there was some difference in the importance of the various Medicaid programs that hint at a need for more program evaluation. While it is entirely logical that the Buy-In program predicted employed status over NLF by an estimated probability of 116%, the significance of Buy-In coverage was no different than NonMDC. Much more study is needed on trends in Buy-In coverage, which is extremely low at 1.6% in the general service population that received mental health services in SFY 2014 from OhioMHAS' providers.

In pondering the role coverage played on labor force status, it is important to remember that Functioning scores predicted the probability of employed status over NLF by 132% and that was no association was found between coverage and mean Functioning scores. The sample provides evidence that the ABD group, while statistically predictive of NLF status, was no more functionally impaired than those with NonMDC or MAGI or Buy-In coverage. Longitudinal study is needed on trends in ABD versus Buy-In and MAGI coverage among mental health consumers.

Measuring the dependent variable—labor force status—proved more difficult than originally anticipated. When almost 9% of a sample skip over a key question, questions arise about measure validity and reliability. With extensive analysis of the missing data and subsequent responses, we are confident a reliable and valid solution emerged with the final categorizations. Nevertheless, careful study of the missing data prompted speculation about an intriguing item response pattern. Over 90% of the sample were covered by Medicaid, a means-tested benefit needed to pay for services. Of the Medicaid covered group, close to 60% were qualified as ABD. This group was much more likely to perceive potential loss of benefits as a barrier to employment than respondents covered by some of the other Medicaid programs. Although one might speculate that there is a certain amount of "working under the table" or informal attachment to the labor market among people with means-tested benefits, there is no way to know from the study's labor force status measure how much formal and informal labor market activity is being reflected. Along with its inherent limitations as a self-report measure, the MDS 13 does not capture information about whether pay from employment is reported to state and federal tax authorities.

The sample data are rich with information on how certain factors associate with incentives and barriers to employment despite problems deriving from a valid labor force status variable from a self-report survey measure as well as the disproportionate representation of ABD coverage and NLF status. Given the significant strength of the incentives subscale and payment program coverage in predicting labor force status, it should not be surprising that respondents with ABD coverage had lower mean incentive subscale scores than those with Buy-In, MAGI, or NonMDC coverage. Additional evidence that the barriers subscale is a relatively weak predictor of labor force status is found in the lack of significant variation by program coverage in mean scores on the barriers measure. The development of a statistical model using the larger sample with completed A-ECM scales as the dependent variable is warranted.

Implications for Program and Policy

As discussed earlier, the finding that incentives to employment substantially predict labor force status has implications for employment program design. A strengths-based approach that emphasizes the positive aspects of employment is recommended. No doubt some attention should be paid to addressing barriers, but such attention comes with the caveat that self-reported functional impairment proved to be a stronger predictor of NLF status than the perception of barriers such as loss of government benefits, loss of free time, drug testing, increased stress and stigma. And although functional impairment appears to play a role in labor force status, its predictive strength weakens among those who identify as unemployed and looking for work. The desire or perceived need to work implied by the unemployed, but looking status may be factors that over-ride the individual's functional impairment due to serious mental illness.

Careful consideration should be given to incentivizing uptake of Buy-in and MAGI coverage for persons with serious mental illnesses. Low-income workers with newly identified psychiatric disorders who lack coverage for treatment may naturally gravitate to the MAGI option. But what of the existing 45% of the service population covered as Aged, Blind and Disabled? Where the study sample is concerned, ABD status has little relation to functional impairment. Findings also indicate that concern over loss of benefits is a barrier to employment for certain segments of those with Medicaid coverage. At the same time, evidence from the Medicaid service population database suggests limited uptake of the Buy-In option by mental health consumers. The study results strongly support the need for an information campaign regarding coverage benefits and employment.

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Employment Questionnaire

Ohio Department of Mental Health and Addiction Services
Office of Quality Planning and Research

Please help us understand more about your employment experience:

1. Which choice best describes your current employment status? (Choose only one)

O a. Full-time competitive employment (35 or more hours a week at a job for which anyone can apply)
O b. Part-time (Less than 35 hours a week or year-round)
O c. Sheltered Employment (must have disability to apply for job)
O d. Unemployed, actively looking for work
O e. Not in labor force (retired, disabled, homemaker, volunteer, student without a job, etc.)

2. If you are currently employed, about how long have you been in your current position?

O a. Less than a year
O b. More than one year, but less than five years
O c. More than five years, but less than ten years
O d. More than ten years
O e. Doesn't apply—I'm not currently employed

3. If you are currently NOT employed, have you ever been employed?

O a. No O b. Yes

4. If you are currently NOT employed, but have had a job in the past, about how long has it been since you had a job?

O a. Less than a year
O b. More than a year, but less than five years
O c. More than five years, but less than ten years
O d. More than ten years
O e. Doesn't apply – I've never had a job

Whether employed or not, people have beliefs about having a job. Please read each statement and fill in the bubble that best describes how much you agree or disagree.

	Strongly Agree	Agree	Neither Agree or Disagree	Disagree	Strongly Disagree
5. Having a job makes me a more responsible person	O	O	O	O	O
6. Having a job causes me to lose government benefits.	O	O	O	O	O
7. Having a job reduces my anxiety.	O	O	O	O	O
8. Having a job causes me to lose my free time.	O	O	O	O	O
9. Having a job shows people that I can handle work stress.	O	O	O	O	O
10. Having a job reduces my depression.	O	O	O	O	O
11. Having a job causes me to be tested for illegal drugs.	O	O	O	O	O
12. Having a job increases my stress.	O	O	O	O	O
13. Having a job increases my problem solving.	O	O	O	O	O
14. Having a job causes me to experience discrimination because of my mental illness.	O	O	O	O	O

Thank You for Participating

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