Changing Labor Markets and Mental Illness:
Impacts on Work and Disability

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Introduction

Many of the sequelae of mental illness – motivational, affective, and cognitive – translate into impairments in the skills that contribute to labor market productivity. A recent review summarized the evidence on cognitive dysfunction for seven categories of mental illness (Millan et al. 2012) concluding that for many people with mental illness, "cognitive dysfunction is broad-based and seriously affects real-world functioning." More specifically, this review elucidates the important impacts of mental illness on attention, working memory, executive function, speed of processing information, and social cognition. These deficits combined with some of the motivational (e.g., sense of purpose, goal orientation) and affective features of mental illnesses, limit productivity. The impact on productivity stemming from mental illness is exacerbated by the onset of a number of these illnesses in late adolescence and early adulthood, compromising the accumulation of human capital in the forms of education, training and job experience, leaving people with these diagnoses at a lifelong disadvantage (Breslau et al. 2008). While there is a great deal of heterogeneity in the impacts of mental disorders on various dimensions of productivity, mental illnesses have consistently been shown to create large disease burdens.

For many people with a mental illness, as for most people, work is beneficial (Luciano AE, GR Bond, RE Drake, 2014). For people with severe mental illnesses, work has a therapeutic effect and leads to more social interaction and better general well-being.

The skill impairments associated with mental illness have always made it challenging to integrate people with severe mental illness into the workforce. However, there is good reason to believe that, despite improved treatment, the changing nature of work makes this integration more challenging. The 21st century labor market demands a different set of skills than were needed in the past. Automation of routine tasks has been accelerating; technological improvements in information and communications technology require a workforce that has the capacity to engage in non-routine cognitive-intensive work (Gaggl and Wright 2017) . These technological trends decrease demand for low-wage jobs that require workers who can perform routine cognitive and non-cognitive tasks. This pattern of change in workforce demand may have profound effects on the employment prospects for people with mental illnesses. Specifically, if people with mental illnesses are disproportionately employed in jobs where the demand for the skills that they retain is declining they may be disproportionately disadvantaged by the evolution of U.S. labor markets. This, in turn, raises concerns about both the economic and therapeutic circumstances this sub-population will face in the coming decades.

In this paper, we describe three issues of relevance to the dynamic relationships between mental illness and the changing labor market: What are the trends in labor force participation (LFP) for people with mental illnesses for the years 1997-2017; what are the trends over time in disability application among people with mental illnesses; and does the composition of skills required by jobs held by people with mental illnesses differ from that of the general population? We use data from the National Health Interview Survey (NHIS) for the years 1997-2017 and the Occupational Information Network (O*NET) survey of jobs. We offer some hypotheses about what our findings mean for employment of people with these illnesses in the coming decades.

Data and Approach

A. Overview of Approach and Analyses

We first describe unadjusted differences in LFP across time (1997-2017) among those with no, mild, moderate, and severe mental illness, stratified by gender (male versus female). Given differences in characteristics across mental health status that might also be associated with LFP, we then decompose differences in LFP using two different approaches. The first approach is informed by Krueger (2017), and weights overall LFP by the population shares of age, gender, and mental health status of 1997 and again by population shares in 2017. The second approach uses the Blinder-Oaxaca decomposition method to explain differences in LFP between individuals with and without serious psychological distress by observable demographic factors (age, race/ethnicity, educational attainment, marital status, family structure, and geographic region) and general health status relative to the unexplained difference that we infer represents the portion of the LFP gap explained by serious psychological distress independent of these other observable characteristics (Jann, 2008). We applied these same analyses to trends in SSDI applications.

Finally, we examined differences in skill mix of jobs held by people with various levels of psychological distress. Skills were classified using the taxonomy developed by Acemoglu and Autor (2011): (1) non-routine cognitive: analytical; (2) non-routine cognitive: interpersonal; (3) routine cognitive; (4) non-routine manual: physical; (5) routine manual. In each of the four categories of mental illness (none, mild, moderate, severe), we compare the average standard deviations above or below the mean density of a given set of skills in that year across 1997-2017, stratified by gender (male versus female).

Decomposition analysis

The decomposition of changes in labor force participation makes use of two approaches. The first follows a method presented recently by Krueger (2017). He specifies a decomposition of changes in labor force participation over time as follows.

(1) $L_t = \Sigma L_{it} (p_{it}/\Sigma p_{it}) = \Sigma L_{it} w_{it}$

(2) $\Delta L = \Sigma \Delta L_{it} w_{it-k} + \Sigma \Delta w_i L_{it}$ and $\Delta L = \Sigma \Delta L_{it} w_{it} + \Sigma \Delta w_i L_{it-k}$

Where L_{it} is the labor force participation rate for population group i at time t (in years), p_{it} is the size of the population of group i at time t and w_{it} is the population share of population group i at time t. The first equation in (1) weights by the population group shares at the beginning of the period (e.g. 1997) and the second weights by the population share at the end of the time period (e.g.2017). Therefore, (2) decomposes the changes in overall labor force participation (LFP) rates into one component made up of the change in the LFP rate within a population group and a second made up of changes in the composition of the population with respect to the i groups. We apply the same approach to decomposing the rates of applying for Social Security Disability Insurance (SSDI).

In order to better understand the effect of psychological distress on LFP and applications for SSDI, we used a linear probability model to conduct the Blinder-Oaxaca decomposition analysis using a finer set of demographic, human capital and health status characteristics[1]. These characteristics include, race/ethnicity indicators, educational attainment, marital status, parental status, geographic region, and general health status. The grouping variable indicates whether an individual had no mental illness (0-4 on the K-6) or if they had severe psychological distress (13-24 on the K-6).

B. Data

We rely on two sets of data: The National Health Interview Survey (NHIS) and the O*NET database on occupational skills. The NHIS is a large national household survey that collects information on about 87,000 people who are members of roughly 35,000 households. The NHIS collects detailed data on household demographics, income, employment, occupations and indicators of mental health status. The NHIS yielded 646,279 person-year survey responses during the 1997-2017 time-frame (945,815 under age 65). The two main outcomes we examine are Labor Force Participation (LFP) and application for Social Security Disability Insurance (SSDI). Our LFP measure is based on questions that ask whether an individual is working for pay or working not for pay at a family owned business or looking for work. The SSDI application indicator is based on a question that directly asks whether financial support from SSDI was received.

The NHIS collects information on symptoms of mental illnesses focusing on psychological distress using the so-called K-6 measurement scale (Kessler et al, 2002). While the scale does not yield specific diagnoses, it has been found to be a reliable measure of the overall population prevalence of mental illnesses as well as the

[1] Because most of our explanatory variables are dummy variables the convenience of using the linear probability model comes at a relatively small cost with respect to the estimated precision of coefficient estimates (Wooldridge, 2002).

prevalence of serious mental illnesses (e.g. bipolar disorder, schizophrenia and major depression). In particular, is has been found to produce consistent estimates across surveys and populations and has shown little bias in estimated rates of illness by education and gender when compared to structured clinician interviews. The K-6 estimates of psychological distress and serious psychological distress are available in the NHIS for the years 1997-2017. We use the K6 scores to construct 4 levels of mental illness severity: none, mild, moderate and severe. The cut off scores used to classify people into severity groups are based on a 2008 study that compared the K6 score with clinician diagnoses based on a structured diagnostic interview. The K6 scores were used as explanatory variables in a model predicting the presence of a diagnosis based on the structured interview. The parameters of that model were then used to construct the severity groupings (Colpe et al, 2010). To ensure that we had sufficient samples for each level of mental health status we pooled data into three- year intervals: 1997-1999, 2006-2008, and 2015-2017.

Each survey respondent, both those currently working and those who had ever worked, was asked about their current or most recent occupation. The occupations were classified according to modified census codes that were expanded to 94 discrete occupations in 2004. These categories were aggregated into 23 broader occupational categories. However, because the coding changed in 2004, we used data from the census on apportionment of the older occupation codes into the new codes to obtain consistent occupation classification for 1997-2003.

We used the data on occupations held by respondents along with the O*NET data to classify respondents according to the skill composition of their jobs. The O*NET data are compiled by the Bureau of Labor Statistics (BLS) of the Department of Labor. The database measures 400 variables describing job skill, ability and knowledge requirements by industry and occupation. These variables are classified according to BLS 2010 Standard Occupational Codes (SOC) and are further expanded into additional O*NET-SOC occupations. These eight-digit O*NET-SOC codes were collapsed into six-digit SOC codes and cross-walked to the 2010 census occupation codes used in the NHIS data. The O*NET values by occupational codes were merged onto the census occupational codes for everyone in the NHIS survey with occupational information. We then followed the procedures set out by Acemoglu and Autor (2011) to produce composite scores for each occupation described above that summarize the skill requirements of the job.[2]

Results: Trends in Labor Force Participation

Table 1 shows results for the relationship between indicators of psychological distress and aggregate labor force participation among adults aged 18-64.

[2] One concern in looking at the impact of mental illness on labor force participation is the possibility of reverse causality. People's mental health may deteriorate because they have left the labor force or transferred to different kind of job. We draw on some previous literature and our own investigations reported elsewhere that suggest that the evidence in support of endogeneity tends to be weak. We therefore proceed assuming mental disorders and severe disorders particularly are exogenous.

Table 1

Table 1: Labor force participation by mental health status, stratified by gender (Ages 18-64)

Gender	K-6 Score	1997-1999	2006-2008	2015-2017	Percentage-point △
Female					
	None (0-4)	71.13%	71.11%	70.88%	-0.25%
	Mild (5-9)	64.29%	62.34%	63.86%	-0.43%
	Moderate (10-12)	54.84%	49.17%	54.03%	-0.82%
	Severe (13-24)	43.71%	35.73%	37.82%	-5.89%
	Overall	68.47%	67.65%	67.41%	-1.06%
Male					
	None (0-4)	85.80%	84.47%	82.08%	-3.72%
	Mild (5-9)	76.47%	71.76%	70.42%	-6.05%
	Moderate (10-12)	62.75%	52.85%	56.44%	-6.31%
	Severe (13-24)	46.11%	38.91%	37.69%	-8.41%
	Overall	83.26%	81.08%	78.25%	-5.00%

Notes

[a]Change is between the 1997-1999 band and the 2015-2017 band

For both women and men, the data show a clear gradient in labor force participation by severity of psychological distress. In 1997-99, women with severe psychological distress were only 61.45% as likely to participate in the labor force as those who reported no symptoms of psychological distress. Men with severe psychological distress were even more disadvantaged, with a rate of participation only 53.7% that of men no symptoms of psychological distress.

The temporal patterns of participation by illness severity vary by gender. There was little change in labor force participation (LFP) between 1997-1999 and 2015-2017 for women with no significant symptoms of psychological distress. Between 1997-1999 and 2006-2008, the period of the recession, LFP among women with any mental illness declined. The magnitude of the decline around the time of the recession was directly related to illness severity, ranging from roughly 3% for those with mild illness to 18% for the severely ill group. LFP returned to pre-recession levels by 2015-2017 for women with mild and moderate conditions, but the LFP rate for women with severe psychological distressed recovered less and did not return to 1997 levels. LFP in this group was 13.48% below 1997-1999 levels in 2015-2017.

LFP rates for working age men fell between 1997-1999 and 2006-2008 for all symptom severity groups and did not consistently recover by 2015-2017. Men with no significant symptoms of psychological distress experienced a 3.7 percentage point or 4.3% decline in LFP rate from the 1997-1999 interval to 2015-2017. Among those with mental health conditions LFP fell, with the declines increasing with illness severity -- by between 7.9% for those with mild illnesses and 18.2% for those with severe illnesses.

Table 2

Table 2: Overall labor force participation by mental health status (Ages 18-64)

K-6 Score	1997-1999	2006-2008	2015-2017	*Percentage-point △
None (0-4)	78.57%	77.90%	76.58%	-1.98%
Mild (5-9)	69.59%	66.52%	66.79%	-2.80%
Moderate (10-12)	57.91%	50.62%	54.98%	-2.93%
Severe (13-24)	44.57%	36.96%	37.77%	-6.80%
Overall	75.72%	74.27%	72.73%	-2.99%

Notes
Change is between the 1997-1999 band and the 2015-2017 band.

Table 2 reports the overall labor force participation rates pooled by gender and stratified by mental health status. The table shows the gradient in LFP by mental health status described earlier. In recent years people with severe psychological distress, as measured by the K6 have LFP rates of slightly less than half (49.3%) of that of people with no significant symptoms of psychological distress. The trend in LFP overall shows a modest decline of just under 3 percentage points. Each of the groups of people with mental health problems had declines in LFP that exceeded those for the overall population.

We used the Krueger decomposition technique to analyze the changes in labor force participation according to whether they occurred due to changes in LFP within a demographic-illness cell or because of changes in the composition of the population. That is, we calculated the labor force participation rate in each three-year interval for each age, gender, and psychological distress category weighted for the population shares either at their 1997 or their 2017 level. Thus, the estimated LFP are those that result from holding constant the population composition. We used equation (2) to construct the aggregate LFP results. Table 3 displays those results.

Table 3

Table 3: Krueger decomposition analysis of labor force participation (Ages 18-64)

Weights	1997-1999	2006-2008	2015-2017
1997	75.70%	75.03%	74.54%
2017	73.36%	72.99%	72.86%

Notes:
Weights were created from stratified cells of gender, age, and mental health status for the year 1997 and 2017.

After holding the demographic and psychological distress mix of the population constant, the results demonstrate population wide LFP be declining slightly, suggesting that there are factors other than shifting demographics underpinning the decline in LFP. However, the decline was less pronounced than was observed in the unadjusted results on Table 2. For example, the decline using the 1997 weight was 40% of the unadjusted change. This suggests that demographic and mental health status changes were responsible for a substantial part of the decline in LFP rates. Specifically, the share of the population experiencing at least some mental illness is growing. For example, the rates of severe psychological distress increased by 18.2% for men and 13.5% for women from the 1997-1999 year-band to the 2015-2017 year-band. These observed increases in the proportion of the population reporting mental illness symptoms are consistent with recent reports that show increases in rates of mental illness for the adult population and especially for those under age 50 (SAMHSA, 2019). Our analysis of the K-6 responses shows that the increases in distress are driven largely by increased prevalence of symptoms of depression and anxiety. Much of the decline in LFP associated with mental illness took the form of early retirement, defined as stating that one is retired prior to age 65. Over time, there was a 114% increase in early retirement rates among those with severe psychological distress compared to a 31% increase in rates for people without any indications of a mental illness.

Table 4 reports the results from the Oaxaca decompositions. Again, these are based on labor supply regressions where the differences between key groups, those with and without severe psychological distress in this case, are decomposed into the part of LFP that is explained by individual characteristics and the unexplained portion that is interpreted as the effect of severe psychological distress. Similar to the results in Table 1, the LFP rate among men without significant symptoms of mental illness was 80.7%, while the rate among those with severe mental illness the adjusted rate was 38.3%. Using a generous set of explanatory variables (including general health status and region of residence), roughly 41% of the difference of 42 percentage points (17 percentage points) between those with severe psychological distress and those without illness can be attributed to differences in the characteristics of people who have severe psychological distress and those without severe psychological distress.[3] For example, those with severe psychological distress are typically older and live in different parts of the country. The presence of severe psychological distress by itself, however, accounts for 59% of the difference or 25 percentage points (unexplained estimate in Table 4).

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Table 4

Table 4: Oaxaca decomposition results for labor force participation (Ages 18-64)

	[a]Male Estimate	[a]Female Estimate
[c]All other MH categories	80.71%	68.49%
Severe Psychological Distress	38.32%	37.14%
Difference	42.39%	31.35%
Explained	17.44%	15.42%
Unexplained	24.96%	15.93%
Percent of difference unexplained	58.87%	50.82%

Notes:
[a] Significant at *p*<0.001
[b]A linear probability model was fit. Percent therefore represent probability of LFP.
[c]All other MH categories = none, mild, moderate

The results are similar for women. The LFP rate for women without severe psychological distress is 68.49%, while that for women with severe psychological distress is 37.14%. Differences in the characteristics of people with severe mental conditions accounts for about 49% of the 31-percentage-point difference in LFP. The presence of severe psychological distress independent of individual characteristics accounts for about 51% of the difference or 16 percentage points.

[3] We include the detailed decompositions results in Appendix A.

Results: Trends in SSDI

In this section we repeat our analyses of LFP looking instead at trends in SSDI applications by working age adults (ages 18-64) stratified by psychological distress and gender. Table 5 presents the results on rates of SSDI application over the 1997-2017 period.

Table 5

Table 5: SSDI applications by mental health status, stratified by gender (Ages 18-64)

Gender	K-6 Score	1997-1999	2006-2008	2015-2017	*Percentage-point △
Female					
	None (0-4)	2.21%	3.17%	4.42%	2.22%
	Mild (5-9)	6.62%	10.62%	11.38%	4.76%
	Moderate (10-12)	12.38%	20.45%	20.83%	8.45%
	Severe (13-24)	21.39%	32.33%	32.68%	11.28%
	Overall	3.90%	5.94%	7.66%	3.76%
Male					
	None (0-4)	2.69%	3.42%	4.59%	1.90%
	Mild (5-9)	9.14%	11.62%	11.91%	2.77%
	Moderate (10-12)	18.52%	26.76%	22.47%	3.95%
	Severe (13-24)	32.18%	36.29%	38.67%	6.49%
	Overall	4.45%	5.78%	7.28%	2.82%

Notes
Change is between the 1997-1999 band and the 2015-2017 band

For both women and men, Table 4 shows that rates of SSDI applications increase with the severity of symptoms. Among women, rates of SSDI applications have increased among all groups, consistent with greater LFP across cohorts (making more women eligible for SSDI). But rates increased most among women with symptoms of psychological distress. By 2015 – 2017, the rate for women with mild symptoms was about 2.6 times the rate of those with no significant symptoms of psychological distress. For women with severe psychological distress, 32.68% applied for SSDI compared to the 4.42% of those without symptoms. For all levels of psychological distress, the rate of applications for SSDI increased monotonically across all three timeframes.

The lower panel of Table 4 shows a somewhat similar temporal pattern for men. As was the case for women, trends in rates of SSDI applications over time are increasing in the severity of psychological distress.

Table 6

Table 6: Overall SSDI application rates by mental health status (Ages 18-64)

K-6 Score	1997-1999	2006-2008	2015-2017	*Percentage-point △
None (0-4)	2.45%	3.30%	4.51%	2.06%
Mild (5-9)	7.71%	11.06%	11.61%	3.90%
Moderate (10-12)	14.77%	22.95%	21.49%	6.72%
Severe (13-24)	25.29%	33.87%	34.99%	9.71%
Overall	4.17%	5.86%	7.47%	3.30%

Notes
Change is between the 1997-1999 band and the 2015-2017 band

Table 6 reports the LFP rates pooled across the genders and stratified by mental health status. For the 2015-2017 period those people with severe psychological distress had SSDI application rates that were 7-fold those without any significant symptoms of psychological distress. For all population segments SSDI applications increased throughout the 20-year period from 4.17% to 7.47%. The rate of increase slowed after the great recession. It is notable that the largest percentage increase in application rates was for people without significant symptoms of psychological distress.

Table 7

Table 7: Krueger Decomposition Analysis of SSDI Application Rates (Ages 18-64)

Weights	1997-1999	2006-2008	2015-2017
1997	4.28%	5.49%	6.23%
2017	5.15%	6.51%	7.37%

Notes:
Weights were created from stratified cells of gender, age, and mental health status for the year 1997 and 2017.

Table 7 reports the results of the Krueger decomposition of aggregate SSDI application rates, holding the demographic and mental health status composition of the population constant at either the 1997 or 2017 population mix. Table 7 shows that under both configurations, the SSDI application rates are trending upwards. The difference in levels in the two trends primarily reflects the aging of the population and the growing prevalence of mental health conditions. We find that holding the population mix constant, SSDI application rates increased continuously over the 20-year period. While the rate of increase appears to be related to the business cycle, the overall trend is upward. This means that there are factors other than mental health status and demographics contributing to an upward trend in SSDI application. We also conducted a Oaxaca decomposition for SSDI application, as we had for LFP. Table 8 reports the results of this decomposition.

Table 8

Table 8: Oaxaca decomposition results for SSDI applications (Ages 18-64)

	[a]Male Estimate	[a]Female Estimate
[c]All other MH categories	4.95%	4.89%
Severe Psychological Distress	36.35%	29.78%
Difference	-31.40%	-24.89%
Explained	-12.62%	-10.88%
Unexplained	-18.78%	-14.01%
Percent of difference unexplained	59.80%	56.28%

Notes:
[a]Significant at $p<0.001$
[b]A linear probability model was fit. Percent estimates therefore represent probability of SSDI applications.
[c]All other MH categories = none, mild, moderate

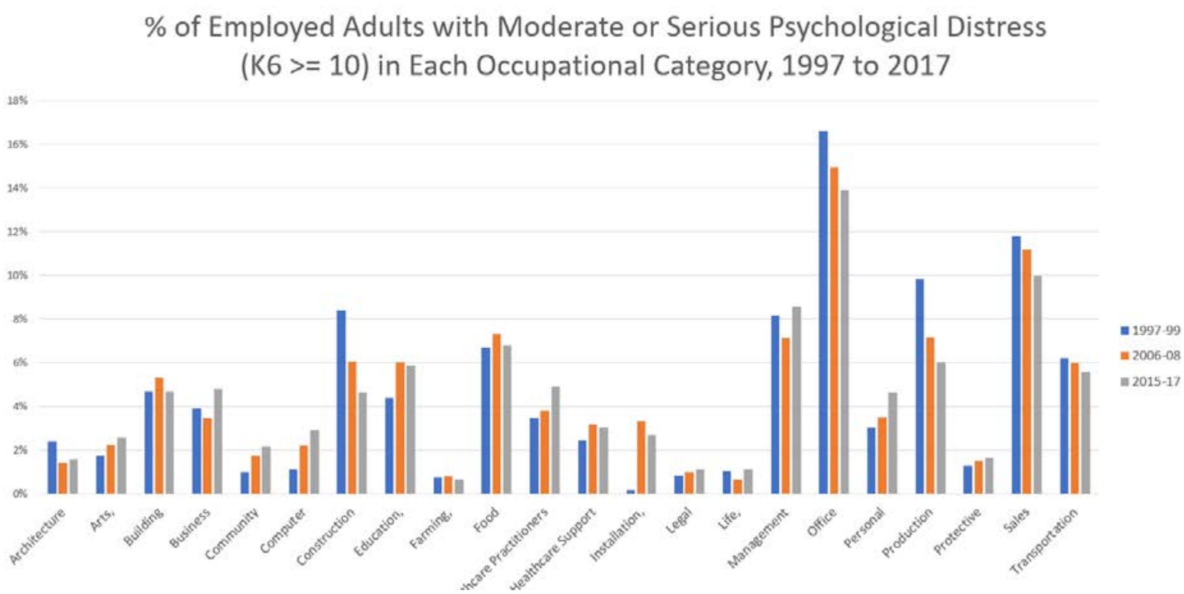
The SSDI application rate for women without serious psychological distress is 4.89%, compared to 29.78% for those with serious psychological distress; this leaves a difference in SSDI application rates of 24.89 percentage points. 10.88 percentage points, or 44.72% of the difference is accounted for by attribute differences between those with serious psychological distress and those without. The remainder of the difference we interpret as being primarily due to the impact of the mental illness itself.

The results for men present a similar pattern. That is, men without serious psychological distress had an SSDI application rate of 4.95% compared to 36.35% among those without serious psychological distress. We estimated that 12.6 percentage points of the 31.4 percentage-point difference was accounted for by differences in individual attributes between the two populations, or 40.2%. Thus, the remaining 59.8% of the difference we interpret as being primarily due to the impact of serious psychological distress.

Results: Occupation and Skill Mix

We begin a consideration of occupational and skill mix of jobs held by people with mental health conditions by reporting the occupational distribution for people with a mental health condition. Figure 1 displays the occupational distribution for people with a mental health condition that is moderate or severe as indicated by their K6 score. We present the distributions for the three time periods reported earlier (1997-1999; 2006-2008; 2015-2017).

Figure 1



We identify several notable patterns in the distribution of people with moderate to severe mental health conditions across occupations. The occupations with the highest concentration of people with a mental health condition are office workers, sales, production, management, construction and food preparation. Office, sales and construction shares of the labor force declined markedly during the 20 years of observation. The jobs held by people with mental illnesses appear to be somewhat more concentrated within a few occupations than the mix for the overall labor force, with a disproportionate share engaged in office work, sales and food preparation jobs that tend to be relatively low wage-low skill occupations. Yet there is heterogeneity within those jobs and the skill composition may be changing over time. To address this issue, we focus on the skill-task composition of jobs. Building on the work of Autor (2019), Nedelkoska and Quintini (2018) and Manyika et al (2017) we consider the skill mix of the jobs held by people with mental illnesses. We do this by analyzing the use of the merged O*NET - NHIS data described earlier.

Table 9 provides estimates from the merged O*NET and NHIS.

Table 9

Table 9: Average task skill decomposition by gender and level of psychological distress (Ages 18-64)

		Non-Routine Cognitive: Analytical		Non-Routine Cognitive: Interpersonal		Routine Cognitive		Non-Routine Manual: Physical		Routine Manual	
	K-6 Score	1997	2017	1997	2017	1997	2017	1997	2017	1997	2017
Female											
	None (0-4)	0.18	0.10	0.26	0.16	0.13	0.02	-0.30	-0.35	-0.16	-0.28
	Mild (5-9)	0.04	-0.09	0.15	-0.03	0.14	0.13	-0.20	-0.26	-0.08	-0.16
	Moderate (10-12)	-0.20	-0.20	-0.09	-0.13	0.20	0.12	-0.05	-0.08	0.20	0.02
	Severe (13-24)	-0.25	-0.30	-0.09	-0.16	-0.04	0.19	-0.03	-0.13	0.12	0.00
Male											
	None (0-4)	-0.08	0.00	-0.16	-0.08	-0.09	-0.06	0.21	0.32	0.10	0.21
	Mild (5-9)	-0.21	-0.12	-0.25	-0.17	-0.08	0.00	0.28	0.35	0.16	0.28
	Moderate (10-12)	-0.48	-0.33	-0.45	-0.24	-0.13	0.03	0.52	0.52	0.43	0.47
	Severe (13-24)	-0.43	-0.51	-0.41	-0.41	-0.16	0.09	0.36	0.68	0.38	0.63

The table entries represent the average standard deviations above or below the mean density of a given set of job skills in that year. It is scaled so that the standard deviation ranges in value from -1 to 1 with a mean of zero. A negative value indicates that people with a specific set of characteristics are under-represented in occupations with the identified skill characteristics (e.g. Non-Routine Cognitive) relative to the overall employed population. We report on 1997 data as a type of baseline.

One interesting feature of the table is that the representation of people with mental illness symptoms varies quite systematically within job categories. For each occupational category, those with more symptoms are more (or less) represented than those with fewer symptoms. Jobs held by women and men have somewhat different occupational profiles (note that the standard deviations are calculated from the population mean for the combined population of women and men).

People with moderate to severe psychological distress are consistently under-represented in occupations with skill demands involving Non-Routine Cognitive Analytical and Non-Routine Cognitive Interpersonal skills. This under-representation has been growing over time, implying that even within these categories, the job challenges for people with mental illness have been growing.

Research by Autor, Levy and Murname (2003) and Autor and Salomons (2018) shows that skill demand has been growing for jobs requiring non-routine analytic and interpersonal skills – those where people with mental illnesses are under-represented, while job demand has been declining for occupations that require routine and non-routine manual skills -- jobs where people with mental illnesses are increasingly over-represented. The projections for demand for skills suggest that further declines can be expected in routine manual and routine cognitive skill set jobs. This suggests that the trends of reduced LFP and higher disability claims among people with mental illnesses we observed in the earlier tables are likely to be exacerbated by the further evolution of the labor market.

Concluding Observations

The analysis presented has described patterns of LFP and SSDI application for people with mental health conditions relative to the rest of the population. We also examined whether people with mental health conditions are more frequently in jobs that require a different set of skills than the jobs held by other workers. Our analysis leads us to several observations and a hypothesis to be explored. First, the LFP rates of men with all levels of mental health conditions and women with severe conditions were substantially lower than those of people without mental health related symptoms. The data also show that these groups were strongly affected by the recession and that their levels of LFP have not returned to pre-recession levels. Holding constant the demographic and mental health status composition of the population suggests that LFP rates have been either level or slightly decreasing over the 20 years we observe. That decomposition also indicates that the aging of the population and the increasing prevalence of mental health conditions is influencing lower levels of observed LFP. A third observation on LFP is that for severe conditions over half the difference is LFP is due to the mental illness holding individual attributes including human capital characteristics constant.

The results on SSDI application rates show an overall upward trend that is common to both sexes and all mental health status categories. The level differences for all populations with a mental health condition were considerably higher than for people without significant symptoms of mental illnesses. The results show some changes in the rate of applications for SSDI that track the business cycle, but the overall pattern was consistent pre and post-recession. Our decomposition analysis indicates that the majority of the difference in SSDI application rates between those with moderate to severe mental health conditions and those without any condition was due to the mental illness itself, after accounting for individual attribute differences.

Finally, our analysis of skill mix by mental health status shows that working people with mental health conditions hold jobs with a substantially different skill mix than the rest of the labor force. Moreover, it appears they hold jobs that are projected to be most at risk of being eliminated by mechanization and AI. This leads us to posit that some of the recent disproportionate effects of mental health conditions of LFP may be due to changes in skills demand that make it harder to match people with mental health conditions to jobs where their skills can effectively be put to work.

Appendix

Oaxaca Decompositions of Labor Force Participation and SSDI applications by Serious Psychological Distress Status (18-64)

		Labor Force Participation				SSDI Applications			
		Female		Male		Female		Male	
Overall									
	All other MH categories	68.49%	***	80.71%	***	4.89%	***	4.95%	***
	Severe Psychological Distress	37.14%	***	38.32%	***	29.78%	***	36.35%	***
	Difference	31.35%	***	42.39%	***	-24.89%	***	-31.40%	***
	Explained	15.42%	***	17.44%	***	-10.88%	***	-12.62%	***
	Unexplained	15.93%	***	24.96%	***	-14.01%	***	-18.78%	***
Explained									
	Age	0.15%	***	0.54%	***	-0.36%	***	-0.51%	***
Race/Ethnicity (ref = White)									
	Black	-0.02%	*	0.06%		-0.02%	**	-0.01%	
	Hispanic	0.04%	***	0.04%		0.04%	***	-0.02%	
	Asian	-0.20%	***	-0.09%	***	-0.05%	***	-0.04%	***
	Ever Married	-0.01%		0.58%	***	-0.06%	***	-0.11%	***
	Has Children	-0.19%	***	0.38%	***	-0.05%	***	-0.11%	***
Highest Level of Education (ref = less than high school)									
	High School	-0.95%	***	-0.49%	***	0.08%	***	0.09%	***
	Some College	0.25%	*	0.29%	***	-0.02%		-0.08%	***
	College Graduate	3.48%	***	1.73%	***	-0.44%	***	-0.51%	***
	Masters	1.86%	***	1.02%	***	-0.26%	***	-0.33%	***
	Ph.D.	0.22%	***	0.16%	***	-0.02%	***	-0.05%	***
	Fair-poor health	10.70%	***	13.20%	***	-9.74%	***	-10.93%	***
	Midwest	0.02%		0.01%		0.00%		0.00%	
	South	0.07%	**	-0.01%		0.00%		-0.01%	
	West	-0.01%		0.00%		0.00%		0.00%	
Unexplained									
	Age	14.28%	***	18.17%	***	-19.95%	***	-23.59%	***
Race/Ethnicity (ref = White)									
	Black	0.11%		-0.41%		0.14%		0.79%	**
	Hispanic	-1.34%	***	0.15%		1.25%	***	0.91%	**
	Asian	-0.18%	*	-0.21%	*	0.01%		0.19%	*
	Ever Married	-2.42%	**	0.97%		0.42%		1.01%	
	Has Children	-1.03%		-0.24%		0.95%	*	0.41%	
Highest Level of Education (ref = less than high school)									
	High School	1.99%	***	1.50%	*	-0.88%	*	0.16%	
	Some College	2.00%	***	-0.54%		-1.23%	**	0.11%	
	College Graduate	0.17%		-0.42%		0.02%		0.51%	*
	Masters	-0.04%		-0.16%		0.00%		0.20%	*
	Ph.D.	-0.01%		-0.10%		0.01%		0.12%	**
	Fair-poor health	0.48%		-0.17%		-1.93%	**	-3.30%	***

Midwest	-0.19%		0.61%		-0.46%		-1.60%	**
South	-1.44%	*	1.11%		-0.14%		-3.03%	***
West	-0.29%		0.06%		-0.04%		-0.17%	
_cons	3.84%		4.66%		7.82%	**	8.51%	*

Notes
*$p<0.05$; **$p<0.01$; ***$p<0.001$

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