Center for Financial Security
UNIVERSITY OF WISCONSIN-MADISON
Retirement & Disability Research Center

Isaac Swensen
Montana State University

Carly Urban
Montana State University and Institute for Labor Studies (IZA)

The Effects of Expanding Access to Mental Health Services on SS(D)I Applications and Awards

Center for Financial Security

University of Wisconsin-Madison

1300 Linden Drive
Madison, WI 53706

608-890-0229
cfs@mailplus.wisc.edu
cfs.wisc.edu

The research reported herein was performed pursuant to a grant from the U.S. Social Security Administration (SSA) funded as part of the Retirement and Disability Consortium. The opinions and conclusions expressed are solely those of the author(s) and do not represent the opinions or policy of SSA or any agency of the Federal Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof.

Abstract

The growing number of individuals suffering from a serious mental illness underscores the important role of interventions such as treatments, policies, and programs to support those in need. Such support efforts often interact in unanticipated ways. This paper considers the degree to which access to mental health treatment services affects participation in federal disability programs including the Supplemental Security Income and the Social Security Disability Insurance (SS(D)I) programs. Our main approach uses an identification strategy that leverages county-level variation in the number of mental health treatment establishments to estimate changes in access to mental health treatment on SS(D)I program participation. We also explore a series of event studies and heterogeneity analyses. Our results show that an increase in mental health facilities *increases* participation in SS(D)I programs. A 10 percent increase in a county's number of office-based mental health establishments increases the SSI application rate by 1.2 percent and the SSDI application rate by 0.7 percent. While the overall sample suggests that this does not translate to an increase in SS(D)I awards, we do find increases in awards in counties that have lower household incomes, less educated households, and a higher proportion of residents below the poverty line. This suggests that increasing access to mental health resources can be a pathway through which people suffering from severe mental illness can be diagnosed and access social safety nets.

Keywords: Mental Health, Disability Policy, Supplemental Security Income, SSI/SSDI

JEL Classification Codes: I1, I18, H55

I Introduction

Over 46 million adults suffer from some form of mental illness in the U.S. (Ponte, 2019). Furthermore, 5.2 percent of all adults in the U.S. suffer from Serious Mental Illness (SMI)—mental, behavioral, or emotional disorders resulting in serious functional impairments that substantially interfere with or limit one or more major life activities (Ponte, 2019). The burdens of mental illness are particularly concentrated among those who experience disability due to SMI, where many suffering SMI rely upon government disability benefits to survive. At the same time, less than half of those suffering from mental illness have received some mental health services. In this paper, we ask how additional access to mental health treatment services affects participation in federal disability programs.

Mental health has far-reaching labor market implications. Kessler et al. (2008) use 2002 data and estimate that those with SMI had annual earnings roughly $16,000 less than other respondents with the same values, resulting in a societal-level total of $193 billion.[1] While mental illness is one of the leading causes of sickness absences in most high-income countries (Harvey et al., 2009), fewer than half of American adults suffering from mental illness received mental health services in 2019 (National Alliance on Mental Health, 2019). A common barrier to low treatment rates is the inability to locate a provider (CBHSQ, 2015). Even after one has identified a provider, wait times at outpatient clinics often span weeks or months (Blech et al., 2017; Steinman et al., 2015). At the same time, research suggests that longer wait times lead to less favorable outcomes (Steinert et al., 2017). One possible way to increase labor market participation for those suffering from mental illness could be to provide additional resources that allow individuals to identify and receive treatment for their diagnosed illness.

In this paper, we examine how expansions in office-based mental health establishments affect participation in the Social Security Administration (SSA) programs that support disabled individuals: SSI and SSDI. Using within county variation in the number of establishments, we are able to document the extent to which additional mental health resources can affect SS(D)I participation. To examine the potential that counties that have expansions in establishments are not experiencing these expansions at the same time as there is an uptick in SS(D)I participation we create an event sample of treatment counties—that have only one expansion over the period of study—and comparison counties—that experienced no change over the same period. This allows us to estimate an event study specification and determine the validity of the empirical design.

We posit two potential ways that additional mental health establishments may impact program participation. Since bottlenecks, such as long wait times, reduce access to mental health resources, additional availability of appointments may foster mental health. This treatment could allow individuals to obtain and maintain employment, reducing participation in SS(D)I. Alternatively, additional access may increase the likelihood of proper diagnoses of SMI, which would likely increase the take-up of disability programs.

[1] 75% was due to reduced earnings among those with SMI that had earnings, and 25% was due to a lower probability of having any earnings.

Our work contributes to two main literatures. First, we speak to the literature that examines the link between mental health and labor market participation. Previous work shows that mental illness has far-reaching labor market implications on outcomes including employment, earnings, labor market entry, work hours, and absences.[2] These negative consequences arise through a variety of channels, such as education (Kessler et al., 1995), discrimination (Currie and Madrian, 1999), and job performance (Chatterji et al., 2007). Our work considers the degree to which mental health treatment affects disability program participation which has direct ties to labor market participation.

Second, we contribute to the literature studying the effects of government policies and resources that affect participation in SSI. Broadly, a large literature has shown that economic factors, more aggressive welfare reform (Schmidt and Sevak, 2004), and other policies—like SNAP—affect SSI participation. Deshpande and Li (2019) show that increasing the cost of applying for SSI—through office closures—reduced awards. Similarly, our results examine a policy lever that could reduce the costs of applying—through additional access to resources that could help with diagnoses and completing the SSI application process. While others have explored the effects of health insurance on SS(D)I participation, to the best of our knowledge, we are the first to explore the effects of local availability of mental health treatment on SS(D)I. For example, Burns and Dague (2017) show that expanding Medicaid to childless adults reduced reliance on SSI. However, additional work shows that blanket Medicaid expansions do not affect SSI participation (Schmidt et al., 2020; Soni et al., 2017).

Our findings indicate that an increase in the availability of mental health facilities *increases* participation in disability programs. Overall, a 10 percent increase in the number of office-based mental health establishments in the county increases the SSI application rate by 1.2 percent and increases the SSDI application rate by 0.7 percent. While in the overall sample, this does not translate to an increase in SSI awards that is statistically different from zero, in counties with populations that have lower household income, are less educated, and have a higher proportion of residents below the poverty line, we see that the effects on SSI and SSDI applications are larger in magnitude. Further, we find evidence in all of these subsamples that the higher application rate translates to higher proportions of SSI awards. Since these less affluent counties are the most likely to have populations that struggle with SMI and have earnings consistent with SSI eligibility, these findings suggest that mental health resources are an important link to benefits that may greatly assist with individuals' necessary expenses. Deshpande (2016) found that failing age 18 disability medical review resulted in a sizable reduction in lifetime earnings, and Gelber et al. (2018) show that additional SSDI earnings reduce mortality. Providing additional access to mental health resources can potentially allow individuals suffering from SMI to access SS(D)I income that is likely necessary to meet basic needs. Further, Moore (2015) finds that after individuals lost SSDI eligibility in 1996 when drug and alcohol addictions were no longer listed as qualified conditions, those with two to three year SSDI spells were able to later work at much higher rates. These findings taken with our results suggest that individuals suffering from mental illness may have higher likelihoods of working after a few years of SS(D)I and continuous treatment for the illness.

[2] See for example Ettner et al. (1997); Hamilton et al. (1997); Chatterji et al. (2007); Ojeda et al. (2010); Chatterji et al. (2011); and Banerjee et al. (2017).

We find additional evidence that greater access to office-based mental health establishments that have physicians translates to higher fractions of SSI applications, SSDI applications, and SSI awards. This finding suggests that the presence of a physician may be important for diagnoses and successfully progressing through the SSI screening process. While SSI office closures reduced SSI awards through increased costs (Deshpande and Li, 2019), our work suggests that the converse is also true: reducing costs—by having additional physicians in office-based mental health establishments locally—increases SSI awards.

2 Background

Supplemental Security Income (SSI) and Social Security Disability Insurance (SSDI) are the two largest programs designed to support individuals with disabilities, with roughly $145 billion of spending on SSDI and $55 billion on SSI in 2020. More than six percent of working-age adults receive SSI or SSDI benefits.

The biggest distinguishing factor across the two programs is that SSDI requires that individuals have a sufficient and recent work history in jobs covered by Social Security.[3] For both SSI and SSDI in 2021, those 18-64 would be considered "disabled" if they have a medical de-terminable physical or mental impairment (1) that restricts any substantial gainful activity to less than $1,310 per month and (2) has lasted or can be expected to last for a continuous period of at least 12 months.[4]

Both programs require medical decisions, where the timeframe can vary widely. The initial decision usually takes from three to four months from the initial application, though the timing can vary immensely based on the time it takes to obtain medical evidence from a valid medical source and whether or not additional medical examination is necessary. Duggan et al. (2015) provide a thorough review of the SSI application and review process, as well astrends over time. Roughly 60 percent of recipients under 65 years of age are diagnosed with a mental disorder. Mood disorders including depression, anxiety, and more severe psychosisaccount for nearly half of SSDI beneficiaries claiming under a mental impairment.[5]

While state and federal parity laws for mental health, including the Affordable Care Act, have expanded coverage for mental health services, treatment rates continue to remain low. This could be because access remains limited. For example, wait times at outpatient clinics can span months (Blech et al., 2017; Steinman et al., 2015), and individuals still mention an inability to find a provider as a hurdle to accessing care (CBHSQ, 2015).

[3]For more on the details of the years of coverage needed by age, see https://www.ssa.gov/benefits/disability/qualify.html.

[4]SSDI recipients with annual incomes below the SSI threshold may be eligible to receive benefits from both programs.

[5]Other common diagnoses include schizophrenic and other psychotic disorders and organic mental disorders (SSA, 2020).

One way to measure access to care that has been used in previous research (Deza et al., 2020) is to consider the number of office-based mental health providers in an area. In 2018, four million clients were enrolled in mental health treatment in the U.S., and 95 percent received outpatient treatment in non-hospital mental health centers (Substance Abuse and Mental Health Services Administration, 2019). Further, 14,159 mental health centers ex isted across the U.S. in 2018, where these centers aim to support vulnerable populations (Substance Abuse and Mental Health Services Administration, 2019). Their ultimate goal is to maintain a level of mental and physical health in the community, which could come in a variety of ways. While support will always consist of diagnosing and treating specific mentalillnesses, mental health professionals may further advise patients on resources to access in order to improve their situations. For example, since financial distress can exacerbate mental health conditions, accessing federal benefits—particularly when individuals' diagnosed mental illness can restrict their ability to work—may be an important avenue towards treating the medical condition. Thus, while additional access to treatment facilities may increase the likelihood of individuals to get the necessary help and return to the labor market, treatment may help individuals to access necessary SS(D)I benefits.

It is further possible that expanding mental health services may have different effects on SSI and SSDI applications. The biggest distinguishing factor across the two programs is that SSDI requires that individuals have work histories. This means that SSI applicants who donot qualify for SSDI may have more serious work-limiting mental health illnesses. Thosewho are eligible for SSDI may have had some access to mental healthcare already throughtheir employers. Thus, we may expect a larger—or even different—response when access to treatment is expanded. It is possible that additional access may increase SSI applications,while SSDI applications either remain constant or even fall as individuals obtain access tocare that allows them to continue to work. It is also possible that the expansion of mentalhealth facilities could have the same effect for both populations: allowing both to get proper diagnoses of work-prohibiting conditions that merit SS(D)I applications or allowing both toseek or continue work after obtaining appropriate treatment.

3 Data

We begin with county-by-year data on the number of office-based mental health establish ments from the U.S. Census Bureau's County Business Patterns (CBP). We then obtain administrative records from the Social Security Administration on the number of SSI applications, SSDI applications, and SSI awards by county-year. This section describes the two datasets, as well as summary statistics and trends in our variables of interest.

As our research question of interest is to understand how access to mental health treatment facilities affects participation in SS(D)I, our empirical strategy requires data on access, which we proxy with the number of establishments. The main mental health services data for this study come from the CBP data. These data include the number of establishments—or single physical locations—by industry.[6] For this project, we define "office-based

[6]While the CBP also collect data on the number of employees in each county-year, employment data

mental healthcare providers" using NAICS codes following Deza et al. (2020).[7] Specifically, we choose offices of physicians, mental health specialists (621112) and offices of mental health practitioners except physicians (621330). While our main independent variable of interest will be the sum of the two types of establishments, these classifications will additionally allow us to examine heterogeneity in the *types* of establishments. For example, is the presence of a physician critical for diagnoses?

Next, we obtain administrative counts of prime-aged (18–64) SSI and SSDI applications, as well as SSI new awards directly from SSA for 2010–2016. While SSA has data for all counties and years, they censor all county-year observations with fewer than ten applications or awards. In order to maintain a consistent sample that is not selected based on the presence of the dependent variable, we keep counties that lie within a micropolitan or larger area (e.g., those with CBSA codes). We replace any additional censored cells in the panel with five.[8] Our main dependent variable of interest will be the number of SS(D)I applications—or awards—per 1,000 18–64 year-old residents.

Merging the SSA data with the mental health services data leaves us with a panel of 1,811 counties that we track from 2010–2016. We then supplement our main data with auxiliary datasets in order to control for potentially confounding variables. For example, we obtain data on the county-level annual unemployment rate, per capita median household income, and the fraction of the population in the county living below the poverty rate in case establishments appear during economic downturns. We additionally obtain data on demographic characteristics, such as the percent of the population that are male, white, Black or African American, and ages 18–64 years old.

3.1 Summary Statistics

We begin by documenting trends in establishments over our sample. Figure 1 shows the trends in the county average number of OBMH establishments, as well as the average number of establishments by type, from 2010–2016. While the period saw an overall increase in the total number of establishments, this increase comes primarily from OBMH establishments with a sole focus on mental health as opposed to physician's offices that include mental health specialists. Further, the maps in Figure 2 show the overall expansion and contraction of mental health establishments over our time period. Specifically, we can see increases and decreases throughout the country with no clear geographic pattern.

We then document the evolution of SS(D)I applications and SSI awards over time in Figure 3. Overall, SSI applications and SSDI applications fell from 2010–2016. However, during the same period, SSI awards fell at a much slower rate than SSI applications. This suggests that the approval rates declined over this period, making it important to investigate how the

are frequently censored and binned into size classes that prohibit a clear measure of employment for mental health treatment facilities.

[7] Previous work leverages similar variation (Swensen, 2015; Bondurant et al., 2018).

[8] This translates to 938 replacements or seven percent of the sample. We also consider analyses where we drop counties with censored observations.

attributes of mental health facilities impact eventual SSI awards. In particular, we explore how the presence of a physician—as compared to other mental health workers—may factor into eventual SSI awards when compared to just applications.

In Table 3, we show the overall statistics of the sample.

4 Empirical Strategy

Our estimation strategy leverages the changing number of physical establishments providing OBMH services within counties over time. The implicit assumption is that the timing of changes in the number of mental health establishments is uncorrelated with other unobserved trends in the counties, particularly as they relate to SS(D)I participation. Previous work has leveraged similar variation to understand the effects of mental health establishments on mortality (Swensen, 2015) and substance abuse (Bondurant et al., 2018).

Our base specification estimates Equation 1, where our main dependent variables of interest ($SS(D)I_{csy}$) are SSI applications, SSDI application, or SSI awards per 10,000 residents in county c in state s, and year y. Our main independent variable of interest (MH_{csy}) is the number of office-based mental health treatment facilities in the given county and prior year. We lag this variable, as a new establishment may not immediately result in new patients and diagnoses. In all specifications, we include county-level fixed effects (δ_{cs}) and year fixed effects (γ_y). Our base specifications further include controls for local economic conditions and demographics (X_{csy}). These controls include the unemployment rate, per capita median household income, the percent of the population below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. All of our specifications cluster standard errors at the county level—the level of policy variation. Our specifications further weight observations by county-level population. This means each county does not equally contribute to the overall estimate of α_1. We provide a robustness test where we do not weight our regressions

$$\mathbf{SS(D)I_{csy}} = \alpha_1 \mathbf{MH_{csy}} + \delta_{\mathbf{cs}} + \gamma_{\mathbf{y}} + \beta \mathbf{X_{csy}} + \epsilon_{\mathbf{csy}} \tag{1}$$

In additional specifications, we probe the robustness of the base model. First, we show results that include state-by-year fixed effects. This accounts for changing policies at the state level that could affect the generosity of the safety net, as well as access to mental health resources. Second, we show specifications that omit the county-level control variables. Third, we show unweighted results that allow each county to equally weight more- and less-populated counties in the regression. Fourth, we show results that drop all counties with any censored SSA data in our time frame. We also explore the heterogeneity in the types of establishments to determine if the presence of physicians is an important component of diagnosing mental health conditions.

Since the variation of interest is based on the expansion and contraction of OBMH establishments, we are implicitly using a continuous treatment two-way fixed effects difference-in-difference estimation strategy. As such, our model assumes that outcomes in treated counties (i.e., counties experiencing a change in the number of treatment facilities) would have trended similar to outcomes in untreated counties in the absence of the treatment. While not directly testable, we can establish that areas with increases in establishments were not trending differently than those without changes prior to the expansion. That is, we employ an event study approach that limits the sample to either (1) treated counties that experience a change in the number of facilities only once in the panel or (2) counties that experience no changes over the entire panel. We also limit the treated counties to those that experience an opening in 2012 or later to ensure several pre-treatment years. We then estimate our baseline model but include interactions for each potential period—except for the year before treatment—interacted with whether or not the county was ever treated in our period.

Since we restrict the sample for the event study, we report which counties remain in this sample in Figure 4. Counties in orange are those that have an event, counties in blue are the comparison counties with no event over the period, counties in gray are in the remaining regressions but not in the event sample, and counties in white are not in the sample (not in micropolitan or larger areas). Though not perfect, our event study sample gives us a clean setting with which to understand how counties are trending prior to changes in the number of establishments.[9]

The event studies for SS(D)I applications appear in Figure 5. We find no evidence that counties with events were trending differently than counties without events prior to the event in either the top panel (SSI applications) or the bottom panel (SSDI applications). The top panel suggests that after the expansion in mental health facilities, SSI applications rise, and that rise is sustained over time. For SSDI, applications rise in the short-run and appear to rise over time, but the coefficients are not as precisely estimated.

Figure 6 shows the event studies for SSI awards, where the pattern mimics that of SSI applications. While at first, it seems that the evidence of SSI awards is more pronounced than for applications, the magnitude of the effect on applications is much smaller. Overall, the results from the event studies suggest that there is no clear pre-trend in SS(D)I participation prior to the opening of establishments.

5 Results

While the event studies provide interesting evidence of a new establishment on SS(D)I participation, we seek to understand the overall relationship between the number of OBMH establishments and participation in the SS(D)I programs. We document the overall baseline results in Table 1, where there additional OBMH facilities increase SS(D)I applications. Using the mean participation levels, we calculate that a 10 percent increase in the number of facilities increases the SSI application rate by 0.097 or 1.2 percent. This suggests that increasing access to mental health resources could allow people suffering from severe

[9]As shown in Appendix Table 4 the counties out of our sample are very small in terms of population and number of treatment facilities.

mental illness to potentially obtain a proper diagnosis in order to start the application process. We see a similar relationship when we consider SSDI: a 10 percent increase in the number of facilities increases the SSDI application rate by 0.076, or 0.7 percent. The overall evidence on SSI awards is less precisely estimated and half the magnitude of the effect on SSI applications: a 10 percent increase in the number of OBMH facilities increases SSI awards by 0.013 or 0.5 percent.

We probe the robustness of our results by plotting coefficients from a variety of specifications in Figures 7 and 8. Our results on applications (Figure 7) remain consistent when we include state-by-year fixed effects, omit county-level covariates, and drop censored counties. Our results are stronger when we no longer weight the regressions by population and instead allow each county, regardless of its size, to contribute equally to the regressions. This finding suggests that the effect of mental health resources in counties within micropolitan areas that are relatively smaller in size are likely to be larger than the effect in urban areas. One potential explanation for this result could be that larger cities have had more access to mental health establishments for longer periods and see less of a response to expansions than relatively smaller cities.

When considering the robustness of our results on SSI awards, our results are more sensitive (Figure 8). For example, when we include state-by-year fixed effects, our results are no longer statistically different from zero, but they are also not statistically different from our baseline effect. The same is true when we no longer include county-level controls. Our results do remain robust to dropping censored counties. As with the findings on applications, our estimates are again strengthened when we do not weight our regressions by population. This provides additional evidence that less populated areas may experience a greater response in applications and awards when additional mental health resources become available.

In an additional robustness check, we use data from the Centers for Medicare and Medicaid Services (CMS) to measure the annual number of Medicaid and Medicare-certified mental health professionals in the county. Using the CMS measure instead of the CBP to measure establishments, our results remain substantively similar but a bit noisier. These results are in Appendix Figures 11 and 12.

5.1 Heterogeneity

After documenting the overall effect, we next take a closer look at the types of OBMH establishments that change SS(D)I participation. Specifically, we examine the extent to which the presence of physicians in establishments increases diagnoses and subsequently, applications that are successfully awarded. Figure 9 shows the results from a regression that includes the number of facilities with physicians and the number of facilities without physicians in the same model. Here, we see that across all of our specifications, both types of establishments increase SSI and SSDI applications. Though the coefficients of the number of OBMH facilities without physicians are more precisely estimated, the coefficients on the number of OBMH facilities with physicians are larger in magnitude.

While Figure 9 suggests that both types of OBMH facilities matter for SS(D)I applications, the findings presented in Figure 10 show that the presence of physicians in OBMH facilities matters a lot for new SSI awards. The coefficients on the number of OBMH facilities without physicians are not statistically different from zero in most specifications, and they are small in magnitude. This finding suggests that working with a physician, as opposed to another mental health professional, may be important for eventually receiving SSI benefits. These findings could also explain why we do not find consistent evidence when we exploring the effect of the total number of OBMH establishments on SSI awards in Figure 8.

We also examine heterogeneity by county-level economic characteristics. Specifically, we split the sample by counties with above and below median poverty levels, median household income, and education.[10] These results, shown in Table 2, suggest increases in applications after additional OBMH are established that are concentrated in higher poverty, lower income, and less educated areas. In each of those samples, we find clear evidence that additional establishments increase the number of SSI awards. Notably, these categories may be correlated and measuring similar county attributes. Nonetheless, our results suggest that counties with less affluent populations may have large groups of individuals suffering from undiagnosed mental illness without the capacity to work that either do not realize that SSI is an option or have not had the resources to follow through on their path to apply for and receive benefits.

6 Discussion

This paper documents that increased access to office-based mental health facilities—particularly those where physicians are present—increases the rate of SS(D)I participation in a county. Specifically, we calculate that a ten percent increase in the number of facilities increases the SSI application rate by 1.2 percent. The effects are even larger among counties with less affluent populations, where we additionally find that the increased rate of applications translates into higher rates of SSI awards. These findings suggest that increasing access to mental health resources can be a pathway through which people suffering from severe mental illness can become properly diagnosed and access the safety net.

Early evidence suggests that the COVID-19 pandemic had dire effects on the mental health of Americans. One statistic in particular suggests a 1,000 percent increase in emergency hotline calls from people in emotional distress.[11] To the extent that some of the mental illness suffered has long-term consequences, the results from this study suggest that additional resources to address these mental health strains may simultaneously increase applications for federal disability benefits.

Future work should consider the ways in which mental health treatment facilities can help individuals transition off of disability benefits and back into the workforce. Are there certain

[10]Above median counties for each category include those that average greater than or equal to 10.8 percent of households in poverty, $23,900 in per capita income, or 86 percent of households with at least a high school education.

[11]See https://www.washingtonpost.com/health/2020/05/04/mental-health-coronavirus/.

diagnoses for which treatment can allow those to re-enter the labor market? Are there others where this is not feasible? In addition, while offices of mental and behavioral health increased SS(D)I participation in the short-run, it could be that early access to treatment as a young adult reduces later-life reliance on federal disability programs. Future work should consider these possibilities.

References

Banerjee, S., P. Chatterji, and K. Lahiri (2017). Effects of psychiatric disorders on labor market outcomes: a latent variable approach using multiple clinical indicators. *Health economics 26*(2), 184–205.

Blech, B., J. C. West, Z. Yang, K. D. Barber, P. Wang, and C. Coyle (2017). Availability of network psychiatrists among the largest health insurance carriers in Washington, DC. *Psychiatric Services 68*(9), 962–965.

Bondurant, S. R., J. M. Lindo, and I. D. Swensen (2018). Substance abuse treatment centers and local crime. *Journal of Urban Economics 104*, 124–133.

Burns, M. and L. Dague (2017). The effect of expanding Medicaid eligibility on Supplemental Security Income program participation. *Journal of Public Economics 149*, 20–34.

CBHSQ (2015). Behavioral health trends in the united states: Results from the 2014 national survey on drug use and health. *HHS Publication No. SMA 15-4927, NSDUH Series H-50* .

Chatterji, P., M. Alegria, M. Lu, and D. Takeuchi (2007). Psychiatric disorders and labor market outcomes: evidence from the national latino and asian american study. *Health economics 16*(10), 1069–1090.

Chatterji, P., M. Alegria, and D. Takeuchi (2011). Psychiatric disorders and labor market outcomes: Evidence from the national comorbidity survey-replication. *Journal of health economics 30*(5), 858–868.

Currie, J. and B. C. Madrian (1999). Health, health insurance and the labor market. *Hand- book of labor economics 3*, 3309–3416.

Deshpande, M. (2016). Does welfare inhibit success? the long-term effects of removing low-income youth from the disability rolls. *American Economic Review 106*(11), 3300–3330.

Deshpande, M. and Y. Li (2019). Who is screened out? Application costs and the targetingof disability programs. *American Economic Journal: Economic Policy 11*(4), 213–248.

Deza, M., J. C. Maclean, and K. T. Solomon (2020). Local access to mental healthcare and crime. Technical report, National Bureau of Economic Research.

Duggan, M., M. S. Kearney, and S. Rennane (2015). The supplemental security income program. In *Economics of Means-Tested Transfer Programs in the United States, Volume 2*, pp. 1–58. University of Chicago Press.

Ettner, S. L., R. G. Frank, and R. C. Kessler (1997). The impact of psychiatric disorders on labor market outcomes. *ILR Review 51*(1), 64–81.

Gelber, A., T. Moore, and A. Strand (2018). Disability insurance income saves lives. *Un-published paper.*

Hamilton, V. H., P. Merrigan, and É. Dufresne (1997). Down and out: estimating the relationship between mental health and unemployment. *Health economics 6*(4), 397–406.

Harvey, S. B., M. Henderson, P. Lelliott, and M. Hotopf (2009). Mental health and employ- ment: much work still to be done. *The British Journal of Psychiatry 194* (3), 201–203.

Kessler, R. C., S. Heeringa, M. D. Lakoma, M. Petukhova, A. E. Rupp, M. Schoenbaum, P. S. Wang, and A. M. Zaslavsky (2008). Individual and societal effects of mental disorders on earnings in the united states: results from the national comorbidity survey replication. *American Journal of Psychiatry 165*(6), 703–711.

Moore, T. J. (2015). The employment effects of terminating disability benefits. *Journal of Public Economics 124*, 30–43.

National Alliance on Mental Health (2019). Mental health by the numbers. Technical report.

Ojeda, V. D., R. G. Frank, T. G. McGuire, and T. P. Gilmer (2010). Mental illness, nativity, gender and labor supply. *Health Economics 19* (4), 396–421.

Ponte, K. (2019). People with mental illness can work. Technical report, National Alliance on Mental Illness.

Schmidt, L. and P. Sevak (2004). AFDC, SSI, and welfare reform aggressiveness: Caseload reductions versus caseload shifting. *Journal of Human Resources 39* (3), 792–812.

Schmidt, L., L. D. Shore-Sheppard, and T. Watson (2020). The impact of the ACA Medicaid expansion on disability program applications. *American Journal of Health Economics 6*(4), 444–476.

Soni, A., M. E. Burns, L. Dague, and K. I. Simon (2017). Medicaid expansion and state trends in Supplemental Security Income program participation. *Health Affairs 36* (8), 1485–1488.

SSA (2020). Annual statistical report on the social security disability insurance program, 2019. *SSA publication* (13-11826).

Steinert, C., K. Stadter, R. Stark, and F. Leichsenring (2017). The effects of waiting for treatment: A meta-analysis of waitlist control groups in randomized controlled trials forsocial anxiety disorder. *Clinical Psychology & Psychotherapy 24* (3), 649–660.

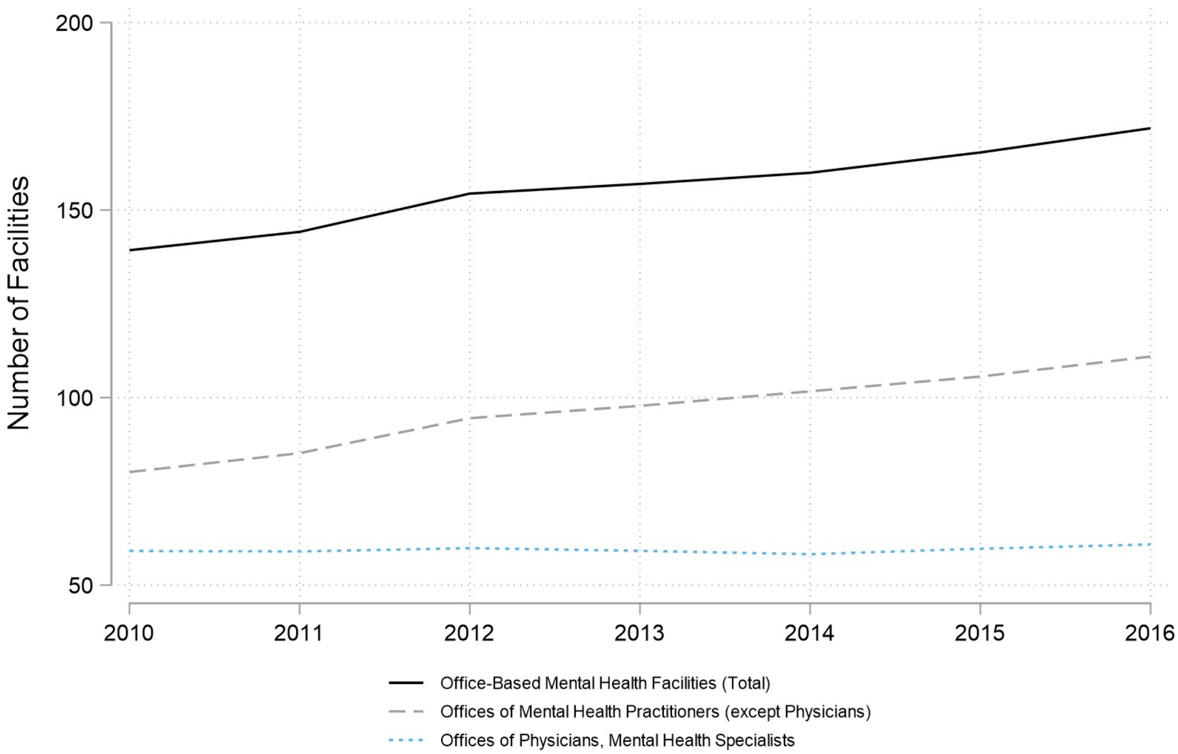
Steinman, K. J., A. B. Shoben, A. E. Dembe, and K. J. Kelleher (2015). How long do adolescents wait for psychiatry appointments? *Community Mental Health Journal 51* (7), 782–789.

Substance Abuse and Mental Health Services Administration (2019). National Mental Health Services Survey (N-MHSS): 2018 Data on mental health treatment facilities.

Swensen, I. D. (2015). Substance-abuse treatment and mortality. *Journal of Public Economics 122*, 13–30.

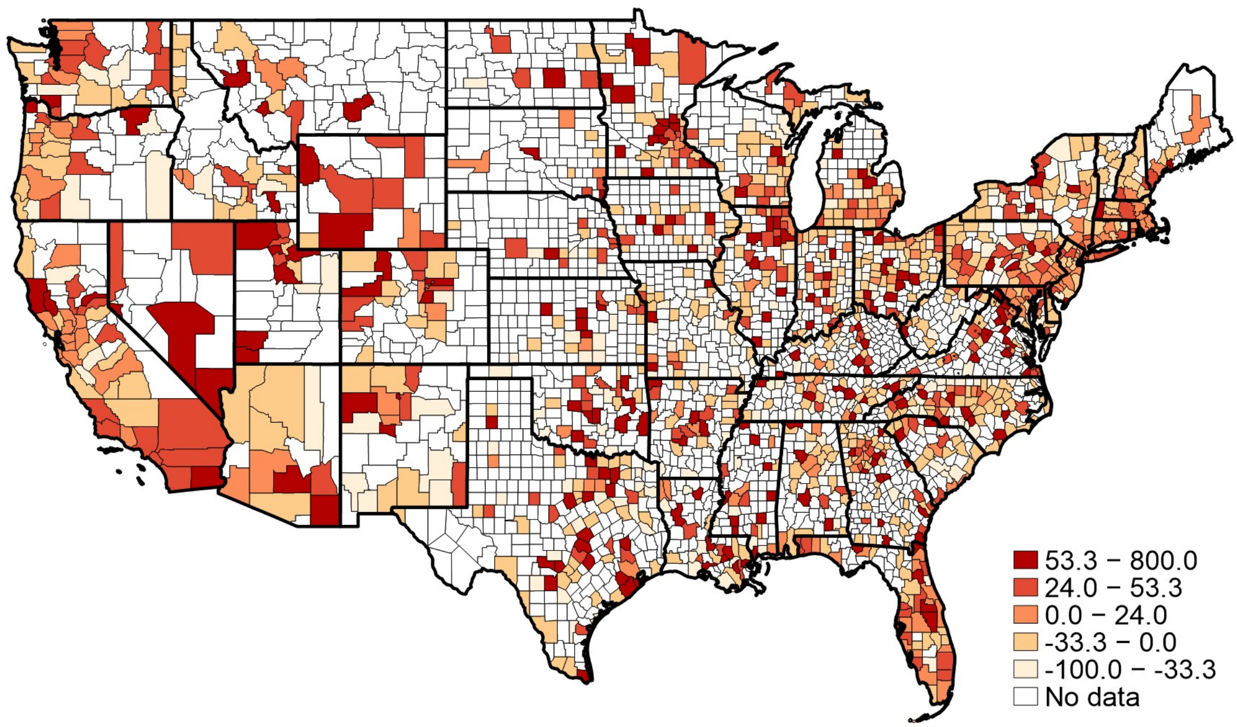
Tables and Figures

Figure 1: Trends in OBMH Establishments



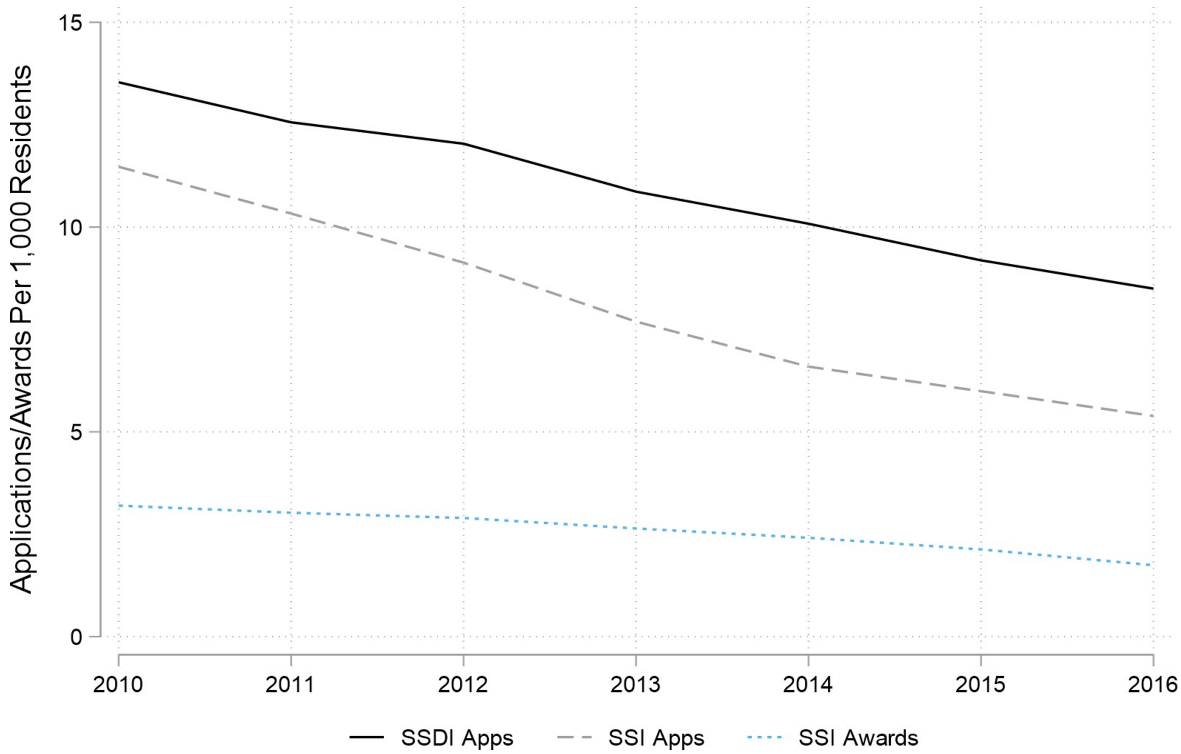
Notes: The graph plots the average annual number of office-based mental health facilities in each county from 2010-2016. Averages are weighted by each county's age 18-64 population. Data were obtained from the U.S. Census Bureau's County Business Patterns and facilities were identified using the following North American Industry Classification Codes: offices of physicians, mental health specialists (621112), and offices of mental health practitioners except physicians (621330).

Figure 2: Map of Offices of Behavioral and Mental Health Establishments over time (Percent Change from 2010 to 2016)



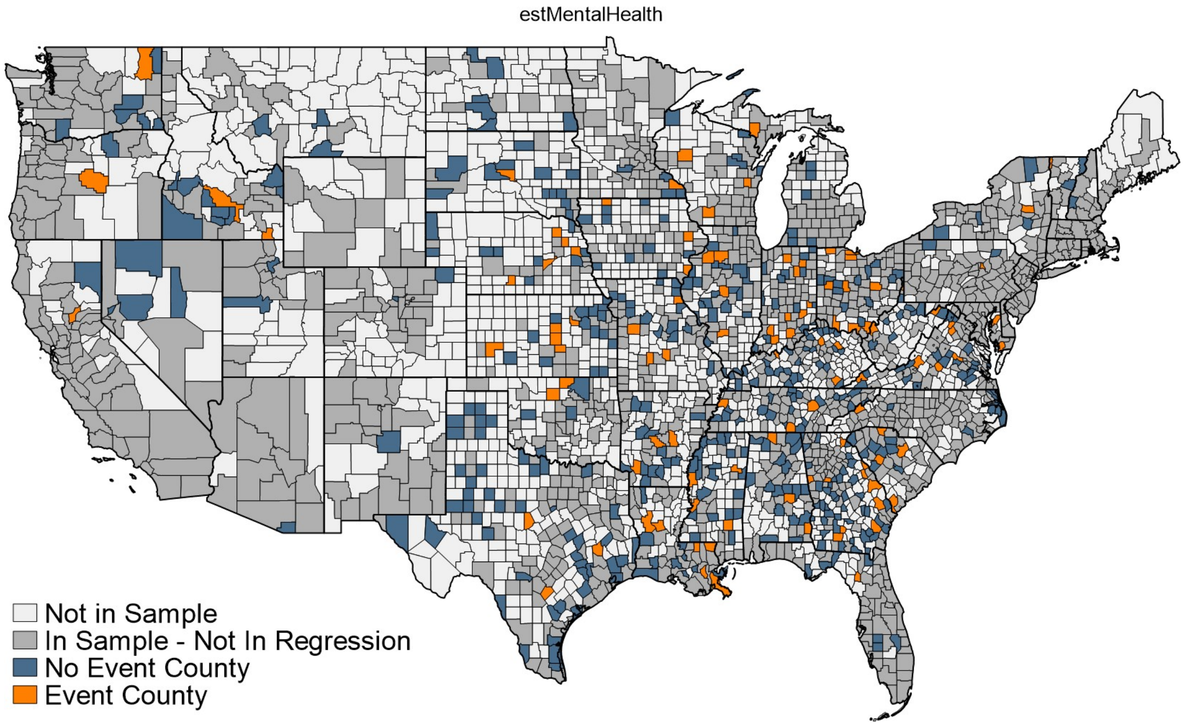
Notes: The maps show the percentage change in the number of office-based mental health facilities in each county from 2010 through 2016. Data were obtained from the U.S. Census Bureau's County Business Patterns and facilities were identified using the following North American Industry Classification Codes: offices of physicians, mental health specialists (621112), and offices of mental health practitioners except physicians (621330).

Figure 3: Trends in SS(D)I Applications & Awards



Notes: The graph plots the average number of applications and awards per 1,000 residents ages 18-64 from 2010-2016. Averages are weighted by each county's age 18-64 population. Data were obtained from the Social Security Administration.

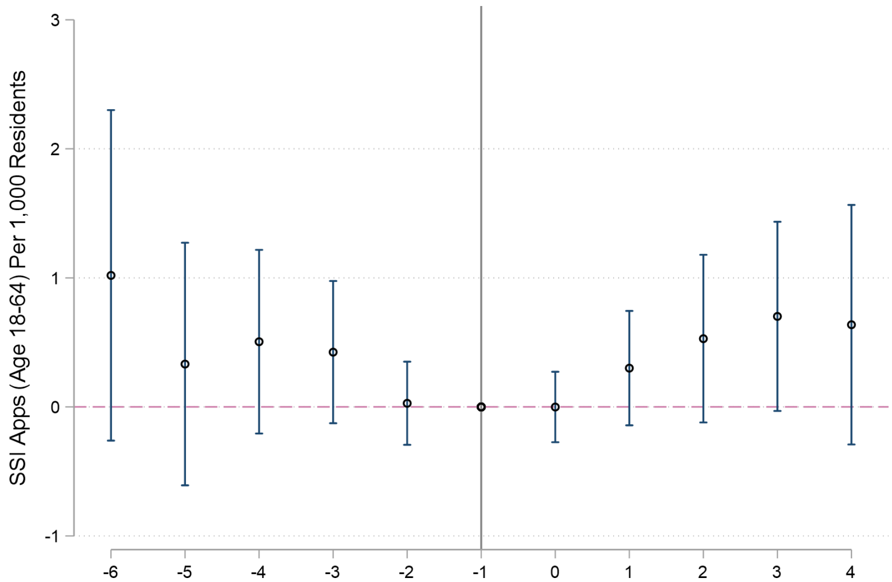
Figure 4: Event Study Sample



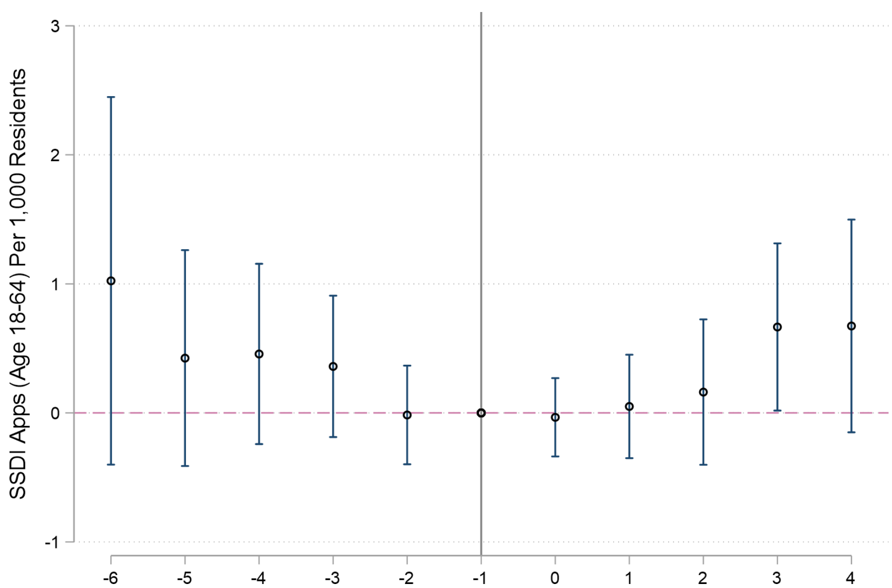
Notes: The map highlights the restricted sample of counties used in our event study analysis. Counties in orange are those that have a change in the number of facilities only once in the panel and counties in blue are those that experience no changes over the entire panel. Counties in gray are in our main analysis but not in the event sample, and counties in white are not in any of our analyses (not in micropolitan or larger areas).

Figure 5: Event Studies (Applications)

SSI Applications

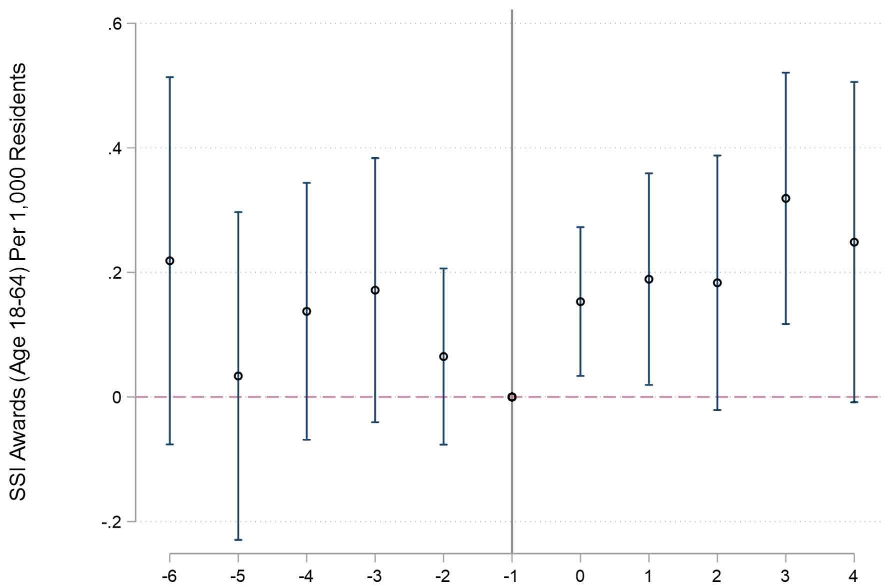


SSDI Applications



Notes: The figures plots coefficients and 95 percent confidence intervals of annual indicators for each year leading up to and following an increase in the number of OBMH treatment facilities. The sample is limited to (i) treated counties that only experience one increase in the number of facilities from 2012 onward, and (ii) control counties that do not have any changes in the number of facilities in our panel. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. Standard-error estimates allow for clusters at the county level.

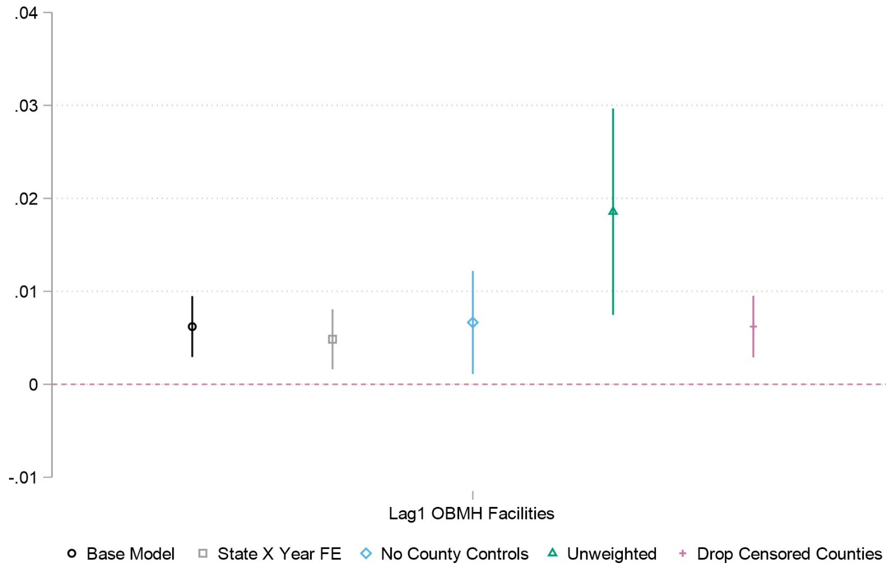
Figure 6: Event Studies (SSI Awards)



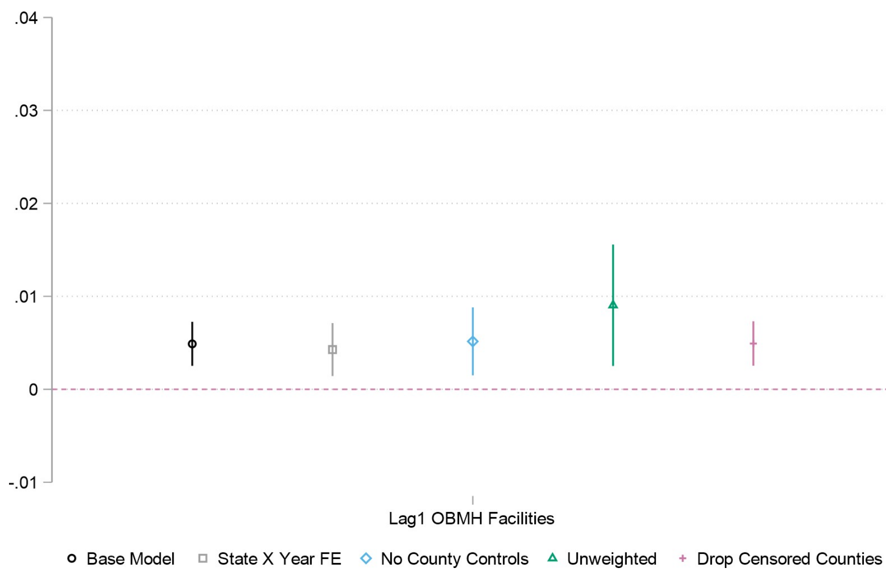
Notes: The figure plots coefficients and 95 percent confidence intervals of annual indicators for each year leading up to and following an increase in the number of OBMH treatment facilities. The sample is limited to (i) treated counties that only experience one increase in the number of facilities from 2012 onward, and (ii) control counties that do not have any changes in the number of facilities in our panel. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. Standard-error estimates allow for clusters at the county level.

Figure 7: Results: Applications

SSI Application Rate

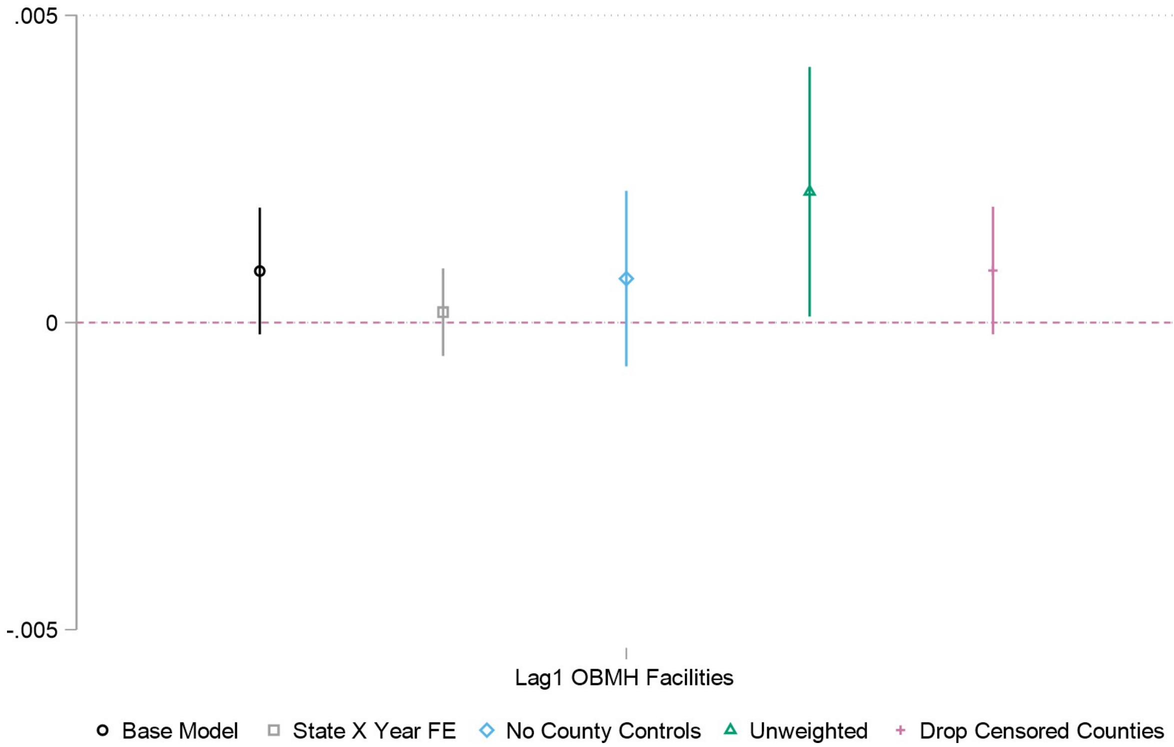


SSDI Application Rate



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of applications per 1,000 residents ages 18-64. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

Figure 8: Results: SSI Award Rate



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of awards per 1,000 residents ages 18-64. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

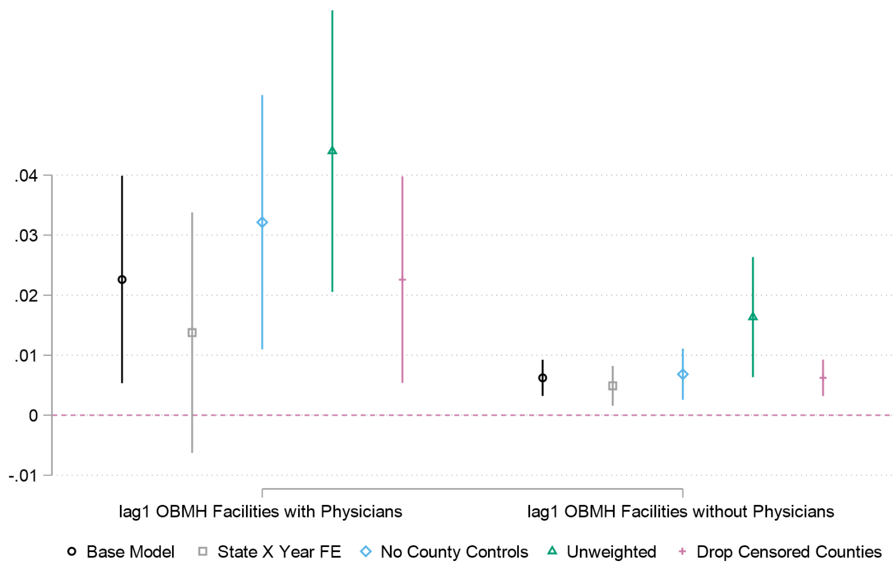
Table 1: Main Results

	(1) SSI App Rate	(2) SSDI App Rate	(3) SSI Award Rate
Lag1 OBMH Facilities	0.00621***	0.00488***	0.00084
	(0.00167)	(0.00121)	(0.00053)
DV Mean	8.06	10.95	2.57
Unique Counties	1,811	1,801	1,811
N	12,677	12,677	12,677

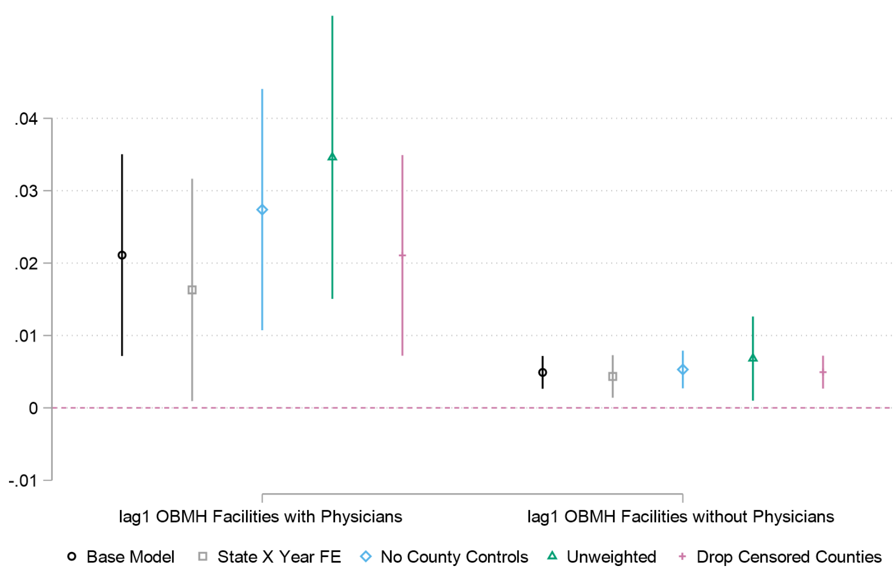
Notes: The table shows estimated coefficients of the lagged number of OMBH facilities. Outcomes are the number of applications and awards per 1,000 residents ages 18-64. The model includes county and year fixed effects in addition to county-level control variables including the unemployment rate, per capital household income, percent of residents that are below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

Figure 9: Heterogeneity by Facility Type: Applications

SSI Application Rate

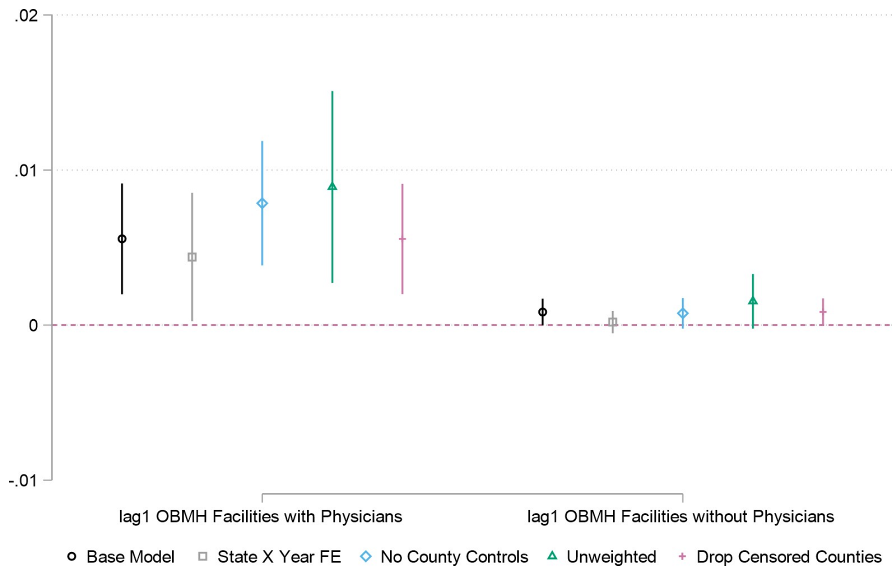


SSDI Application Rate



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of applications per 1,000 residents ages 18-64.. Facility types are identified using NAICS codes for *offices of physicians, mental health specialists* (621112) and *offices of mental health practitioners except physicians* (621330). The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

Figure 10: Heterogeneity by Facility Type: Awards



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of applications and awards per 1,000 residents ages 18-64. Facility types are identified using NAICS codes for *offices of physicians, mental health specialists* (621112) and *offices of mental health practitioners except physicians* (621330). The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

Table 2: Results by Poverty, Per-Capita Income, and Education

	High Poverty	Low Poverty	High Income	Low Income	High Education	Low Education
SSI App Rate						
Lag1 Facilities	0.00993***	0.00125	0.00101	0.02934*	0.00166	0.01007***
	(0.00184)	(0.00389)	(0.00137)	(0.01633)	(0.00485)	(0.00232)
SSDI App Rate						
Lag1 Facilities	0.00773***	0.00096	0.00182	0.01142	-0.00306	0.00812***
	(0.00134)	(0.00329)	(0.00116)	(0.01569)	(0.00356)	(0.00180)
SSI Award Rate						
Lag1 Facilities	0.00190***	-0.00069	-0.00032	0.01035**	-0.00220*	0.00197**
	(0.00071)	(0.00108)	(0.00040)	(0.00476)	(0.00115)	(0.00080)
Depvar Means:						
SSI App Rate	12.6	6.9	7.2	12.4	7.3	12.2
SSDI App Rate	16.2	10.3	10.5	16	10.7	15.8
SSI Award Rate	4	2.2	1.3	3.8	2.3	3.8
N	6,349	6,328	6,342	6,335	6,342	6,335

Notes: The table shows estimated coefficients of the lagged number of OMBH facilities. Outcomes are the number of applications and awards per 1,000 residents ages 18-64. Above median counties for each category include those that average greater than or equal to 10.8 percent of households in poverty, $23,900 in per capita income, or 86 percent of households with at least a high school education. The model includes county and year fixed effects in addition to county-level control variables including the unemployment rate, per capital household income, percent of residents that are below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

7 Appendix

Table 3: Summary Statistics

	mean	std. dev.
Outcomes:		
SSI Apps (Age 18-64) Per 1,000	8.1	4.3
SSDI Apps (Age 18-64) Per 1,000	11	4.6
SSI Awards (Age 18-64) Per 1,000	2.6	1.3
Measures of treatment:		
Office-Based Mental Health Facilities	156.1	293.7
OBMH Facilities with Physicians	59.4	114.2
OBMH Facilities without Physicians	96.7	181.1
Covariates:		
Unemployment Rate	8.7	2.5
Per Capita Income	28,964	7,314
Percent Below Poverty	11	4.5
Percent Male	49.6	1.5
Percent White	78.1	14.2
Percent African American	14.2	12.9
Percent Ages 18-64	62.9	3
Population Ages 18-64	786,434	1,294,366
Number of Counties	1,811	
Observations	12,677	

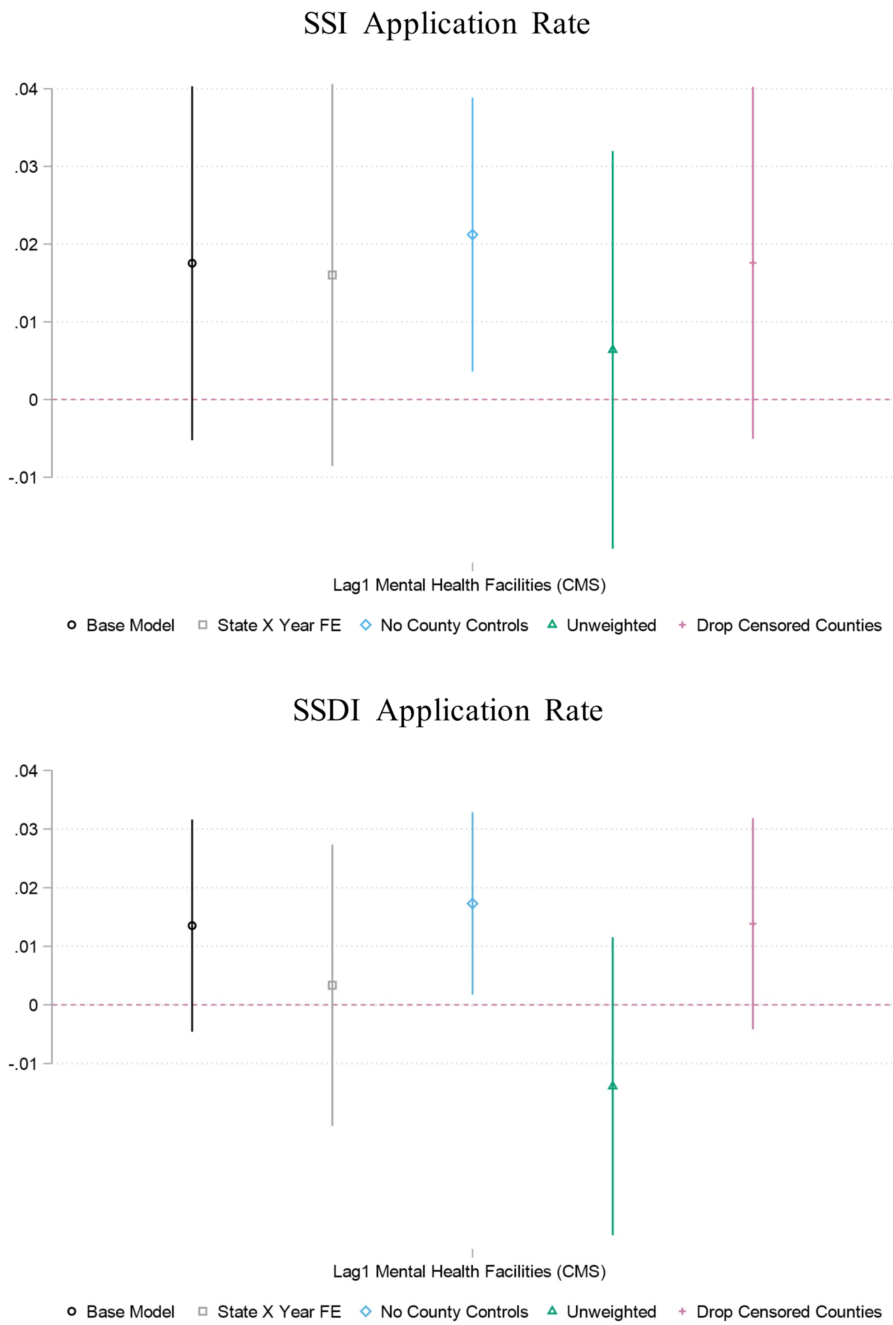
Notes: Program participation data were obtained from the Social Security Administration. Treatment facility data were obtained from the U.S. Census Bureau's County Business Patterns and facilities are identified using the North American Industry Classification Codes for *offices of physicians, mental health specialists* (621112) and *offices of mental health practitioners except physicians* (621330). Covariate data were obtained from the Cancer SEER population data and the U.S. Census.

Table 4: Summary Statistics-Comparing out of sample counties

	In Sample	Out of Sample
Measures of treatment:		
Office-Based Mental Health Facilities	156.1	0.78
OBMH Facilities with Physicians	59.4	0.17
OBMH Facilities without Physicians	96.7	0.6
Covariates:		
Unemployment Rate	8.7	8.7
Per Capita Income	28,964	21,389
Percent Below Poverty	11	13.4
Percent Male	49.6	51.3
Percent White	78.1	86.9
Percent African American	14.2	9.7
Percent Ages 18-64	62.9	59.2
Population Ages 18-64	786,434	13,744
Number of Counties	1,811	1,293

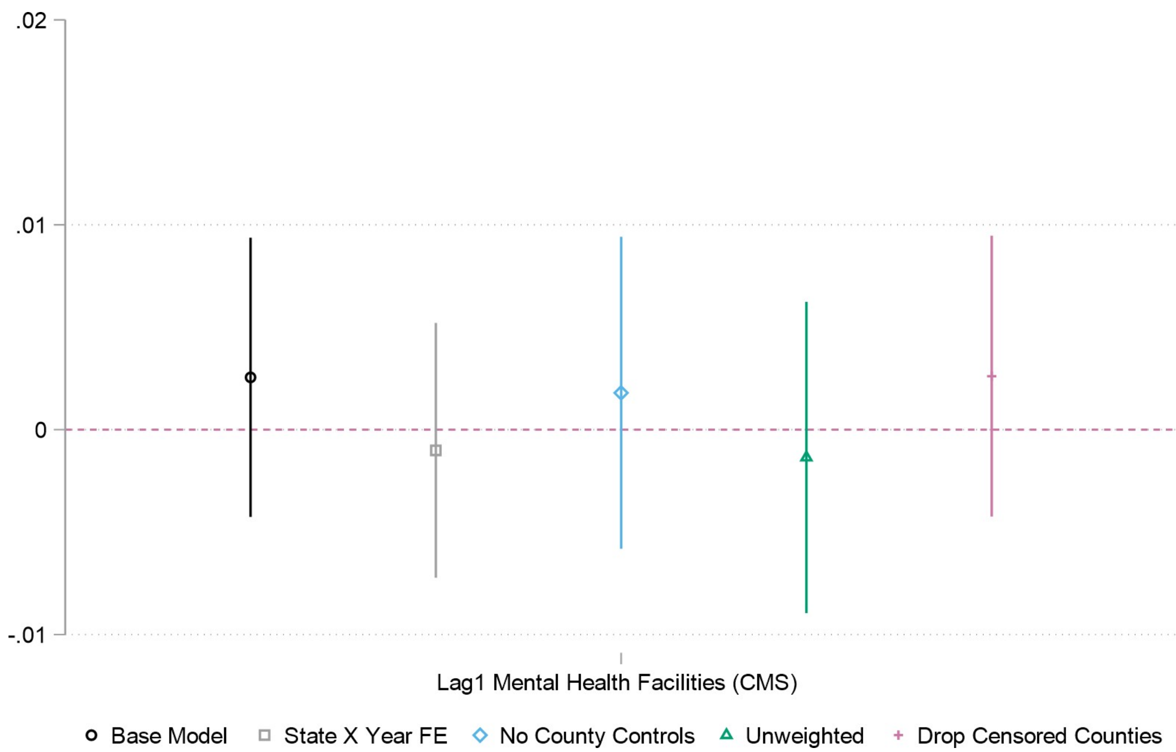
Notes: Program participation data were obtained from the Social Security Administration. Treatment facility data were obtained from the U.S. Census Bureau's County Business Patterns and facilities are identified using the North American Industry Classification Codes for *offices of physicians, mental health specialists* (621112) and *offices of mental health practitioners except physicians* (621330). Covariate data were obtained from the Cancer SEER population data and the U.S. Census.

Figure 11: Results using CMS data: Applications



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of applications per 1,000 residents ages 18-64. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.

Figure 12: Results using CMS data: SSI Award Rate



Notes: The figure plots coefficient estimates and 95 percent confidence intervals of the lagged number of OMBH facilities. Outcomes are the number of awards per 1,000 residents ages 18-64. The model includes county and year fixed effects and county-level control variables including the unemployment rate, per capital household income, percent of residents below the poverty line, percent male, percent white, percent Black or African American, and percent ages 18-64. The estimates are weighted by the age 18-64 county population and standard-error estimates allow for clusters at the county level.