Geographic Variation in Mental Health Treatment Utilization: Evidence from Migration

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June 21, 2023

Abstract

The older population bears a heavy burden of mental illness. Despite the availability of effective treatments, including services (e.g., psychotherapy) and drugs (e.g., antidepressants, antipsychotics), this paper documents substantial geographic variation in treatment utilization rates among Medicare enrollees. Exploiting patient migration, I show that 45.8% of service utilization variation is attributable to place-specific factors, compared to 15.1% for drug utilization. Further analyses suggest the role of provider accessibility in explaining the different place effects between service and drug use. Regarding health outcomes, I find that higher treatment utilization is associated with lower risks of suicide and self-harm-related Emergency Department visits. (*JEL* H51, I11, I12, I14)

*Princeton University. Email: hd5220@princeton.edu. I am grateful to Janet Currie, Mark Duggan, Maya Rossin-Slater and Heidi Williams for their guidance and support throughout this project. I would also like to thank Liran Einav, Matt Gentzkow, Petra Persson, Maria Polyakova, Heather Royer, Hannes Schwandt, Jonathan Skinner, Amanda Starc, and many seminar participants for their valuable comments. This project was supported by Leonard W. Ely and Shirley R. Ely Graduate Student Fellowship through the Stanford Institute for Economic Policy Research. All errors are my own.

1 Introduction

About one in five American adults report symptoms of mental illness, such as depression and anxiety, in an average year (SAMHSA, 2020). These illnesses generate large private and social costs.[1] Suicide, as the most extreme outcome, is the tenth leading cause of death in the U.S., and the rate has increased by over 30% in the past two decades (Hedegaard and Warner, 2021). Among all age groups, men over the age of 65 exhibit the highest rates of suicide, illustrating the significant mental health burden borne by the older population.[2] Although treatments such as psychotherapy and medication have been shown to be effective for many mental health conditions,[3] their utilization varies significantly across geographic areas.

For example, among Medicare enrollees over the age of 65, 15.9% in Massachusetts have medical service claims with a primary diagnosis of mental illness, and 26.2% have drug claims for antidepressants and antipsychotics annually. In contrast, in Arizona, the rates are 7.5% and 21.6% respectively.[4] This could reflect a lower prevalence of mental illness in Arizona, but the suicide rates – 8.2 per 100,000 in Massachusetts and 17.2 per 100,000 in Arizona – suggest otherwise.[5] Other factors, such as the availability of mental health treatment in certain areas or the propensity to seek mental health care, might also be contributing to these geographic differences. Understanding these underlying causes is essential for creating effective policies to improve the efficiency of care delivery and enhance mental health outcomes.

In this paper, I analyze the geographic variation in mental health treatment utilization

[1] APA (2013) estimates that direct spending on mental health treatment is $179 billion in 2014 and more than 60% is paid by public payers. This is before counting in hundreds of billions dollars indirect cost in additional medical spending by mental health patients (Montz et al., 2016; Figueroa et al., 2020), productivity loss and other transfer programs (Insel, 2008).

[2] Appendix Figure A1 shows that male suicide rates rise sharply with age after 65 years, significantly exceeding those of non-elderly adults and adolescents.

[3] Psychotherapy and medications, such as antidepressant and antipsychotic drugs, show treatment effects in randomized controlled trials APA (2013), although the efficacy and tolerability of the medications vary substantially across patient groups (Fournier et al., 2010; Leucht et al., 2013). Economic studies document mixed evidence on the effect of mental health drugs on other medical spending and labor market outcome (Duggan, 2005; Laird and Nielsen, 2017; Bütikofer et al., 2020; Biasi et al., 2021; Shapiro, Forthcoming).

[4] Mental health service and drug utilization rates are calculated by the author using the 20% Medicare claims data during 2006-2018, among fee-for-service Medicare beneficiaries with full coverage of Part A, B and D. See Section 2 for details.

[5] Suicide rates are among population above age 65, from the CDC Underlying Cause of Death database, 1999-2019.

using administrative claims and enrollment data for a random 20% sample of traditional Medicare enrollees from 2006-2018. Following the patient migration design (Finkelstein et al., 2016), I examine the changes in the likelihood of using mental health service and drug among individuals who move to regions with different utilization rates. This research design, widely used in studying the causes of geographic disparities in health care, allows the analysis to control for time-invariant patient-side factors using individual fixed effects. Therefore, any observed changes in an individual's treatment utilization can be attributable to the changes in place-side factors due to migration, shedding light on the relative importance of place effect in driving the geographic distribution of health care utilization.[6]

In the analysis, I distinguish between mental health service use (i.e., psychotherapy) and drug use (i.e., antidepressants, antipsychotics) for the following reasons. Firstly, the geographic distribution of these two types of treatment utilization shows distinctive patterns. Some regions, like Alabama, exhibit high mental health drug use rates (28.6%) coupled with low mental health service rates (7.1%). Conversely, regions like New York reveal a lower drug use rate (22.1%) and a higher service use rate (13.9%). Secondly, prior research shows that mental health drugs are frequently prescribed without a psychiatric diagnosis (Mojtabai and Olfson, 2011; Driessen et al., 2016). As such, their usage may not exclusively reflect mental health treatment. Thirdly, the utilization of mental health services and drugs could be influenced by different factors. For instance, mental health services such as psychotherapy are typically provided by specialized mental health professionals, whereas a substantial portion of mental health drugs are prescribed by primary care physicians and nurse practitioners. Consequently, the uneven geographic distribution of mental health specialists is likely to affect service use more than drug use. To make robust comparisons between mental health service and drug use, I employ the same sample of movers with full Medicare Part D coverage each year, and require continuous enrollment across the moving years to avoid potential endogenous response in Part D enrollment.

The event-study analysis shows that, following a move to an area with a one percentage

[6] This approach has been used in a variety of contexts, such as research on health care spending (Finkelstein et al., 2016; Agha et al., 2019; Godøy and Huitfeldt, 2020), physician practice styles (Molitor, 2018; Doyle and Staiger, 2022), health and longevity (Deryugina and Molitor, 2018; Finkelstein et al., 2021b), emergency department utilization (Zeltzer et al., 2021), opioid abuse (Finkelstein et al., 2021a), and health insurance enrollment (Cabral et al., 2023).

point higher service utilization rate, an individual's service use probability increases by 0.4-0.5 percentage points. The response is immediate after the move and remains relatively stable for eight years following the move. The difference-in-differences estimation reveals that, on average, a one percentage point increase in local service utilization rate results in a 0.458 percentage point increase in an individual's probability of using mental health services. This suggests that 45.8% of the variation in service use between the destination and origin areas can be explained by place-specific factors, while the remainder is attributable to patient-specific characteristics. This magnitude of place effect is similar to the estimate found for general health care spending (Finkelstein et al., 2016). However, when it comes to mental health drug use, place-specific factors explain only 15.1% of the variation. These results are robust to a number of sensitivity checks, including the use of balanced samples, different geographic units, and moving between regions with smaller or larger differences in treatment use rates.

To explore within the place component and to understand why it differs between service and drug use, I estimate area fixed effects using a broader sample consisting of both movers and non-movers, and correlate these with various place characteristics. Since this analysis uses a sample of individuals with the same insurance, it essentially eliminates the potential influence of disparate insurance coverages on the observed geographic differences in mental health treatment use. Remaining in consideration are factors such as environmental conditions, like temperature and pollution, that might affect people's mental health status.[7] Additionally, local public attitudes can affect patients' willingness to seek mental health care, possibly more so than for physical health conditions (Bharadwaj et al., 2017).[8] Moreover, the accessibility to mental health care providers may constrain the use of mental health treatment. The distribution of mental health professionals is extremely uneven across geographic areas, with half of U.S. counties lacking any psychiatrists, and is often discussed as one of the main barriers to sufficient provision of mental health services (Thomas et al., 2009; Bishop et al., 2016; Beck et al., 2018). Bivariate OLS results indicate that regions

[7] See literature reviewed in Liu et al. (2021), Ventriglio et al. (2021)

[8] For instance, stigma towards mental illness in certain areas may discourage people from seeking care, while more readily available information about treatment options in other areas may facilitate their use of these treatments.

with higher mental health service utilization rates tend to have colder temperatures, higher provider density, and more positive public attitudes towards mental illnesses. In contrast, all these place-side factors exhibit weaker and insignificant correlations with the place effect for drug use. In the post-Lasso multivariate regression, only the density of mental health professionals remains significantly correlated with the place effect for service use.

Heterogeneity analyses among movers from different origins and subsequently moving in opposite directions also underscore the role of provider accessibility in driving the geographic differences in treatment use. Specifically, movers, especially those from areas with median service use rates, exhibit larger responses in service use to an increase in regional service use rates than to an equivalent decrease. This observation aligns with the hypothesis that access to mental health professionals poses a significant barrier to mental health service use. A downward move to regions with insufficient access to mental health specialists imposes a hard constraint on service use, thereby triggering larger responses. For drug use, no significant asymmetry is observed in response to different moving directions, regardless of origin quintile. This is consistent with the understanding that mental health medications are frequently prescribed by various physicians, not only psychiatrists, therefore may be less influenced by the scarcity of mental health specialists in certain areas.

Lastly, I investigate the health outcomes associated with the observed geographic variation in mental health treatment use. At the regional level, I correlate suicide and self-harm emergency department (ED) rates with the estimated place effects, which account for differences in population composition and control for patient-side confounders. The results indicate that an area with a standard deviation higher in the place effect of service utilization is associated with 1.950 fewer suicide deaths per 100,000 residents - a 12.3% reduction relative to the mean. The link between drug use and suicide rates is less pronounced, with a standard deviation in drug use place effect correlating to a reduction of 0.492 suicide deaths per 100,000, or 3.1% relative to the mean. Correlations with self-harm ED rates shows consistently negative yet insignificant results. On the individual level, there is suggestive evidence that moving to places with a one percentage point higher service use rate leads to a 0.00446 percentage point, or 13.6%, decrease in the probability of a self-harm ED visit. Meanwhile, changes in local drug utilization rates do not seem to contribute to a decrease in self-harm

ED visits. Together, these findings indicate a positive relationship between increased mental health treatment utilization, especially services, and improved mental health outcomes.

This paper contributes to a small but growing literature on mental health in economics, which traditionally focuses on adolescents and working-age adults (Chatterji et al., 2011; Banerjee et al., 2017; Persson and Rossin-Slater, 2018; Cuddy and Currie, 2020a,b; Biasi et al., 2021; Persson et al., 2021). Senior adults, despite facing a similar or potentially greater mental health burden, remain an understudied population within the literature. Focusing on pre-retirement older adults, Cutler and Sportiche (2022) shows a negative impact of the Great Recession on the mental health of financially vulnerable homeowners.[9] Beyond this, discussions about older adults' mental health conditions and care use are mostly from the public health and psychiatric literature, most of which relies on survey data with limited size and subjective recall of service use (e.g., Klap et al., 2003; Karlin et al., 2008; Byers et al., 2012; Frost et al., 2019). Moreover, with the rapidly aging population in the US, the need to support mental health of the elderly is becoming increasingly urgent.[10]

Utilizing administrative claim data for the older population, this paper also enriches the literature discussing potential drivers of mental health treatment utilization (Baicker et al., 2013; Bharadwaj et al., 2017; Cowan and Hao, 2020; McClellan et al., 2020; Cuddy and Currie, 2020b; Cronin et al., 2020). This paper begins by documenting the geographic differences in mental health treatment utilization among people covered by the same insurance and evaluates the relative importance of place- and patient-side factors. Through comparing results for services and drugs, and by conducting regional cross-sectional regression and heterogeneity studies, I argue that the mental health professional workforce is one of the important determinants of mental health service use. This provides valuable policy implications for promoting the use of mental health services among the Medicare population.

This paper is also built on the important literature on geographic variation in health care (e.g.,Cutler and Sheiner (1999); Baicker et al. (2006); Skinner (2011); Chandra and

[9]However, Cutler and Sportiche (2022) does not find a significant impact of the Great Recession on seniors aged 65 to 74. The authors argue this is probably because the retired group is less affected when the decline in house price impacts the labor market.

[10]According to National Population Projections Tables (detailed age and sex composition of population), the population over age 65 is predicted to grow by 53% by 2050, while the population age 18-64 is only growing by 11%. Accessed at `https://www.census.gov/data/tables/2017/demo/popproj/2017-summary-tables.html` on July 13, 2021.

Staiger (2007); Doyle (2011); Finkelstein et al. (2016); Molitor (2018); Cutler et al. (2019). Most of these studies are in the context of health care for physical conditions, such as heart attacks and childbirth deliveries. This paper fills the gap by focusing on mental conditions and identifies several unique features in the use of mental health care.[11] Firstly, while place effect for mental health service use is approximately the same as the estimates for general health care spending in Finkelstein et al. (2016), the place effect for drug explains only one-fifth of the regional differences. Secondly, the observed asymmetry in service use underscores the critical role provider availability, drawing attention to an even more acute shortage of psychiatrists compared to that of general physicians. Lastly, although a significant portion of the research on geographic variation in physical health care does not identify a correlation between treatment intensity and health outcomes (Baicker et al., 2006; Moscone et al., 2019), this paper demonstrates a positive relationship between mental health treatment use and outcomes, making it distinct from many other types of health care on the "flat-of-the-curve" (Enthoven, 1978; Fuchs, 2004).

The paper is organized as follows. Section 2 introduces the setting, data, and descriptive facts about geographic variations in mental health care. Section 3 presents the movers design strategy and results on place effects. Section 4 explores the mechanism. Section 5 discusses the consequence of mental health care geographic disparity and Section 6 concludes.

2 Background and Data

2.1 Mental Illnesses and Treatment

Mental illnesses are health conditions that involve changes in emotion, thinking, or behavior. These conditions may be occasional or long-lasting, and can impair an individual's ability to carry out daily activities and maintain healthy relationships with others.[12] Common types

[11] A handful of papers have documented geographic variation in mental health care among the younger population. Golberstein et al. (2015) show that average annual inpatient days related to mental illness, ambulatory visits, psychotropic medication fills, and spending on psychiatric care varied widely across regions among Medicaid recipients. Sturm et al. (2003) show difference in self-reported children's mental health care use rates, and Cuddy and Currie (2020b) show the difference in adolescents' mental illness medication use.

[12] American Psychiatric Association, "What is Mental Health", `https://www.psychiatry.org/patients-families/what-is-mental-illness`.

of mental illnesses include cognitive disorders (e.g., delirium, dementia, amnestic), alcohol- and substance-related disorders, mood disorders (e.g., depression, bipolar disorder), anxiety disorders, and schizophrenia.[13] Among these, patients with cognitive disorders may exhibit distinct care utilization behaviors since they often have limited treatment options and are more likely to rely on caregivers (e.g., nursing homes) for health management and treatment decision. Additionally, due to regulations on substance abuse confidentiality, claims for alcohol- and substance-related disorders are redacted from our current Medicare data.[14] Therefore, the main analysis in this paper will primarily focus on mood disorders, anxiety, schizophrenia, and other psychotic disorders.

Patients experiencing mental health symptoms can seek diagnosis and treatment from psychiatrists, psychologists, and primary care physicians (PCPs). During the diagnosis process, physicians perform psychological evaluations asking about patients' thoughts, feelings, and behaviors.[15] The diagnostic criteria are set by the American Psychiatric Association (APA) and published in *The Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5).* Following a diagnosis, treatments including psychotherapy/counseling, medications, and various types of medical or behavioral therapy can be prescribed. Psychotherapy/counseling and other behavioral therapy often involves mental health specialists and clinical social workers, and can take place in a variety of settings, including physicians' offices, hospital psychiatric units, psychiatric hospitals, and community mental health centers. These services are covered by Medicare Part A for inpatient services or Part B for outpatient and physician services.[16] Patients don't need a referral to visit psychiatrists or psychologists who accept Medicare. Medications such as antidepressants, antipsychotics,

[13] The categorization of common mental illnesses is based on the International Statistical Classification of Diseases and Related Health Problems (ICD) and the Clinical Classifications Software (CCS) by Agency for Healthcare Research and Quality (AHRQ). Other mental illnesses less commonly seen (among older adults) include adjustment disorders, attention-deficit conduct and disruptive behavior disorders, developmental disorders, impulse control disorders, and personality disorders.

[14] For more details, see Substance Abuse Confidentiality Regulations, `https://www.samhsa.gov/about-us/who-we-are/laws-regulations/confidentiality-regulations-faqs`. The regulations were updated in 2017, which permitted Medicare to include substance use disorder claims for research purposes. To maintain consistency, these claims are removed across all sample years.

[15] Physicians often use questionnaires to assess patients' symptoms and evaluate the severity of conditions, for example, PHQ-9 for depression screening. They may also order physical exams and lab tests to rule out physical causes of symptoms.

[16] Medicare Advantage plans (or Part C) are also required to cover the same mental health services as original Medicare.

and anxiolytics are also commonly prescribed for mental health conditions. Prescription drug coverage under Medicare Part D varies by plan, but all plans are required to cover all antidepressants, and antipsychotics. Drugs specifically targeting anxiety, however, are not always covered. Notably, benzodiazepines were excluded from Part D coverage between 2006 and 2012 and, even after the exclusion was lifted, were only on average covered by of 83.4% of plans.[17] Therefore, the main analysis will primarily focus on antidepressants and antipsychotics.

2.2 Data

The primary data source for this paper is administrative claims data for a 20% random sample of Medicare fee-for-service recipients from 2006 to 2018. Medicare is a national health insurance program for people above age 65, and younger people receiving Social Security Disability Insurance (SSDI) benefits or with End Stage Renal Disease (ESRD). Besides traditional Medicare (or fee-for-service Medicare), approximately 30% of eligible beneficiaries chose Medicare Advantage (or Part C) plans during the study period, for whom I do not observe claim records in the data. The data include enrollment registers and claim records for inpatient admissions, outpatient services, physician services, and prescription drugs.

Sample The analysis sample is constructed based on the enrollment register at patient by year level, which includes information on patients' gender, age, race, residential zip code, and enrollment status in each month. Focusing on the older population, the baseline sample is restricted to Medicare recipients aged between 65 and 99 years old who are fully enrolled in Medicare Part A and B. This consists of 10,429,638 patients (66,609,088 patient-year observations). Since one of the main outcomes is prescription drug utilization, the baseline sample further requires full coverage of Medicare Part D,[18] which reduces the sample size to 6,729,094 patients (36,052,599 patient-year observations).

[17]Benzodiazepines are depressants that enhance the effect of the neurotransmitter gamma-aminobutyric acid (GABA), resulting in sedative, hypnotic (sleep-inducing), anxiolytic (anti-anxiety), anticonvulsant, and muscle relaxant properties. Coverage rates for different benzodiazepines after 2013 range from 49.5% for Oxazepam to 100% for Clobazam.

[18]Robustness checks also examine service use regardless of Part D coverage.

The geographic unit used in the analysis is Hospital Referral Region (HRR), as defined by the Dartmouth Atlas of Health Care.[19] There are 306 HRRs nationwide, organized according to patients' residential zip codes. HRRs are intended to approximate markets for tertiary hospital care. In mental health care settings, 75.7% of the claims with physicians were filed within the residential HRR of Medicare patients.[20]

From the baseline sample, movers are identified as people whose residential zip code changed across HRRs during the sample period. To have a clear assignment of years to pre- and post-moving periods, I keep people who moved only once over the sample period. Moreover, I require that the share of medical claims from the destination HRR increased by at least 0.75 in the post-move years to make sure that it is an actual physical move instead of just a change in mailing address.[21] Also, to avoid selection in Part D enrollment due to moving, only movers with continuous Part D coverage across moving years are selected into the final sample. In the end, the movers sample consists of 141,740 movers (1,150,872 patient-year observations). Non-movers, on the other hand, are identified as people who never moved across HRRs, comprising 6,107,210 patients (31,976,080 patient-year observations).

Service and Drug Use Measurements for mental health service use are constructed using claim data for inpatient, outpatient, and physician services. These datasets are at claim (and service item) level, including information on patient ID, date of service, place of service, provider ID and specialty, diagnoses, procedures, and payments. Diagnoses are recorded using International Classification of Disease (ICD) codes.[22] Patients with at least one claim that has mental illness as the primary diagnosis are identified as users of mental health

[19]More details on the definition of HRR and crosswalk files from zip codes to HRRs can be found at `https://data.dartmouthatlas.org/downloads/methods/geogappdx.pdf` and `https://data.dartmouthatlas.org/supplemental/#boundaries`.

[20]For comparison, 58.3% of the mental health claims with physicians were made within the residential county, and 95.0% within their residential state. These geographic units will be used in robustness checks for estimating place effect.

[21]This is calculated at patient-year level as the number of medical claims with provider zip code inside the mover's destination HRR divided by the number of medical claims with provider zip code inside either their origin or destination HRRs. The average change in this destination claim share among the the movers sample is reported in Appendix Figure A3.

[22]During the sample period, Medicare claims use ICD-9 code to record diagnoses in 2006-2015Q3, and switched to ICD-10 in 2015Q4. ICD codes for different types of mental health conditions are reported in Appendix Table A1.

service.[23] In addition to the main measurement, I also constructed indicators for mental health services by different providers and places of service. Measurements for mental health drug use are constructed using prescription drug claims, which include information on patient and prescriber IDs, filling date, National Drug Code (NDC), and payments. Patients with at least one claim for antidepressants or antipsychotics are identified as users of mental health drugs.

Mental Health Outcomes While the claim data provide detailed information on (mental) health care use, health outcomes are harder to observe. At the regional level, suicide rate from the CDC Underlying Cause of Death database, 1999-2019, is used as a severe and negative mental health outcome. In the individual-level analysis, however, suicide death cannot be directly observed since the cause of death information is not available in our current Medicare sample. Instead, I use emergency department (ED) visits due to self-harm injury as another adverse outcome of severe mental health conditions. These visits are identified using external cause of injury codes (E–codes), which are separately coded from the main diagnosis codes in Medicare inpatient records since 2009 and Medicare outpatient records since the year after.[24] Therefore, when using this measurement, the analysis sample is restricted to 2010-2018.

Summary Statistics Table 1 presents summary statistics on demographic characteristics, patients' mental health service/drug utilization and regional utilization rates in residential HRRs. Compared to those who have never moved across HRRs, movers tend to be older, and are less likely to be male and Medicare-Medicaid dual eligible. Average Medicare Part A/B

[23]The reason for only considering the primary diagnosis when identifying mental health claims is to exclude claims for other diseases with a mental health condition recorded as a comorbidity. When a mental health disorder is recorded as a secondary or higher order diagnosis in physician claims before 2015 (when ICD-9 is used), 64.8% also have a primary diagnosis related to a mental health disorder. Among claims that do not list mental illness in the primary diagnosis but do list one in a subsequent diagnosis, the most common types of primary diagnoses (collapsed to 3-digit ICD code) are essential hypertension (13.4%), diabetes mellitus (6.2%), general symptoms (6.1%), disorders of lipoid metabolism (4.0%), and symptoms involving the respiratory system and other chest symptoms (2.8%).

[24]The list of E-codes related to self-harm is based on the Clinical Classifications Software (CCS) by the Agency for Healthcare Research and Quality (AHRQ), including E950-E959 (Suicide And Self-Inflicted Injury) in ICD-9 codes, X71-X83 (Intentional self-harm) and T36-T65, T71 (Poisoning, Toxic Effects, and Asphyxiation) with "2" in the 6th digit representing intentional self-harm. Before 2009, only 20% of ED visits for injury and poisoning had E-codes reported, whereas over 90% had E-codes reported after 2010.

spending for movers over all the observed years is very similar to that for non-movers, but it is much lower in the pre-moving period when they have relatively similar ages compared to non-movers. In terms of mental health service/drug use, movers have similar utilization rates in the pre-moving period compared to non-movers, but higher utilization rates in the post-moving period. These patterns suggest that movers are not very different in their mental health conditions before they move from non-movers. The increased mental health care service/drug rates, along with higher overall health spending after relocation, can be partially attributed to the fact that these individuals are mechanically older in the post-moving period. However, it is also possible that the act of moving itself has impact on individuals' (mental) health. To account for these factors, age group fixed effects and the number of years relative to moving fixed effects will be controlled in the regression models. Lastly, mental health service/drug utilization rates, defined as the share of patient-year observations with any mental health service/drug claim within the residential HRR, do not differ between movers and nonmovers, or between the years before and after moving. This suggests that there is no systematic migration pattern, such as people being more likely to leave low utilization areas and to move to higher utilization areas.

Regional Characteristics Multiple datasets are used to construct regional charactistics. The number of providers (i.e., psychiatrists, psychologists, clinical social workers, PCPs and nurse practitioners) are calculated based on provider specialty information from the Medicare Data on Provider Practice and Specialty (MD-PPAS) and service zip code from physician claims data. A variety of public datasets on regional characteristics are also used to supplement the analysis, including the Provider of Services (POS) File - Hospital & Non-Hospital Facilities data, the Behavioral Risk Factor Surveillance System (BRFSS) survey data, the American Community Survey, the U.S. Monthly Climate Normals, and the U.S. Air Quality Data. Detailed descriptions for each data source and variable construction are outlined in Appendix A.

2.3 Geographic Disparities in Mental Health Treatment Utilization

Over the thirteen-year sample period, 26.9% of Medicare beneficiaries in the baseline sample have had at least one diagnosis of mental illnesses, and 39.6% have made at least one claim for a mental health drug. These rates could potentially be higher if we consider the fact that not all individuals are observed throughout the entire sample period. In an average year, 10.7% of beneficiaries have at least one mental health service claim, and 23.9% have at least one mental health drug claim.[25]

Mental health service/drug utilization rates vary substantially across the United States. As shown in Figure 1 Panel (a), service use is higher in the Northeastern region, parts of the Midwest, and in Florida and Texas. HRRs in the West exhibit much lower utilization rates. While 23.4% of the Medicare population in Miami, FL makes use of mental health services in an average year, only 6.8% do so in Montgomery, AL. Appendix Figure A2 Panel (a) shows service use for Medicare recipients regardless of Part D coverage, demonstrating a distribution similar to that for Part D enrollees, though rates are generally lower as mental health patients are more likely to have Part D coverage. Alongside the overall service use rate, there is also significant geographic variation in the proportion of beneficiaries using specific types of mental health services For example, as shown in Appendix Figure A2, inpatient mental health care is utilized more frequently in the South, while hospital outpatient department care is utilized more often in the North. Urban areas with high overall mental health service utilization rates tend to have majority of services provided by mental health professionals, such as psychiatrists, psychologists, and clinical social workers. However, rural areas with limited supply of specialists generally exhibit lower overall service use rates and rely more heavily on other providers such as primary care physicians (PCPs).

Mental health drug use rate, as shown in Figure 1 Panel (b), is also highest in Miami, FL (33.2%) and lowest in Honolulu, HI (11.9%). Between these two extremes, drug utilization

[25]The higher utilization rate for mental health drugs than services reveals the fact that a large proportion of antidepressants and antipsychotics are prescribed without a relevant diagnosis (Mojtabai and Olfson, 2011; Carton et al., 2015). In our sample, 69.3% of patient-year observations with mental health drug claims do not have medical claims with a primary mental health diagnosis in the current year (37.0% when considering higher order diagnoses).

rates are higher in the East South Central regions where service use rates are low. For example, 30.6% of Medicare recipients in the baseline sample in Dothan, AL take mental health drugs in an average year, but only 8.6% of them have mental health service visits. Places in the Northeast tend to have high service use rates but low drug use rates. Part of the West, such as HRRs in Nevada, Arizona, and New Mexico, show low utilization rates for both service and drug, which is more clearly depicted in Appendix Figure A2 panel (b) for utilization of either service or drug. The distinction between the geographic distributions of drug and service use could be potentially resulted by the substitution between treatment options, and/or the over- or under-use of one or both treatments, which cannot be definitively confirmed based solely on the observed correlation.

Regarding payment for mental health treatment, places with higher mental health service use rates tend to also have higher mental health service spending conditional on having service usage. Places with different mental health drug use rate, however, exhibit similar average drug spending among people taking them. One possible explanation for these correlations is that places have different proportions of people with mental illness. These patients are able to access similar amounts of mental health drugs but do not have similar access to mental health services. Places with more supply of mental health professionals see higher service utilization at both the intensive and extensive margin. Again, given the complexity of mental health treatment, other combinations of factors could also lead to similar correlation results. Therefore, further analysis is required to more thoroughly understand the driving forces behind these geographic differences.

3 Patient and Place Effects

3.1 Movers Design

To investigate place and patient-specific factors that contribute to the geographic disparity in mental health treatment utilization, I exploit exogenous changes in place-specific factors when patients move across geographic areas. The primary empirical question is whether individuals' likelihood of using mental health treatment changes when they move to areas with different treatment utilization rates. Using the movers sample, I estimate the following event-study specification:

$$y_{it} = \alpha_i + \tau_t + \sum_{s=-8}^{7} \mathbb{1}[s = r(i,t)]\theta_s \delta_i + x_{it}\beta + \epsilon_{it}, \tag{1}$$

where y_{it} is an indicator for patient i having any mental health service/drug claim in year t. δ_i is defined as $\bar{y}_{d(i)} - \bar{y}_{o(i)}$, representing the difference in the HRR mental health service/drug utilization rate between the destination HRR ($d(i)$) and the origin HRR ($o(i)$). These regional utilization rates are calculated using only the non-movers in each year and are merged with each mover based on the year prior to the move, so that utilization behavior of the movers does not enter both sides of the equation. Figure 2 plots the distribution of δ_i for mental health service (Panel (a)) and drug (Panel (b)). Both panels illustrate a broad and approximately symmetric spread of differences in treatment utilization rates between the origin and destination. θ_s is a set of coefficients for each year relative to moving ($r(i,t)$), where relative year -1 is set as the baseline year. Years beyond the scope of eight years before and seven years after the move are grouped together as $s \leq -8$ and $s \geq 7$ respectively. The regression model also incorporates individual fixed effects (α_i) to control for all time-invariant patient characteristics and calendar year fixed effects (τ_t) to account for general time trends. x_{it} further include relative year fixed effect, which control for changes in mental health treatment use related to relocation but are uniform across all moving directions, as well as 5-year age groups fixed effects.

The key parameter of interest, θ_s, can be interpreted as the response to changes in local utilization rates, under the assumption that there are no other factors systematically varying with the moving direction and also affecting movers' mental health treatment use. This assumption could be violated if, for example, people who have increasing needs of mental health conditions choose to move to places with higher utilization rates.

To test this, I use the American Community Survey (ACS) data from 2006 to 2018 to examine whether people's moving direction is correlated with major life events such as divorce, death of a spouse, or retirement that may negatively affect mental health status.[26]

[26] A substantial body of research has shown that losing partners can have a severe negative impact on the mental health of the older population (e.g., Mazure, 1998; Lindeboom et al., 2002; Siflinger, 2017). The effect

Since the ACS only provides past residential information at the state level, I calculate the difference in the mental health service/drug utilization rate between the destination and origin states, instead of HRRs. Appendix Table A2 shows that changes in the local mental health service utilization rate are not significantly different for movers who divorced or became widowed in the past year. For movers who retired last year, the local mental health service use rate is also similar between their origin and destination states. The local mental health drug use rate is slightly higher in the destination, but the magnitude is very small compared to the standard deviation across states.

Furthermore, if individuals with deteriorating mental health are more likely to move to areas with better access to mental health treatment, we should expect an upward trend in coefficients θ_s in the years preceding the move. This can be explicitly seen in the event study results and provides a more direct test of the assumption.

3.2 Event Study Estimates

Figure 3 Panel (a) plots coefficients θ_s estimated from Equation (1), representing how individual mental health service use adjusts in response to changes in local utilization rates. The coefficients for the years leading up to the move are consistently close to zero from $s = -8$ to $s = -1$. This suggests that no differential trends in mental health service use among movers are systematically correlated with moving directions. In other words, there is no evidence indicating selective migration based on people's mental health service use trajectories. The change in the local mental health service utilization rate takes effect on an individual's service use immediately after moving. People who move to areas with a one percentage point higher mental health service utilization rate raise their likelihood of using mental health service by 0.3 percentage points in the year of the move ($s = 0$). Since people might move in the middle of the year and are only partially "treated" in year 0, the $s = 0$ estimate represents an underestimation of the response.[27] After the move year, an individual's likelihood of using

of retirement on the mental health status of the elderly has shown mixed evidence in the literature, varying by voluntary and involuntary retirements, different health indexes, and strategies in addressing endogenous retirement decisions (Nishimura et al., 2018).

[27] Appendix Figure A4 presents event studies plots for subgroups of movers based on the share of claims from the destination HRRs in year 0. This can be seen as a proxy for the time of the move. Individuals with a higher share of their claims occurring in the destination HRR are likely to move earlier in the year,

mental health services increases by 0.4-0.5 percentage points in response to a one percentage point increase in the local utilization rate. This result implies that 40-50% of the difference in the mental health service use rate between the destination and origin HRRs is absorbed after moving. This magnitude of place effect aligns with the 50% place effect observed for total health care spending (Finkelstein et al., 2016). Appendix Figure A5 plots the event study results for all movers, regardless of their Part D coverage, showing a slightly larger response to the change in local utilization rate (also calculated among all non-movers with and without Part D coverage).

The result for mental health drug use, as depicted in Figure 3 Panel (b), present a distinct pattern compared to mental health service use. In the years prior to the move, coefficients are also close to zero, except a small bump in years -6 to -4. This is unlikely to be driven by selection in moving direction, as this would imply that people migrating to places with higher mental health drug utilization rates are more prone to have consumed these drugs beyond, but not within, three years prior to relocation. Furthermore, Appendix Figure A6 demonstrates no such pre-trend when using a set of balanced samples. In the years after the move, event coefficients are approximately 0.2 in both Figure 3 Panel (b) and Appendix Figure A6 Panel (d) and (f). This indicates that an individual's likelihood of taking mental health drugs increases by only 0.2 percentage points in response to a one percentage point increase in the local utilization rate. In other words, the place effect for mental health drug use is 20%, substantially smaller than that for mental health service use. This could be due to the fact that mental health services are typically offered by mental health professionals such as psychiatrists and psychologists, whereas mental health drugs can be prescribed by a wider range of practitioners, including primary care physicians and nurse practitioners.[28] Consequently, the distribution of mental health professionals, as an important place-specific factor, affect the use of mental health services, but not necessarily the use of drugs. This hypothesis will be further explored in Section 4.

A series of robustness checks are performed to ensure the results are not driven by specific migration directions or the definition of geographic area. Appendix Figure A7 presents event

and therefore exhibit a larger effect size at year 0.

[28] In the Medicare sample, 23.6% of antidepressants and antipsychotics are prescribed by psychiatrists, and 55.9% are prescribed by primary care physicians and nurse practitioners.

study plots using different subsamples of movers, i.e., those migrating between HRRs with above median (or top quartile or top decile) and HRRs with below median (or bottom quartile or bottom decile) treatment utilization rates. All figures are similar to each other and to the main results. Appendix Figure A8 shows robustness results with local utilization rates measured using different geographic units. The sample includes movers crossing state borders. Again, similar results are observed regardless of whether the utilization rates are measured at state, county, and hospital service area (HSA) level.[29]

3.3 Difference-in-Difference Estimates

Table 2 summarizes the place effects for mental health service and drug use from difference-in-differences estimations. The sample excludes the year of moving, and all post-moving years are aggregated into one indicator ($Post$), interacted with the destination-origin difference in the mental health service/drug utilization rate (δ_i). The coefficient for this interaction term reflects the overall response after moving. An individual's probability of using mental health service increases by 0.458 percentage points when moving to places with a one percentage point higher service utilization rate, while the likelihood of taking mental health drugs only increases by 0.151 with a similar increase in local drug use rate. Females exhibit higher utilization rates for both mental health services and drugs and are more responsive to changes in local utilization rates.

Given the inherent differences in the causes and treatments, the size of the place effect may vary across different mental illness categories. This heterogeneity is tested in Appendix Table A3. In each regression, the outcome variable denotes whether the patient has any medical claims related to a particular type of mental illness diagnosis, or if there are any claims for antidepressants or antipsychotics within the given year. Changes in local utilization rate also correspond to the mental health treatment measure in use. As shown in Columns (1)-(3), mental health service use for schizophrenia shows a relatively smaller place effect compared to

[29]HSAs are also defined by the Dartmouth Atlas of Health Care by assigning zip codes to the hospital area where the greatest proportion of their Medicare residents were hospitalized. There are in total 3,436 HSAs across the U.S. See `https://data.dartmouthatlas.org/downloads/methods/geogappdx.pdf` and `https://data.dartmouthatlas.org/supplemental/#boundaries` for more details on the definition of HSA and crosswalk files from zip codes to HSAs.

anxiety and mood disorders. This aligns with evidence from genetic epidemiology suggesting that genetic factors, which do not change when people move, have a more pronounced influence on schizophrenia (Bienvenu et al., 2011). Meanwhile, since antipsychotics are more likely to be prescribed by psychiatrists than antidepressants (44.0% vs. 17.0%), access to psychiatrists plays a more significant role in the usage of antipsychotics. Thus, place-specific factors end up accounting for more geographic differences in antipsychoics use than antidepressant use, although the place effect is still smaller than that for service use.

Place effects may also vary when considering specific service providers and treatment intensity. Appendix Table A4 Columns (1)-(4) present regression results for mental health services delivered by different types of providers, namely, hospital inpatient department, hospital outpatient department, mental health professionals (i.e., psychiatrists, psychologists, and clinical social workers), and primary care physicians. All these measures exhibit larger place effects than the main outcome due to potential provider substitution. For instance, people moving to areas with fewer mental health professionals might switch from visiting psychiatrists to primary care physicians. While the use of any mental health service remains unchanged, service use for specific providers converges to the local utilization pattern. Conditional on care/drug use, spending on mental health service/drug also responds to the change in local average spending upon moving. As reported in Columns (5)-(6), the place effect is 0.592 for mental health services spending and 0.293 for mental health drug spending. These reflect intensive margin responses and are larger than the extensive margin responses in the main result. One possible explanation is that the intensity of treatment could be more influenced by provider's practice style, which varies as a part of the place-specific factor.

Three sets of robustness check results are further reported in Appendix Table A5 to A6. First, instead of only using the primary diagnosis, Columns (1)-(3) in Appendix Table A5 measure mental health service use based on all diagnoses in the medical claim. This includes claims with mental illness coded as comorbidities. As a result, the average utilization rate doubles, but the magnitude of the place effect is substantially smaller. Second, Columns (4)-(6) examine mental health drug usage, which includes the use of anxiolytics. The place effect here is also smaller than the main result and predominantly driven by women. Lastly, Appendix Table A6 excludes patients who have nursing home claims within the given year.

Among these movers, only 28.3% of the geographic differences in service use and 12.1% of the differences in drug use can be attributed to place-specific factors. This suggests that nursing facilities potentially act as an important channel transmitting local utilization patterns to people who moved in. The Nursing Home Reform Act of 1987 mandates regular mental health evaluations for nursing home residents. Consequently, patients moving into a nursing home might be more exposed to local practice styles and consequently converge more towards the average utilization rate.

4 Mechanisms

Empirical results so far indicate that place effects explain approximately half the geographic disparity in mental health service utilization rates, but only a fifth for mental health drug use. In this section, I explore the potential place-specific characteristics that contribute to the place effect and discuss what drives the distinction between mental health service and drug use.

4.1 Correlates of Place Effects

To explore which place-specific factors are correlated with the place component of mental health treatment utilization, I first estimate the HRR fixed effect for an individual's use of mental health service and drug using the following equation,

$$y_{iht} = \alpha_i + \tau_t + \rho_{r(i,t)} + \eta_h + x_{it}\beta + \epsilon_{iht}. \tag{2}$$

The specification is estimated using data on both movers and non-movers. The outcome variable y_{iht} is the indicator of patient i living in HRR h having any mental health service/drug claim in year t. As in Equation (1), α_i is beneficiary fixed effects, τ_t is calendar year fixed effects, $\rho_{r(i,t)}$ is fixed effects for the year relative to moving, and x_{it} includes 5-year age bin fixed effects. For all movers, the year of moving is dropped. For the non-movers, all year relative to moving indicators ($\rho_{r(i,t)}$) are set to zero. These non-movers help to more accurately estimate the HRR fixed effect (η_h). This key estimator represents the place component in determining mental health service/drug use for each HRR. A higher η_h means this place has a higher utilization rate after controlling for a patient's individual effect.

Next, I explore the correlation between the estimated HRR fixed effects (η_h) and a series of place-specific characteristics. The factors considered include environmental conditions, such as average temperature, number of days with extreme temperature, precipitation levels, and PM2.5 levels, which are recognized in prior literature for their significant impact on mental health (e.g., Liu et al. (2021), Ventriglio et al. (2021)). With respect to healthcare resources, I consider both the number of mental health specialists, such as psychiatrists, psychologists, and clinical social workers, and the capacity of institutional providers, indicated by the number of psychiatric hospitals, psychiatric units in general hospitals, and psychiatric beds. I also include providers not specialized in mental health, such as primary care physicians and nurse practitioners, as general medical resource indicators. Furthermore, I assess the role of local public attitudes, which include sympathy towards people with mental illness and perceived effectiveness of mental health treatment. I also take into account average demographic and economic characteristics, including age, gender, race, Medicaid eligibility among the Medicare sample, and household income and education level for the population over age 65.

The distribution of these factors across HRRs is detailed in Appendix Table A7. Notably, we observe considerable differences in mental health provider availability. For instance, while New York City has 2.9 psychiatrists (in addition to 2.6 psychologists and 3.0 clinical social workers) per thousand Medicare recipients, Oxford, MS only has 0.19 psychiatrists (0.15 psychologists and 0.8 clinical social workers). This stark contrast in the availability of providers suggests unequal access to mental health care across regions, which could contribute to the differences in utilization rates, especially for services that rely more on mental health professionals. Social perceptions also vary across geographic areas, potentially due to differences in cultural background, population compositions, or local information channels, and can affect people's likelihood of seeking mental health care when needed.

Figure 4 exhibits the correlation between HRR characteristics and the the place effects for mental health service (Panel (a)) and drug (Panel (b)) use. In each figure, coefficients estimated from separate bivariate OLS regressions are displayed on the left, and coefficients from post-Lasso multivariate OLS are displayed on the right.[30] All covariates are standardized to mean zero and standard deviation one. The sample includes 225 HRRs for which I observe the full set of HRR characteristics. All regressions are weighted by the number of Medicare patients in each HRR used in estimating place effects.

Bivariate OLS regression results indicate that the place effect for mental health service use is higher in HRRs with warmer temperatures, a higher supply of mental health professionals, and less prevalent negative attitudes towards mental illness. The place effect is also positively associated with the average Medicare population being older, comprising a larger share of females, and having higher household income. As for mental health drug use, the correlations between place effect and place-specific characteristics are not as strong as those for mental health service use. Coefficients are only statistically significant for the number of psychiatric units, share of male, and the level of population income.

In the post-Lasso multivariate OLS estimation, the place effect for mental health service use remains significantly and positively correlated with the per capita number of psychologists and the number of psychiatric hospitals, as well as the average age and income level. When these covariates are held constant, the number of other physicians and population education level displays negative associations with the place effect. Regarding the place effect of mental health drug use, only the number of psychiatric units and median household income are selected and retain marginal significance. These findings suggest that the uneven distribution of mental health professionals is more closely tied to the geographic disparities of mental health service use than to mental health drug use. This aligns with the fact that many mental health drugs are not prescribed by psychiatrists. However, it should be noted that this cross-sectional correlation does not necessarily imply that an increased supply of mental health specialists leads to more mental health service use. The distribution of providers could be endogenous, as regions with a higher demand for psychiatric services might naturally attract more providers.

[30] The post-Lasso multivariate OLS is estimated in two steps. First, the full set of HRR characteristics is included in a Lasso regression, where the penalty level is chosen based on a 10-fold cross validation. Then, the set of covariates chosen by the Lasso regression is included in a multivariate OLS.

4.2 Heterogeneity

Different place-specific factors can cause varying impacts on individuals moving to areas with higher ("moving-up") or lower ("moving-down") mental health treatment utilization rates. The impacts of these moves might also be heterogeneous depending on whether local resources act as constraints. For example, if limited access to mental health professionals is a significant barrier, moving to a low-utilization area could trigger a larger response than moving to a high-utilization one. This response could be particularly significant for individuals for whom the move imposes or eases a constraint. Meanwhile, if moving to a high-utilization area raises one's awareness of mental health issues and treatments, it's unlikely that moving to a low-utilization area would reverse this understanding. As a result, the effect of "moving-up" might be smaller than "moving-down".

To explore these hypotheses, I estimate a difference-in-difference regression model for five subsets of movers, grouped by the quintile of the treatment utilization rate in their original HRRs. The regression model, displayed below, includes interaction terms between the post-period indicator ($Post_{it}$) and the destination-origin difference in mental health treatment rate (δ_i) that are specific for upward and downward moving. In this model, θ^{up} represents changes in response to δ_i when individuals are moving to areas with higher utilization rates ($\delta_i > 0$). Conversely, θ^{down} represents the response when individuals are relocating to areas with lower utilization rates ($\delta_i \leq 0$).

$$y_{it} = \alpha_i + \tau_t + \theta^{up} Post_{it} \times \delta_i \times \mathbb{1}(\delta_i \geq 0) + \theta^{down} Post_{it} \times \delta_i \times \mathbb{1}(\delta_i < 0) + x_{it}\beta + \epsilon_{it}, \quad (3)$$

The estimated coefficients are plotted in Figure 5 and reported in Appendix Table A8. For mental health service use (Panel (a)), movers exhibit larger responses to an increase in regional service use rates than to an equivalent decrease. Such asymmetry is most pronounced among movers from the median quintile HRRs, with a point estimate of 1.15 when moving down and 0.408 when moving up, a difference significant at the 5 percent level. Movers from the higher quintile HRRs shows even larger responses to downward moves but the confidence intervals also expanded as there are fewer people moving downwards. They also shows larger responses in upward moves compared to those moving out from median HRRs.

This likely reflects these movers transitioning to regions with more mental health service providers, thus relieving the constraints imposed by limited access. Movers from top quintile HRRs also exhibit slightly larger responses to downward moves, although the difference is less significant. These individuals, despite moving downwards, probably still reside within HRRs with a sufficient supply of mental health service providers, thereby avoiding drastic reductions in access.

In contrast to the service utilization results, the mental health drug use findings (Panel (b)) do not present significant asymmetric responses across the moving directions among all subgroups of movers. Again, this discrepancy is consistent with the understanding that access to mental health medication does not depend heavily on the availability of mental health specialists. For instance, it may be difficult to schedule psychotherapy sessions in areas lacking psychiatrists or psychologists, yet individuals can typically continue to receive their prescriptions from primary care physicians, resulting in a smaller impact on mental health drug use.

5 Health Outcomes

Does increased utilization of mental health treatment improve patients' mental health status? In this section, I explore the relationship between mental health service/drug use and the incidence of negative mental health outcomes – suicide and self-harm behavior.

Figure A9 Panel (a) displays the number of suicide deaths per 100,000 population over age 65 across HRRs. This suicide rate is age- and gender- adjusted, but still varies greatly across HRRs, ranging from 35.9 in Reno, NV to 6.9 in Bronx, NY. The incidence rate is typically higher in the West and lower in the Northeastern region, which contradicts the distribution of mental health service use. A simplistic correlation between the regional suicide rate and the mental health treatment use rate may misrepresent the causal relationship between the two due to potential confounding factors. For instance, a population with a higher prevalence of severe mental illnesses might exhibit both higher treatment utilization and suicide rates. To address this issue, I correlate the regional suicide rate with the place effect estimated in Section 4.1, which takes out patient-side factors related to mental health treatment use.

Panel A in Table 3 presents the results for the overall population, as well as separate results for males and females. In each regression, I control for regional demographic and socioeconomic characteristics, as well as state-level gun ownership policies.[31] Results indicate that HRRs with a higher place effect for mental health service use tend to have a significantly lower suicide rate. A standard deviation higher place effect in service utilization is associated with 1.950 fewer suicide deaths per 100,000 residents (12.3% compared to the mean). The coefficient is more pronounced for males, who have a suicide rate six times higher than that of females. The place effect for mental health drug use is also negatively associated with the regional suicide rate, but to a smaller extent - one standard deviation higher place effect is associated with 04922 (or 3.1%) lower suicide rate.

Another adverse mental health outcome I examine is emergency department (ED) visits due to self-harm, which can be identified in the Medicare claims data from 2010 onwards. Table 3 Panel B presents the correlation between the place effect of mental health treatment and the incidence rate of self-harm ED visits. The correlation is also consistently negative for place effects of both service and drug use for both genders, although the magnitude and significant levels are smaller. It is interesting to note that, while males have a much higher suicide rate compared to females, the rate of self-harm ED visits is, if anything, higher among females. This aligns with the fact that males use more violent methods to commit suicide (Kposowa and McElvain, 2006). Therefore, when interpreting these results, it is worthwhile to keep in mind that they may miss severe self-harm behaviors that do not result in ED visits.

Beyond the regional level analysis, I further applied the movers design to assess whether individuals' mental health outcomes change when they move to places with different mental health treatment utilization rates. Since suicide death cannot be identified in the claims data, I focus on self-harm ED visits in the analysis. Table 4 replicates the difference-in-difference estimation as in Table 2 using the indicator for having any self-harm ED visits as the outcome. We see suggestive evidence that people moving to places with higher service utilization show a sizable decrease in the probability of ED visits due to self-harm. Point

[31] Gun ownership controls include state-level universal background check law, permit to purchase law, and proportion of adults living in a household with a firearm, from RAND State-Level Estimates of Household Firearm Ownership (Schell et al., 2020).

estimate suggests that a one percentage point increase in local mental health service use rate is associated with 0.00446 percentage point lower likelihood of self-harm ED visits, or 13.6% compared to the average incidence rate. The effect is stronger for male and people outside nusing homes (see Appendix Table A9). At the same time, I do not find consistent and significant results when considering changes in local drug utilization rate, potentially due to the smaller first-stage effect on individuals' drug use behavior. This analysis of movers controls for individual time-invariant characteristics, thus the observed changes reflect the impact of place-specific factors. It remains challenging to pinpoint which place characteristics drive the observed effects, and hence, we cannot definitively establish a causal relationship between increased service use and a reduction in self-harm ED visits. However, if there are any confounding factors invalidate these findings, they would need to correlate with both the variations in regional utilization rates and changes in individuals' self-harm ED visit rates, without impacting their mental health service use behavior.

6 Conclusion

In this paper, I use administrative data from Medicare to study the geographic variation in mental health treatment utilization among individuals aged 65 and above. I show that the mental health treatment use rate varies substantially across regions in the United States, with distinctive patterns observed for service use and prescription drug use.

Exploiting changes in the local treatment utilization rate due to migration, I find that individuals moving to places with a one percentage point higher service utilization rate increase their likelihood of using mental health services by 0.458 percentage points. This means that place-specific factors explain about 45.8% of the geographic variation in mental health service use, with the remaining attributable to patient-side factors. In contrast, the place effect only accounts for 15.1% of the geographic differences in mental health drug use.

Delving into the place-specific factors, I explore the correlation between the place effects of mental health service/drug use and HRR characteristics, as well as the heterogeneity among movers from origin HRRs with different levels of treatment utilization rate moving in different directions (i.e., upwards or downwards). Both analyses indicate that a higher number of mental health specialists is strongly correlated with a larger place effect of service use but not with that of drug use, which depends less on specialized providers. This finding suggests that increasing the supply of mental health providers, particularly in areas facing hard constraint, could facilitate increased usage of mental health services. Telemedicine offers an additional solution for addressing the uneven distribution of providers and promoting mental health service use. While the analysis incorporates a broad set of place-specific factors, it may not fully capture all potential mechanisms, such as regional differences in physicians' practice patterns in diagnosis and prescription, which can be important determinants in mental health care delivery (Barnett et al., 2020; Marquardt, 2021). More future work is needed to understand these potential sources of geographic variation.

Regarding the health outcomes associated with geographic variation in mental health treatment, I show a strong and negative correlation between the place effect of mental health service/drug utilization and the regional suicide rate. There is also suggestive evidence that moving to places with more mental health service use is associated with a lower likelihood of self-harm ED visits, especially among males. These findings suggest the marginal benefit of providing more mental health care. Compared to many other types of medical care on the "flat-of-the-curve", mental health care warrants greater attention and resource allocation.

References

Agha, Leila, Brigham Frandsen, and James B Rebitzer, "Fragmented division of labor and healthcare costs: Evidence from moves across regions," *Journal of Public Economics*, 2019, *169*, 144–159.

American Psychological Association (APA), "Recognition of psychotherapy effectiveness," *Psychotherapy (Chicago, Ill.)*, 2013, *50* (1), 102–109.

Baicker, Katherine, Kasey S Buckles, and Amitabh Chandra, "Geographic variation in the appropriate use of cesarean delivery: Do higher usage rates reflect medically inappropriate use of this procedure?," *Health Affairs*, 2006, *25* (Suppl1), W355–W367.

_ , Sarah L Taubman, Heidi L Allen, Mira Bernstein, Jonathan H Gruber, Joseph P Newhouse, Eric C Schneider, Bill J Wright, Alan M Zaslavsky, and Amy N Finkelstein, "The Oregon experiment—effects of Medicaid on clinical outcomes," *New England Journal of Medicine*, 2013, *368* (18), 1713–1722.

Banerjee, Souvik, Pinka Chatterji, and Kajal Lahiri, "Effects of psychiatric disorders on labor market outcomes: A latent variable approach using multiple clinical indicators," *Health Economics*, 2017, *26* (2), 184–205.

Barnett, Michael L, Andrew Olenski, and Adam Sacarny, "Common practice: Spillovers from Medicare on private health care," *NBER Working Paper*, 2020.

Beck, Angela J, Cory Page, Jessica Buche, Danielle Rittman, and Maria Gaiser, "Estimating the distribution of the US psychiatric subspecialist workforce," *Population*, 2018, *600*, 47–6.

Bharadwaj, Prashant, Mallesh M Pai, and Agne Suziedelyte, "Mental health stigma," *Economics Letters*, 2017, *159*, 57–60.

Biasi, Barbara, Michael S Dahl, and Petra Moser, "Career effects of mental health," *NBER Working Paper*, 2021.

Bienvenu, Oscar J, Dimitry S Davydow, and KS Kendler, "Psychiatric 'diseases' versus behavioral disorders and degree of genetic influence," *Psychological medicine*, 2011, *41* (1), 33–40.

Bishop, Tara F, Joanna K Seirup, Harold Alan Pincus, and Joseph S Ross, "Population of US practicing psychiatrists declined, 2003–13, which may help explain poor access to mental health care," *Health Affairs*, 2016, *35* (7), 1271–1277.

Bütikofer, Aline, Christopher J Cronin, and Meghan M Skira, "Employment effects of healthcare policy: Evidence from the 2007 FDA black box warning on antidepressants," *Journal of Health Economics*, 2020, *73*, 102348.

Byers, Amy L, Patricia A Arean, and Kristine Yaffe, "Low use of mental health services among older Americans with mood and anxiety disorders," *Psychiatric Services*, 2012, *63* (1), 66–72.

Cabral, Marika, Colleen Carey, and Jinyeong Son, "Partial Outsourcing of Public Programs: Evidence on Determinants of Choice in Medicare," *NBER Working Paper*, 2023.

Carton, Louise, Olivier Cottencin, Maryse Lapeyre-Mestre, Pierre A Geoffroy, Jonathan Favre, Nicolas Simon, Regis Bordet, and Benjamin Rolland, "Off-label prescribing of antipsychotics in adults, children and elderly individuals: a systematic review of recent prescription trends," *Current pharmaceutical design*, 2015, *21* (23), 3280–3297.

Chandra, Amitabh and Douglas O Staiger, "Productivity spillovers in health care: Evidence from the treatment of heart attacks," *Journal of Political Economy*, 2007, *115* (1), 103–140.

Chatterji, Pinka, Margarita Alegria, and David Takeuchi, "Psychiatric disorders and labor market outcomes: Evidence from the National Comorbidity Survey-Replication," *Journal of Health Economics*, 2011, *30* (5), 858–868.

Cowan, Benjamin W and Zhuang Hao, "Medicaid expansion and the mental health of college students," *NBER Working Paper*, 2020.

Cronin, Christopher J, Matthew P Forsstrom, and Nicholas W Papageorge, "What good are treatment effects without treatment? Mental health and the reluctance to use talk therapy," *NBER Working Paper*, 2020.

Cuddy, Emily and Janet Currie, "Rules vs. discretion: Treatment of mental illness in US adolescents," *NBER Working Paper*, 2020.

_ **and** _ , "Treatment of mental illness in American adolescents varies widely within and across areas," *Proceedings of the National Academy of Sciences*, 2020, *117* (39), 24039–24046.

Cutler, David, Jonathan S Skinner, Ariel Dora Stern, and David Wennberg, "Physician beliefs and patient preferences: A new look at regional variation in health care spending," *American Economic Journal: Economic Policy*, 2019, *11* (1), 192–221.

Cutler, David M and Louise Sheiner, "The geography of Medicare," *American Economic Review*, 1999, *89* (2), 228–233.

_ **and Noémie Sportiche**, "Economic Crises and Mental Health: Effects of the Great Recession on Older Americans," *NBER Working Paper*, 2022.

Deryugina, Tatyana and David Molitor, "Does when you die depend on where you live? Evidence from Hurricane Katrina," *NBER Working Paper*, 2018.

Doyle, Joseph J, "Returns to local-area health care spending: evidence from health shocks to patients far from home," *American Economic Journal: Applied Economics*, 2011, *3* (3), 221–43.

_ **and Becky Staiger**, "Physician Group Influences on Treatment Intensity and Health: Evidence from Physician Switchers," *NBER Working Paper*, 2022.

Driessen, Julia, Seo Hyon Baik, and Yuting Zhang, "Trends in off-label use of second-generation antipsychotics in the Medicare population from 2006 to 2012," *Psychiatric services*, 2016, *67* (8), 898–903.

Duggan, Mark, "Do new prescription drugs pay for themselves?: The case of second-generation antipsychotics," *Journal of Health Economics*, 2005, *24* (1), 1–31.

Enthoven, Alain C, "Cutting cost without cutting the quality of care," *New England Journal of Medicine*, 1978, *298* (22), 1229–1238.

Figueroa, Jose F, Jessica Phelan, E John Orav, Vikram Patel, and Ashish K Jha, "Association of mental health disorders with health care spending in the Medicare population," *JAMA network open*, 2020, *3* (3), e201210–e201210.

Finkelstein, Amy, Matthe Gentzkow, Dean Li, and Heidi Williams, "What drives prescription opioid abuse? Evidence from migration," *Working Paper*, 2021.

_ , Matthew Gentzkow, and Heidi Williams, "Sources of geographic variation in health care: Evidence from patient migration," *The Quarterly Journal of Economics*, 2016, *131* (4), 1681–1726.

_ , _ , and _ , "Place-based drivers of mortality: Evidence from migration," *American Economic Review*, 2021, *111* (8), 2697–2735.

Fisher, Elliott S, Anoop Nanda, Sukdith Punjasthitkul, and Jonathan Skinner, "Aggregating Counties To Hospital Referral Regions Shows That COVID-19 Is Everywhere," *Health Affairs Forefront*, 2020.

Fournier, Jay C, Robert J DeRubeis, Steven D Hollon, Sona Dimidjian, Jay D Amsterdam, Richard C Shelton, and Jan Fawcett, "Antidepressant drug effects and depression severity: A patient-level meta-analysis," *JAMA*, 2010, *303* (1), 47–53.

Frost, Rachael, Angela Beattie, Cini Bhanu, Kate Walters, and Yoav Ben-Shlomo, "Management of depression and referral of older people to psychological therapies: A systematic review of qualitative studies," *British Journal of General Practice*, 2019, *69* (680), e171–e181.

Fuchs, Victor R, "More variation in use of care, more flat-of-the-curve medicine: Why does it occur? What should be done about it?," *Health Affairs*, 2004, *23* (Suppl2), VAR–104.

Godøy, Anna and Ingrid Huitfeldt, "Regional variation in health care utilization and mortality," *Journal of health economics*, 2020, *71*, 102254.

Golberstein, Ezra, Taeho Greg Rhee, and Thomas G McGuire, "Geographic variations in use of Medicaid mental health services," *Psychiatric Services*, 2015, *66* (5), 452–454.

Hedegaard, Holly and Margaret Warner, "Suicide mortality in the United States, 1999-2019," 2021. NCHS Data Brief, no 398. Hyattsville, MD: National Center for Health Statistics. DOI: `https://dx.doi.org/10.15620/cdc:101761.`

Insel, Thomas R, "Assessing the economic costs of serious mental illness," 2008.

Karlin, Bradley E, Michael Duffy, and David H Gleaves, "Patterns and predictors of mental health service use and mental illness among older and younger adults in the United States," *Psychological Services*, 2008, *5* (3), 275.

Klap, Ruth, Kathleen Tschantz Unroe, and Jürgen Unützer, "Caring for mental illness in the United States: A focus on older adults," *The American Journal of Geriatric Psychiatry*, 2003, *11* (5), 517–524.

Kposowa, Augustine J and James P McElvain, "Gender, place, and method of suicide," *Social psychiatry and psychiatric epidemiology*, 2006, *41*, 435–443.

Laird, Jessica and Torben Nielsen, "The effects of physician prescribing behaviors on prescription drug use and labor supply: Evidence from movers in Denmark," *Working Paper*, 2017.

Leucht, Stefan, Andrea Cipriani, Loukia Spineli, Dimitris Mavridis, Deniz Örey, Franziska Richter, Myrto Samara, Corrado Barbui, Rolf R Engel, John R Geddes et al., "Comparative efficacy and tolerability of 15 antipsychotic drugs in schizophrenia: a multiple-treatments meta-analysis," *The Lancet*, 2013, *382* (9896), 951–962.

Lindeboom, Maarten, France Portrait, and Gerard J Van den Berg, "An econometric analysis of the mental-health effects of major events in the life of older individuals," *Health Economics*, 2002, *11* (6), 505–520.

Liu, Jingwen, Blesson M Varghese, Alana Hansen, Jianjun Xiang, Ying Zhang, Keith Dear, Michelle Gourley, Timothy Driscoll, Geoffrey Morgan, Anthony Capon et al., "Is there an association between hot weather and poor mental health outcomes? A systematic review and meta-analysis," *Environment international*, 2021, *153*, 106533.

Marquardt, Kelli, "Identifying physician practice style for mental health conditions," *Working Paper*, 2021.

Mazure, Carolyn M, "Life stressors as risk factors in depression," *Clinical Psychology: Science and Practice*, 1998, *5* (3), 291.

McClellan, Chandler, Mir M Ali, and Ryan Mutter, "Impact of mental health treatment on suicide attempts," *The Journal of Behavioral Health Services & Research*, 2020, pp. 1–11.

Mojtabai, Ramin and Mark Olfson, "Proportion of antidepressants prescribed without a psychiatric diagnosis is growing," *Health Affairs*, 2011, *30* (8), 1434–1442.

Molitor, David, "The evolution of physician practice styles: Evidence from cardiologist migration," *American Economic Journal: Economic Policy*, 2018, *10* (1), 326–56.

Montz, Ellen, Tim Layton, Alisa B Busch, Randall P Ellis, Sherri Rose, and Thomas G McGuire, "Risk-adjustment simulation: plans may have incentives to distort mental health and substance use coverage," *Health Affairs*, 2016, *35* (6), 1022–1028.

Moscone, Francesco, Jonathan Skinner, Elisa Tosetti, and Laura Yasaitis, "The association between medical care utilization and health outcomes: A spatial analysis," *Regional Science and Urban Economics*, 2019, *77*, 306–314.

Nishimura, Yoshinori, Masato Oikawa, and Hiroyuki Motegi, "What explains the difference in the effect of retirement on health? Evidence from global aging data," *Journal of Economic Surveys*, 2018, *32* (3), 792–847.

Persson, Petra and Maya Rossin-Slater, "Family ruptures, stress, and the mental health of the next generation," *American Economic Review*, 2018, *108* (4-5), 1214–52.

_ , Xinyao Qiu, and Maya Rossin-Slater, "Family spillover effects of marginal diagnoses: The case of ADHD," *NBER Working Paper*, 2021.

Schell, Terry L, Samuel Peterson, Brian Garrett Vegetabile, Adam Scherling, Rosanna Smart, and Andrew R Morral, "State-level estimates of household firearm ownership," 2020. RAND Santa Monica, CA.

Shapiro, Bradley, "Promoting wellness or waste? evidence from antidepressant advertising," *American Economic Journaal: Microeconomics*, Forthcoming.

Siflinger, Bettina, "The effect of widowhood on mental health-an analysis of anticipation patterns surrounding the death of a spouse," *Health Economics*, 2017, *26* (12), 1505–1523.

Skinner, Jonathan, "Causes and consequences of regional variations in health care," in "Handbook of Health Economics," Vol. 2, Elsevier, 2011, pp. 45–93.

Sturm, Roland, Jeanne S Ringel, and Tatiana Andreyeva, "Geographic disparities in children's mental health care," *Pediatrics*, 2003, *112* (4), e308–e308.

Substance Abuse and Mental Health Services Administration (SAMHSA), "Key substance use and mental health indicators in the United States: Results from the 2019 National Survey on Drug Use and Health (HHS Publication No. PEP20-07-01-001, NSDUH Series H-55)," 2020. Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. Retrieved from `https://www.samhsa.gov/data/`.

Thomas, Kathleen C, Alan R Ellis, Thomas R Konrad, Charles E Holzer, and Joseph P Morrissey, "County-level estimates of mental health professional shortage in the United States," *Psychiatric Services*, 2009, *60* (10), 1323–1328.

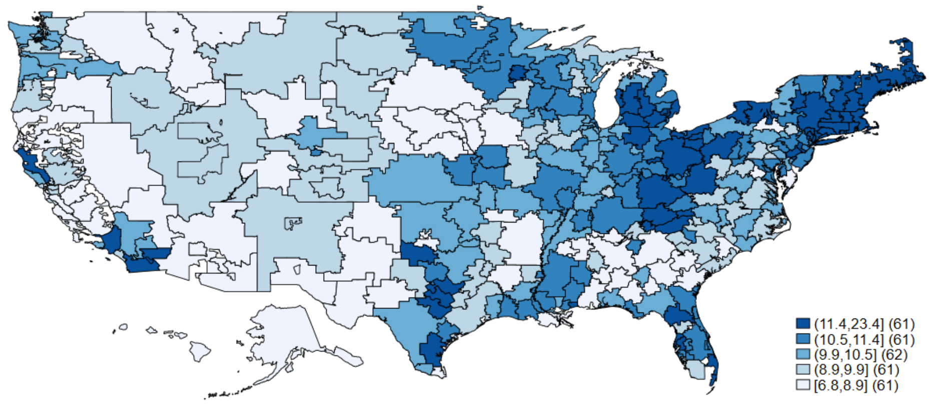
Ventriglio, Antonio, Antonello Bellomo, Ilaria di Gioia, Dario Di Sabatino, Donato Favale, Domenico De Berardis, and Paolo Cianconi, "Environmental pollution and mental health: a narrative review of literature," *CNS spectrums*, 2021, *26* (1), 51–61.

Zeltzer, Dan, Liran Einav, Avichai Chasid, and Ran D Balicer, "Supply-side variation in the use of emergency departments," *Journal of Health Economics*, 2021, *78*, 102453.

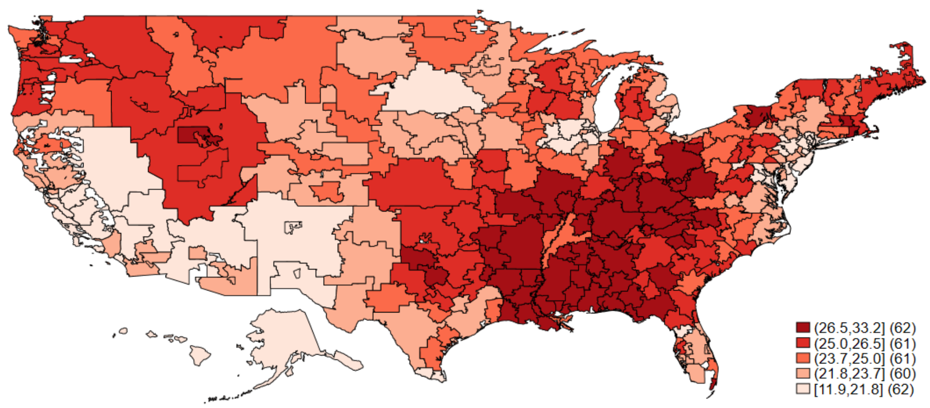
Figures

Figure 1: Mental Health Service and Drug Utilization Rate by HRR

(a) Mental health service use rate (%)



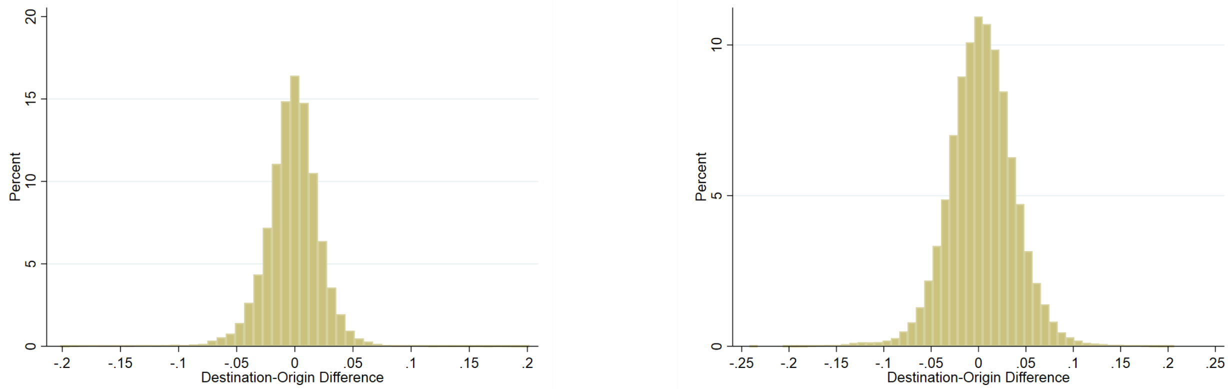
(b) Mental health drug use rate (%)



Notes: These figures illustrate the distribution of mental health treatment utilization rates by Hospital Referral Region (HRR). The sample comprises Medicare FFS beneficiaries aged 65-99, with full-year coverage for FFS Part A, B, and D in each year, drawn from the 20% Medicare FFS claims data, 2006-2018. Panel (a) displays the mental health service usage rate, defined as the proportion of patient-year observations with any medical claim tied to a primary diagnosis of mental illnesses. Panel (b) displays the mental health drug usage rate, defined as the proportion of patient-year observations with any prescription drug claim for antidepressants and antipsychotics.

Figure 2: Distribution of Destination-Origin Difference in Utilization Rate

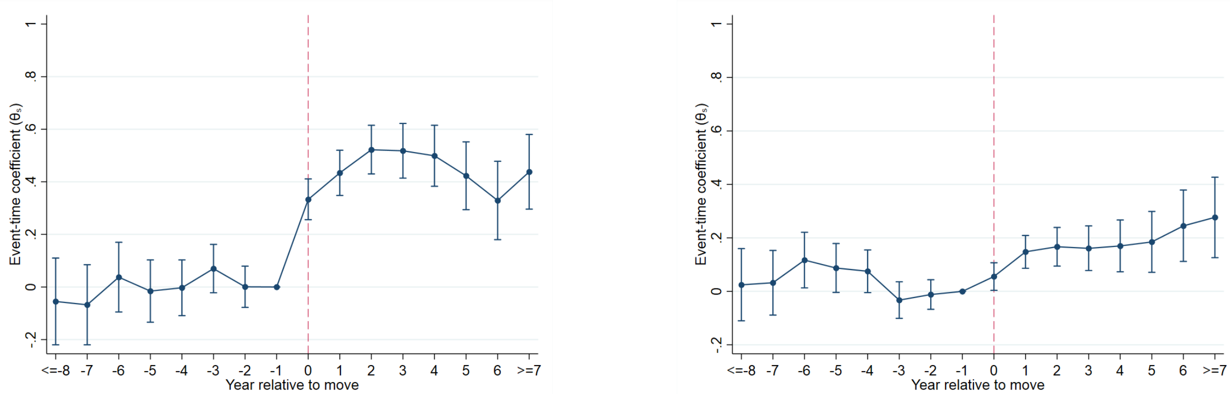
(a) Service (b) Drug



Notes: These figures show the distribution of the difference in mental health service (Panel (a)) and drug (Panel (b)) utilization rates between destination and origin HRRs (δ_i) among all movers. HRR utilization rates are calculated each year using the non-mover sample and are then merged with each mover based on the year prior to the move.

Figure 3: Effect of Local Mental Health Treatment Utilization Rate on Individual's Mental Health Treatment Use

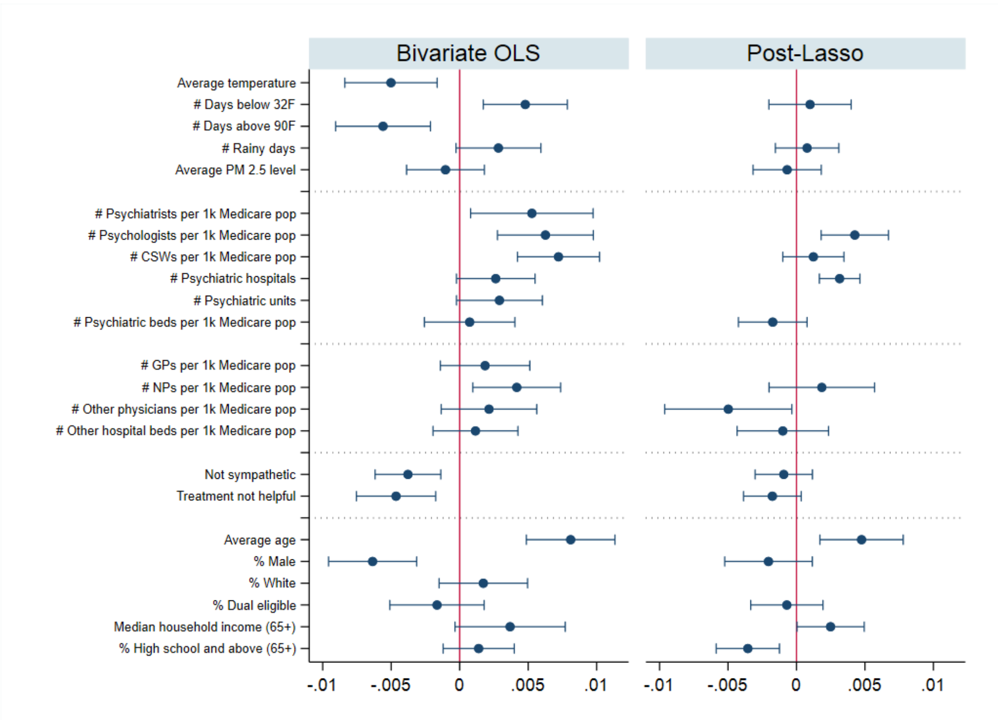
(a) Service (b) Drug



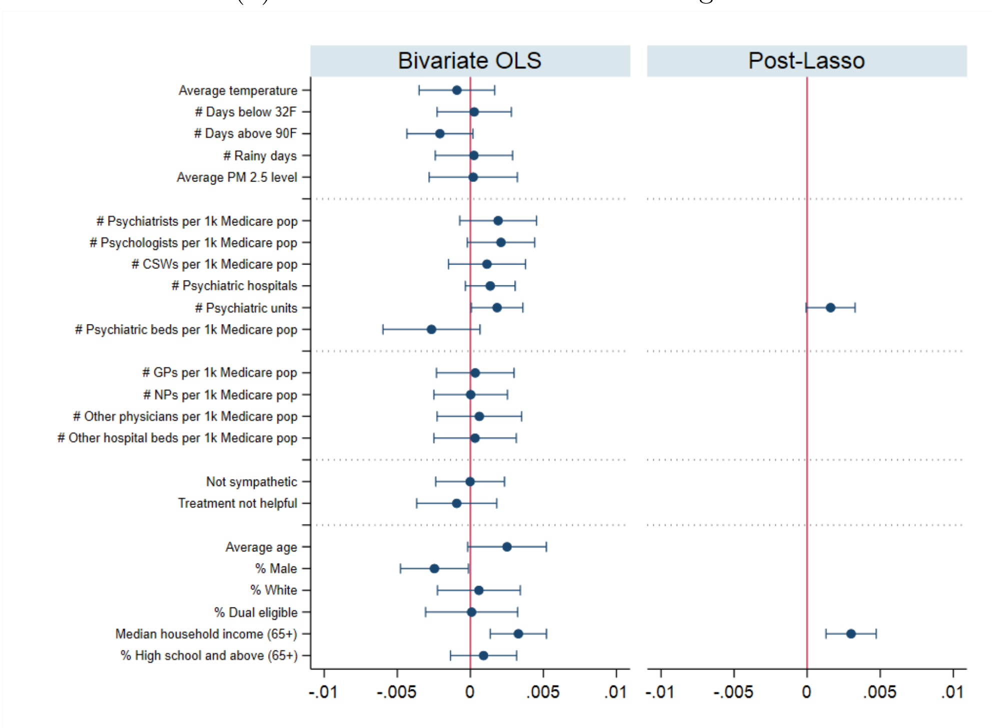
Notes: These figures show coefficients θ_s estimated from Equation (1). The sample includes 1,150,872 patient-year observations. The dependent variable is a binary indicator for whether patient i had any mental health service claim in year t (Panel (a)) or any mental health drug claim (Panel (b)). θ_s are a sequence of coefficients for the interaction terms between destination-origin differences in HRR mental health service/drug utilization rates (δ_i) and indicators for each year relative to moving, where relative year -1 is normalized to 0. Years beyond eight years before and seven years after the move are grouped together as $s \leq -8$ and $s \geq 7$ respectively. The regression includes individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. The dashed lines represent the upper and lower bounds of the 95% confidence interval, based on standard errors clustered at the individual level.

Figure 4: Correlation between Place Effect and HRR Characteristics

(a) Place effect - Mental Health Service Use



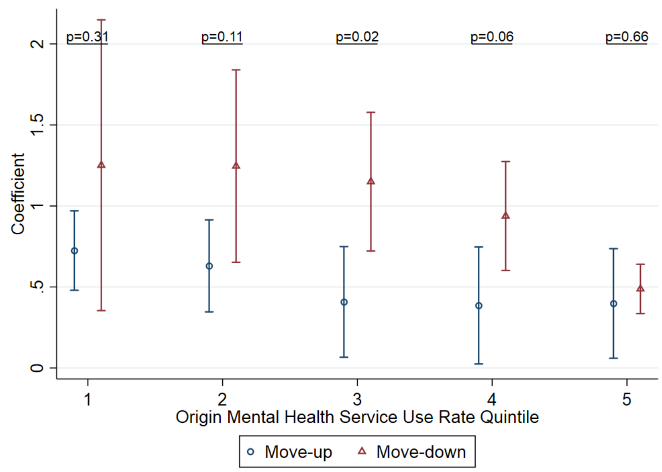
(b) Place effect - Mental Health Drug Use



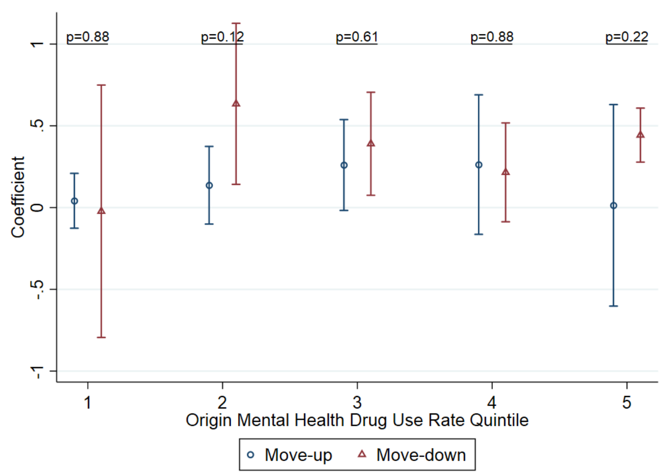
Notes: This figure shows the correlation between HRR characteristics and the place effect of mental health service use (Panel (a)) or drug use (Panel (b)). Each panel displays coefficients estimated from separate bivariate OLS regressions on the left, and coefficients from a post-Lasso multivariate OLS on the right, where the set of covariates are selected based on a Lasso regression with 10-fold cross-validation. The dependent variable is the HRR fixed effect (η_h) estimated from Equation (2) using a sample that consists of all movers (in all years except the year of moving) and non-movers. Place characteristics include climate and pollution, the number of mental health professional providers, the number of other providers, public attitudes towards mental illness and treatment, and average demographic and socioeconomic characteristics. The numbers of physicians are counted using Medicare Data on Provider Practice and Specialty (MD-PPAS) 2008-2018. The number of Medicare FFS recipients is counted using the baseline sample of this analysis, multiplied by 5 to get estimates for 100% of the Medicare population. Demographic measures (i.e., age, gender, race) are based on the sample used in estimating the HRR fixed effect. Data source and variable construction for other measurements are stated in Appendix A. All covariates are standardized to have a mean of zero and a standard deviation of one. The sample includes 225 HRRs for which I observe the full set of HRR characteristics. All regressions are weighted by the number of Medicare patients in each HRR.

Figure 5: Place Effect by Treatment Use Rate in Origin HRR, Move-Up vs. Move-Down

(a) Mental Health Service Use



(b) Mental Health Drug Use



Notes: This figure shows the coefficients θ^{up} and θ^{down} estimated from equation (3), separately for five subsets of movers, grouped by the quintile of the treatment utilization rate in their original HRRs. The dependent variable is a dummy indicator denoting whether patient i had any mental health service (Panel (a)) or drug (Panel (b)) claim in year t. θ^{up} is the coefficient for the interaction term between the post-moving indicator ($Post_i t$) and the destination-origin differences in the HRR mental health treatment utilization rate (δ_i) when $\delta_i > 0$, while θ^{down} is the coefficient when $\delta_i \leq 0$. The regression includes individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. The vertical lines represent the upper and lower bounds of the 95% confidence interval, based on standard errors clustered at the individual level.

Tables

Table 1: Summary Statistics for Mover and Nonmover Samples

	Mover			Nonmover
	All Years	Pre	Post	
Age	76.2	74.0	78.1	74.6
Male	0.348	0.348	0.348	0.401
White	0.886	0.886	0.886	0.833
Medicare-Medicaid dual eligible	0.182	0.171	0.191	0.223
Part A/B spending	12,244	9,141	15,451	12,794
Mental health service use	0.128	0.106	0.153	0.115
Mental health drug use	0.274	0.225	0.324	0.250
HRR mental health service use rate	0.106	0.107	0.105	0.108
HRR mental health drug use rate	0.238	0.235	0.239	0.240
# Patients	141,740	141,740	141,740	6,107,210
# Patient-years	1,150,872	535,639	615,233	31,976,080

Notes: This table presents summary statistics on demographic characteristics and mental health care utilization patterns, as well as regional utilization rates in residential HRRs, for the movers sample before and after moving, and for the non-movers sample. The baseline sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A, B, and D coverage for the full months in each year, derived from 20% of Medicare FFS claims data from 2006 to 2018. Non-movers are individuals who did not change their residential HRR throughout the sample periods, while movers are individuals who changed their residential HRR only once and for whom the share of claims in the destination HRR increased by at least 0.75 after moving. Demographic and care use variables are first aggregated at the individual level (by pre-/post-moving period), then averaged across individuals. The regional average is calculated at the HRR level using the baseline sample, which includes both movers and non-movers.

Table 2: Place Effect of Mental Health Treatment Utilization

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Service Use			Any Drug Use		
	All	Male	Female	All	Male	Female
$\delta_i * Post_{it}$	0.458	0.381	0.496	0.151	0.102	0.178
	(0.0346)	(0.0535)	(0.0446)	(0.0293)	(0.0458)	(0.0377)
Observations	1,008,027	336,129	671,897	1,008,027	336,129	671,897
Dep. Mean	0.118	0.0869	0.134	0.262	0.182	0.303

Notes: This table presents the place effect of mental health service/drug utilization, estimated using the movers sample, excluding the year of the move. The dependent variable is a binary variable indicating whether patient i had any mental health service claim (Columns (1)-(3)) or any mental health drug claim (Columns (4)-(6)) in year t. The main independent variable is the difference in the service/drug utilization rate between the destination and origin (δ_i), interacting with the indicator for the post-moving period. All regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors, clustered at the beneficiary level, are reported in parentheses.

Table 3: Correlation between the Place Effects of Mental Health Treatment Use and Mental Health Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Suicide Rate					
	All	Male	Female	All	Male	Female
Place Effect for Service Use	-107.4	-204.1	-34.13			
	(13.69)	(26.20)	(5.277)			
Place Effect for Drug Use				-26.53	-46.60	-11.41
				(13.23)	(25.19)	(5.387)
Observations	306	306	306	306	306	306
Dep. Mean	15.85	30.90	4.366	15.85	30.90	4.366
Effect of 1 s.d. place effect	-1.950	-3.706	-0.620	-0.492	-0.864	-0.212
	Panel B: Self-Harm Emergency Department Visit Rate					
	All	Male	Female	All	Male	Female
Place Effect for Service Use	-27.13	-13.60	-25.30			
	(26.48)	(31.19)	(32.27)			
Place Effect for Drug Use				-40.91	-11.19	-54.36
				(25.87)	(31.75)	(32.40)
Observations	306	306	306	306	306	306
Dep. Mean	24.44	22.13	25.75	24.44	22.13	25.75
Effect of 1 s.d. place effect	-0.493	-0.247	-0.459	-0.759	-0.208	-1.008
Demographic Controls	X	X	X	X	X	X
Gun Ownership Controls	X	X	X	X	X	X

Notes: This table presents regression results of HRR suicide rates and self-harm emergency department rates on the estimated place effect of mental health service/drug use. Observations are at the HRR level. The outcome in Panel (a) is the suicide rate for the population aged 65 and above, obtained from the CDC Underlying Cause of Death database (1999-2019). Death counts are at the county level, which are aggregated to the HRR level based on zip code crosswalks and population share. The outcome in Panel (b) is the self-harm emergency department visit rate, calculated using the baseline sample of Medicare FFS beneficiaries aged 65-99 with full coverage of Part A, B, and D for each year during 2010-2018. Columns (1) and (4) use age and gender-adjusted rates for the total population, while Columns (2)-(3) and (5)-(6) use gender-specific rates adjusted by age. Place effects are estimated based on Equation (2) using a sample consisting of all movers (in all years except the year of moving) and non-movers. Demographic controls (i.e., share of white population, share of Medicaid-Medicare dual eligible patients, median household income, share of high school graduates) and gun ownership controls (i.e., state-level universal background check law, permit to purchase law, proportion of adults living in a household with a firearm) are included in all specifications. Regressions are weighted by the number of FFS Medicare population in each HRR. Robust standard errors are reported in parentheses.

Table 4: Effect of Mental Health Treatment Utilization on Self-Harm Emergency Department Visit

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Self-Harm Emergency Department Visit					
	All	Male	Female	All	Male	Female
$\delta_i^{Service} * Post_{it}$	-0.00446	-0.00566	-0.00387			
	(0.00240)	(0.00333)	(0.00324)			
$\delta_i^{Drug} * Post_{it}$				-0.000894	0.00145	-0.00221
				(0.00162)	(0.00248)	(0.00210)
Observations	607,717	213,651	394,064	607,717	213,651	394,064
Dep. Mean	0.000329	0.000300	0.000345	0.000329	0.000300	0.000345

Notes: This table presents the effect of changes in local mental health treatment utilization rate on an individual's emergency department visits due to self-harm. The sample includes patient-year observations from 2010-2018 for all movers who changed their residential HRR after 2010, excluding the year of moving. The dependent variable is a binary variable indicating whether patient i had any self-harm emergency department visit in year t. The primary independent variable is the destination-origin difference in the mental health care service ($\delta_i^{Service}$) or drug (δ_i^{Drug}) utilization rate, interacting with the indicator for the post-moving period. All the regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors clustered at the beneficiary level are reported in parentheses.

Appendix

A Additional Data Sources

American Community Survey (ACS) The ACS dataset is used for two purposes: measuring population demographic characteristics and examining potential moving reasons across migration flows. Key metrics from the ACS include median household income and the share of population with a high school degree, both among people above age 65. These measurements are taken from ACS's 5-year estimates for 2010 and 2015, and are aggregated from county to HRR level using the Dartmouth Atlas county-to-HRR crosswalk Fisher et al. (2020). Migrations are identified using individual data from 2006-2018. Only people above age 65 are considered, and only address changes across states are identified as a move. Information on age group, gender, marital status, labor force participation status, and life event in the past year (i.e. divorce, loss of spouse, retirement) are included in models predicting moving direction.

Behavioral Risk Factor Surveillance System (BRFSS) survey data The BRFSS survey is used to measure public attitude toward mental illness across different geographic areas. This telephone-based survey collects health-related data from U.S. residents, including their risk behaviors, chronic health conditions, and use of preventive services. Two questions specifically related to mental health attitudes were posed in 2007, 2009, 2012 and 2013, in 40 states combined. The first question asked whether you agree or disagree with the statement that *"People are generally caring and sympathetic to people with mental illness"*. The second question asked whether you agree or disagree with the statement that *"Treatment can help people with mental illness lead normal lives"*. The answer was in 5-point scale, with "1" representing strongly agree and "5" being strongly disagree. From the responses to these questions, two variables are constructed to gauge average level of perceived sympathy and belief in treatment efficacy by HRR (identified based on zip code).

CDC Underlying Cause of Death database This database provides suicide rates across different geographic areas, gender, and age groups. Derived from death certificates for U.S. residents in 1999-2019, the dataset reports number of deaths, crude death rates and age-adjusted death rates for selected causes-of-death and for different sub-populations. Suicide rates are computed starting with county-level suicides and population counts, then aggregating to the HRR level based on the Dartmouth Atlas county-to-HRR crosswalk. Due to privacy regulations, data representing 0-9 deaths are suppressed. To circumvent an excess of missing values, all available years are included when deriving the suicide rate.

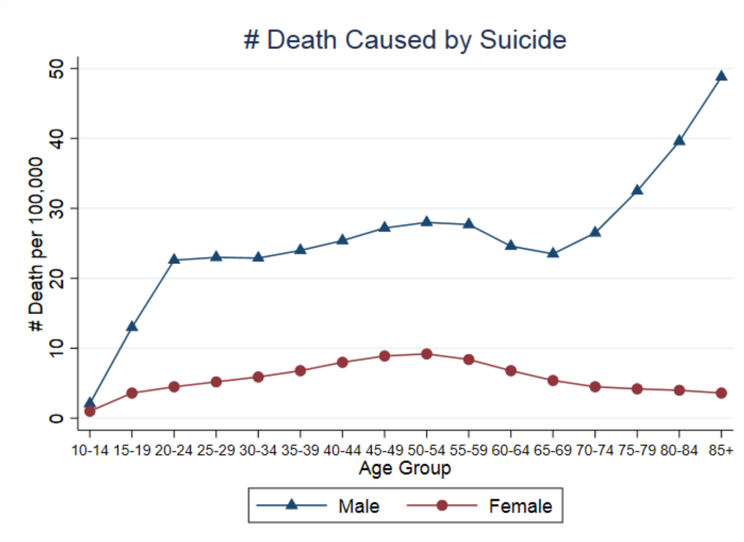
Provider of Services (POS) Files - Hospital & Non-Hospital Facilities data The POS file provides information on the characteristics of hospitals and other health care facilities. Taking the average across datasets from 2006-2018, I compute the number of psychiatric hospitals, the number of psychiatric units in general hospitals, the number of psychiatric beds (per 1,000 Medicare recipients), and the number of all hospital beds (per 1,000 Medicare recipients) for each HRR based on facility's zip code.

U.S. Air Quality Data This dataset, provided by the Environmental Protection Agency (EPA), contains air quality data from outdoor monitors across the U.S. Using annual summary data from 2006-2018, I calculate the average daily PM2.5 level for each HRR based on the county code of each monitor and the Dartmouth Atlas county-to-HRR crosswalk.

U.S. Monthly Climate Normals This dataset, provided by the National Centers for Environmental Information (NCEI), contains information on typical climate conditions collected from 2006-2020. Four metrics are constructed to capture local climate characteristics: average annual temperature, the number of days with minimum temperature below 32 °F annually, the number of days with maximum temperature above 90 °F annually, and average monthly precipitation. All these measurements are aggregated at the HRR level based on the zip code of each weather station.

Appendix Figures

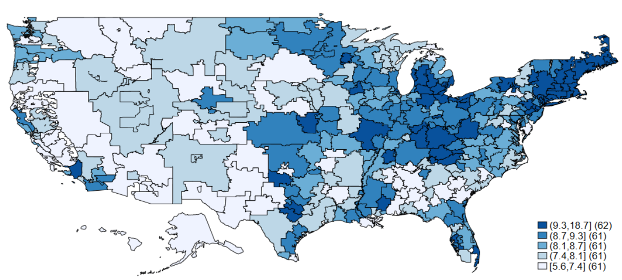
Figure A1: Suicide Rates by Gender and Age



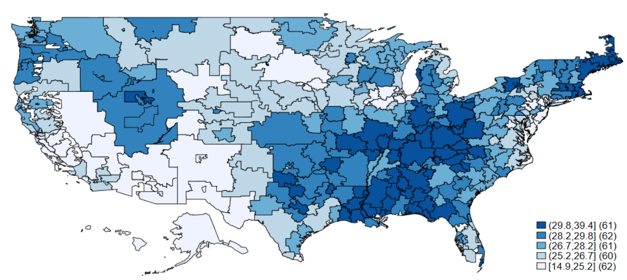
Notes: This figure depicts the suicide rate by gender and five-year age group, using data from the CDC Underlying Cause of Death database, 1999-2019.

Figure A2: Mental Health Treatment Utilization Rate and Average Spending by HRR

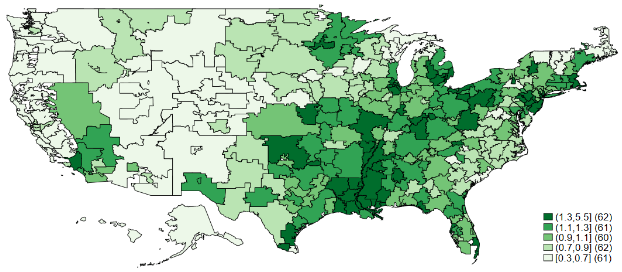
(a) Service (%, including people not covered by Part D)



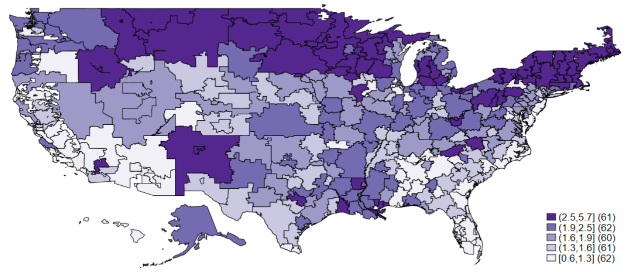
(b) Service or Drug (%)



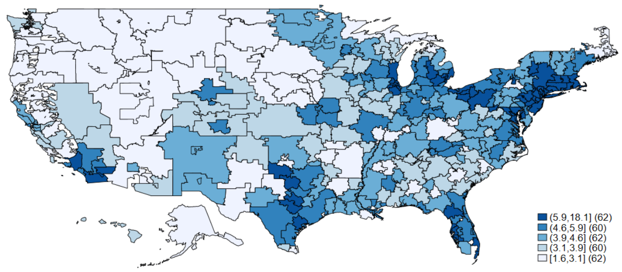
(c) Service - Inpatient (%)



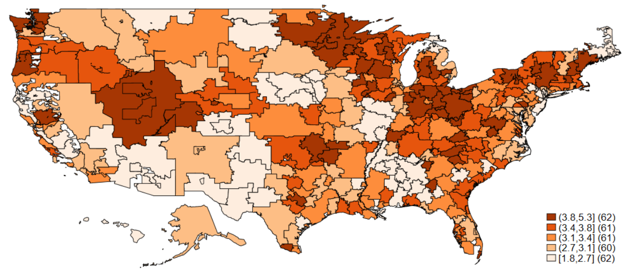
(d) Service - Outpatient (%)



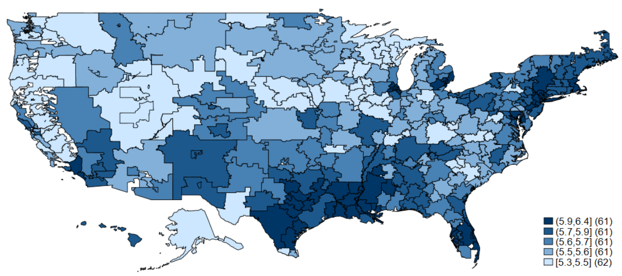
(e) Service - Mental Health Professionals (%)



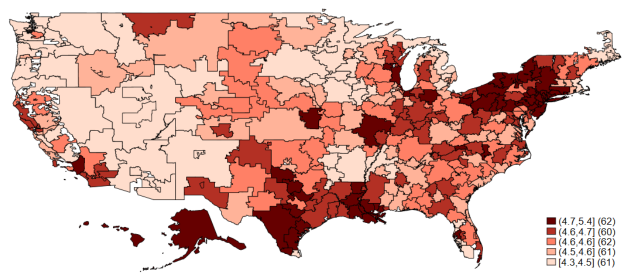
(f) Service - Primary Care Providers (%)



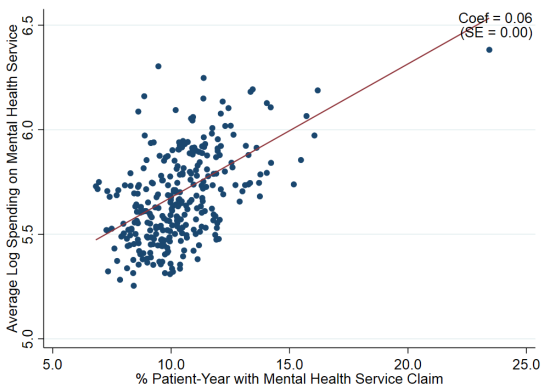
(g) Mental health service spending conditional on service use



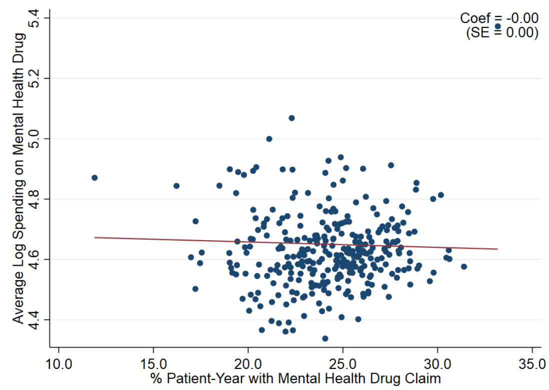
(h) Mental health drug spending conditional on drug use



(i) Correlation between mental health service use rate and average spending conditional on use

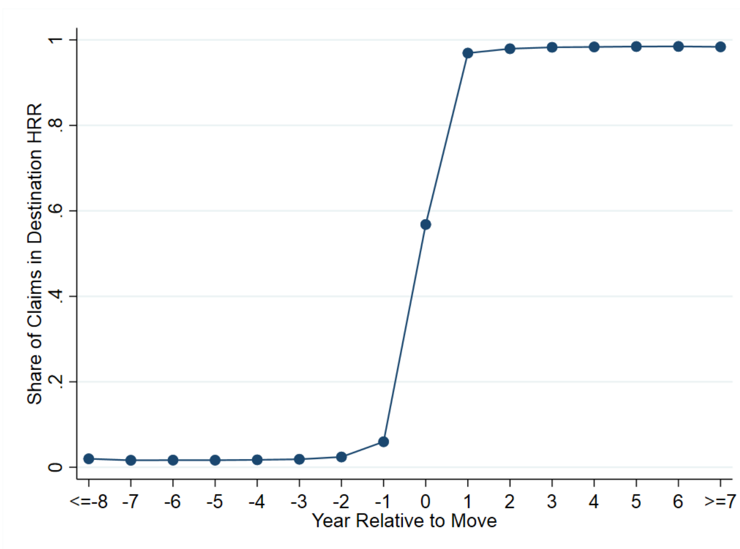


(j) Correlation between mental health drug use rate and average spending conditional on use



Notes: the distribution of mental health treatment utilization rates by HRR. The sample includes Medicare Fee-for-Service (FFS) beneficiaries aged 65-99, with full coverage under Parts A, B, and D (except in Panel (a) where Part D coverage is not required) in each year, drawn from 20% Medicare FFS claims data, 2006-2018. Panel (a) plots the mental health service use rate, defined as the share of patient-year observations with any medical claim having a primary diagnosis related to mental illnesses. Panel (b) plots the share of patient-year observations with either mental health service or drug claim. Panel (c)-(f) plots HRR mental health service utilization rates from specific providers, i.e., hospital inpatient department, hospital outpatient department, mental health professionals (including psychiatrists, psychologists and clinical social workers), and primary care physicians. Panel (g) plots average mental health service spending conditional on service use, and Panel (h) plots average mental health drug spending conditional on drug use. Panel (i) and (j) show scatter plots for HRR mental health service/drug utilization rate and average mental health service/drug spending conditional on usage. The fitted lines, coefficients, and standard errors are derived from regressions weighted by the number of patient-year observations in each HRR.

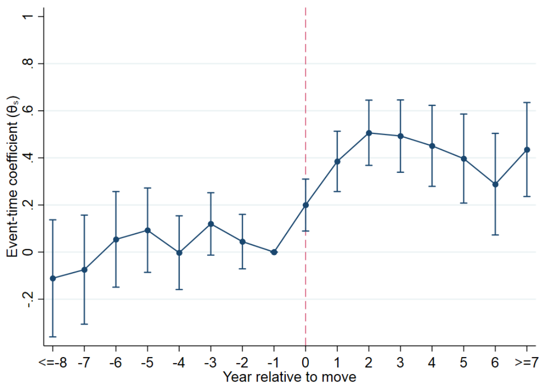
Figure A3: Share of Claims in Destination HRR by Years Relative to Moving



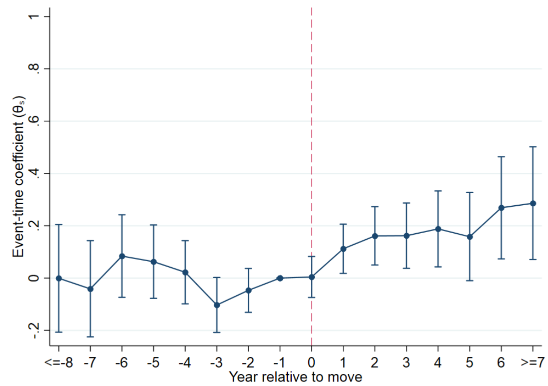
Notes: This figure shows the average share of medical claims from movers' destination HRRs out of all medical claims from either their origin or destination HRRs, by number of years relative to moving.

Figure A4: Place Effect by the Share of Claims from Destination HRRs in Year 0

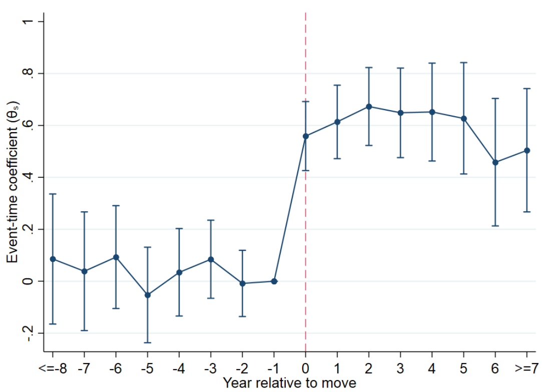
(a) Service - Below Median



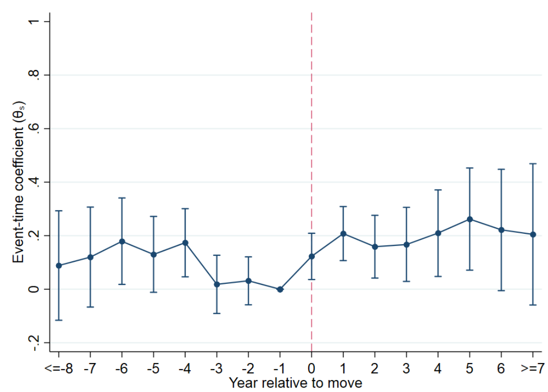
(b) Drug - Below Median



(c) Service - Above Median

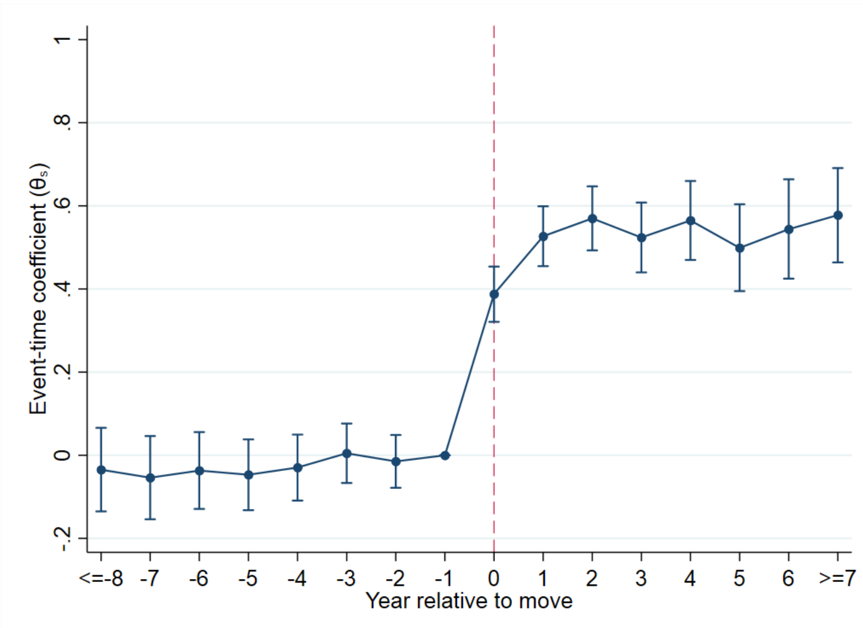


(d) Drug - Above Median



Notes: These figures replicate the event study estimation from Figure 3 using subsets of movers based on the share of claims received from the destination HRR in year 0. Panel (a) and (b) include individuals with a below-median destination claim share in year 0 (499,640 mover-year observations, 60,815 movers). Panel (c) and (d) include individuals with an above-median destination claim share in year 0 (491,616 mover-year observations, 60,210 movers).

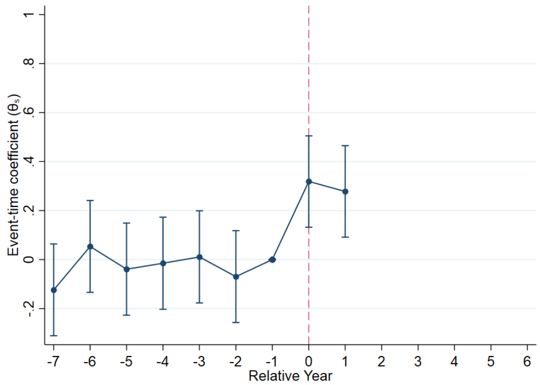
Figure A5: Effect of Local Mental Health Treatment Service Rate on Individual's Mental Health Service Use (not conditional on Part D coverage)



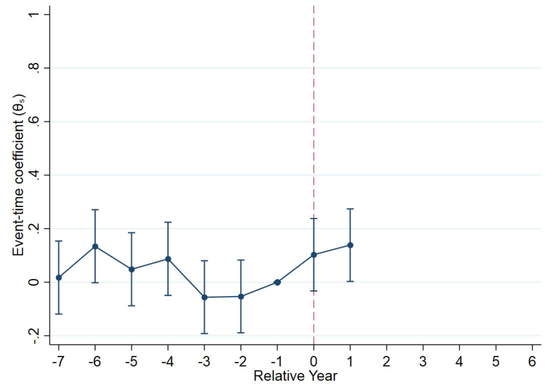
Notes: This figure replicates the event study estimation in Figure 3. The sample does not require Part D coverage and includes 2,840,919 patient-year observations. The dependent variable is a binary indicator for whether patient i had any mental health service claim in year t. The HRR mental health service utilization rate (δ_i) is also calculated among all non-movers, regardless of Part D coverage.

Figure A6: Place Effect: Balanced Panel

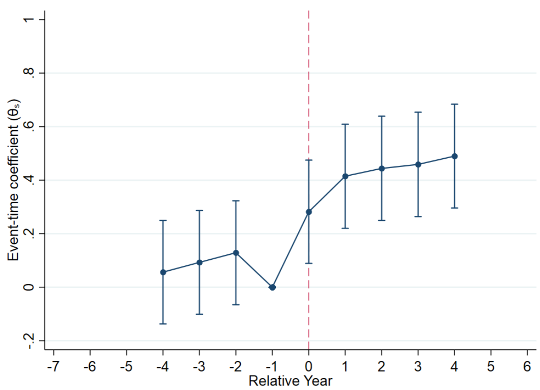
(a) Service - Relative year [-7,1]



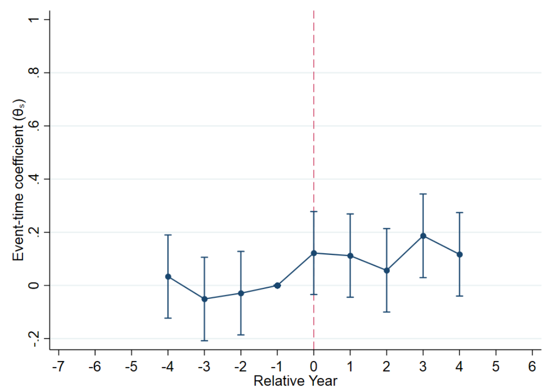
(b) Drug - Relative year [-7,1]



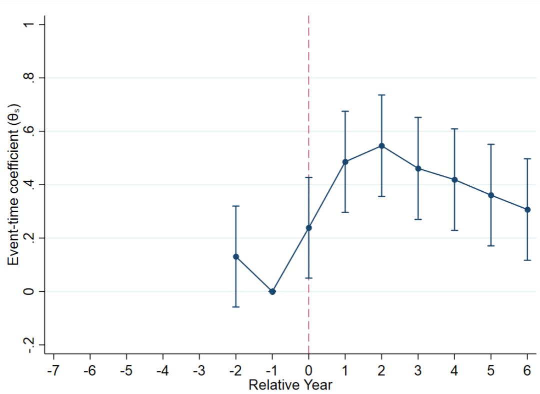
(c) Service - Relative year [-4,4]



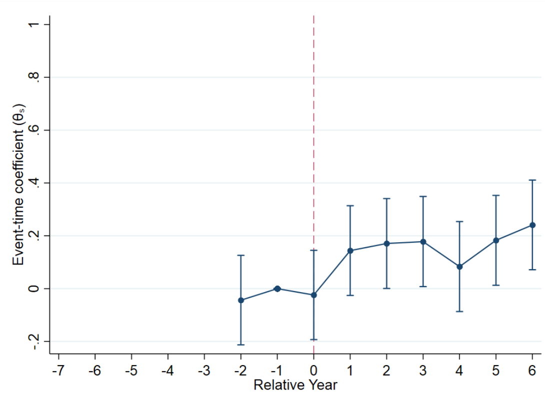
(d) Drug - Relative year [-4,4]



(e) Service - Relative year [-2,6]



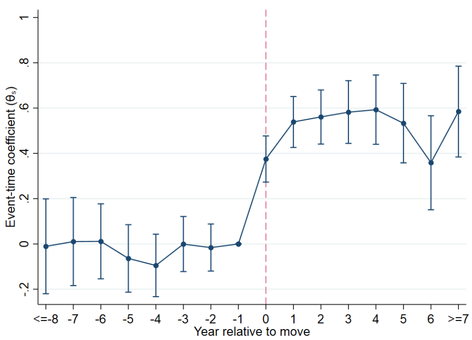
(f) Drug - Relative year [-2,6]



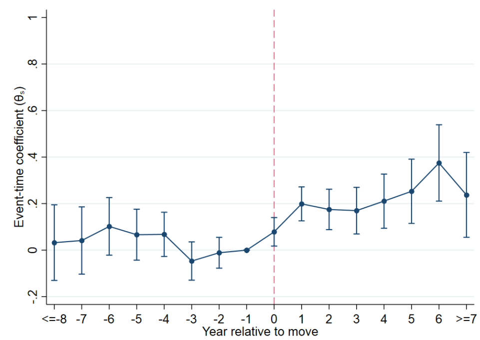
Notes: These figures replicate the event study estimation in Figure 3 using different sets of balanced samples. Panels (a) and (b) use a balanced panel in relative years [-7,1], which includes 224,491 mover-year observations (25,289 movers). Panels (c) and (d) use a balanced panel in relative years [-4,4], which includes 181,302 mover-year observations (20,351 movers). Panels (e) and (f) use a balanced panel in relative years [-2,6], which includes 160,998 mover-year observations (18,166 movers).

Figure A7: Place Effect by Moving Directions

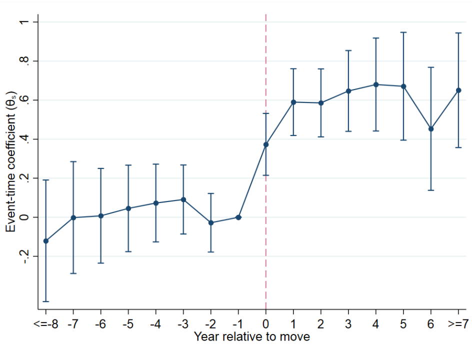
(a) Service - Above & below median HRRs



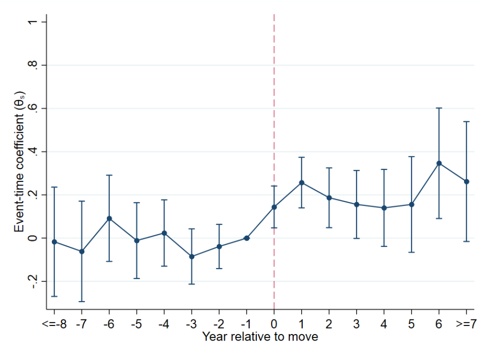
(b) Drug - Above & below median HRRs



(c) Service - Top & bottom quartiles HRRs



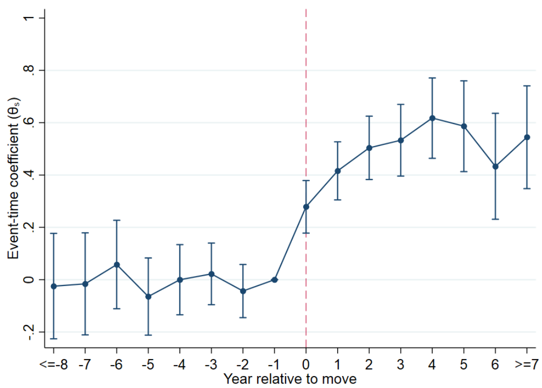
(d) Drug - Top & bottom quartiles HRRs



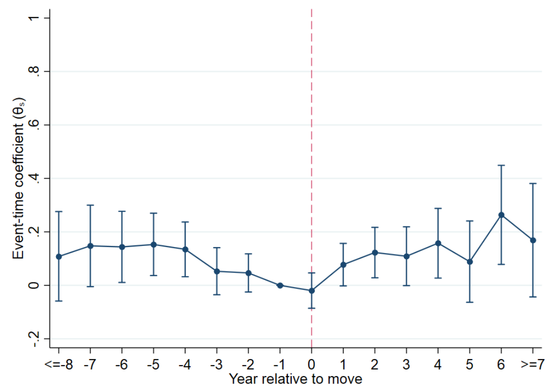
Notes: These figures replicate the event study estimation in Figure 3 using subsets of movers. Panel (a) includes individuals who moved between HRRs with mental health service utilization rates above and below the median (487,737 mover-year observations, 60,161 movers). Panel (b) includes individuals who moved between HRRs with mental health drug utilization rates above and below the median (441,806 mover-year observations, 54,873 movers). Panel (c) includes individuals who moved between HRRs that are in the top and bottom quartiles of mental health service utilization rates (181,302 mover-year observations, 20,351 movers). Panel (d) includes individuals who moved between HRRs that are in the top and bottom quartiles of mental health drug utilization rates (76,083 mover-year observations, 9,466 movers).

Figure A8: Place Effect: Different Geographic Units

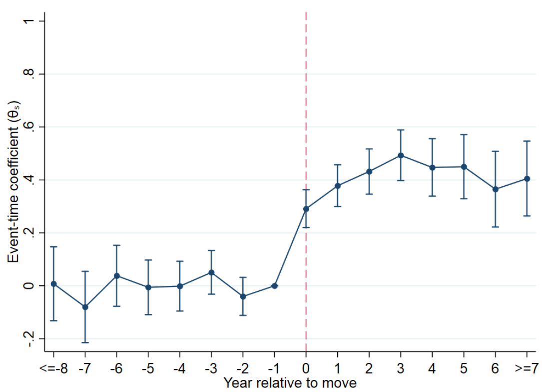
(a) Service - State



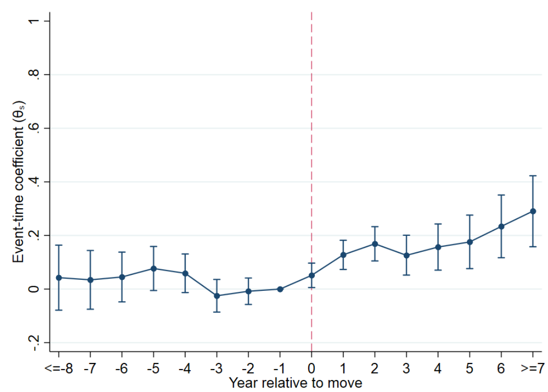
(b) Drug - State



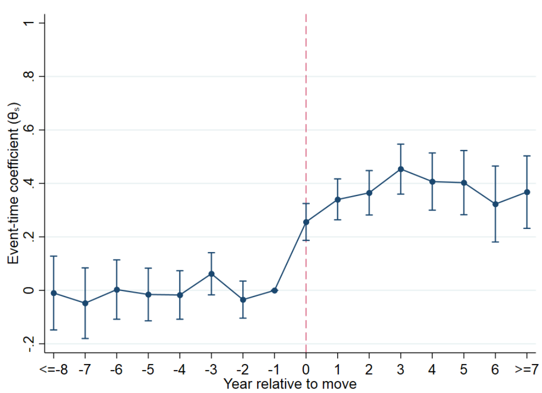
(c) Service - County



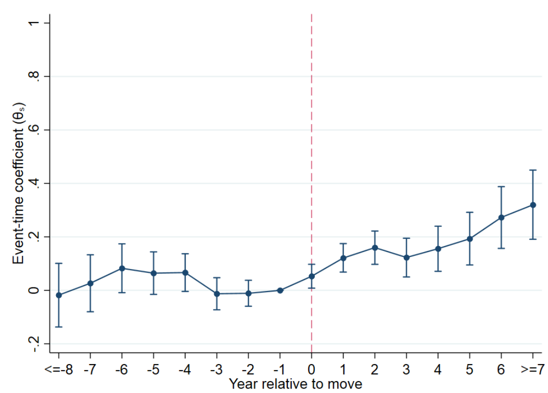
(d) Drug - County



(e) Service - HSA



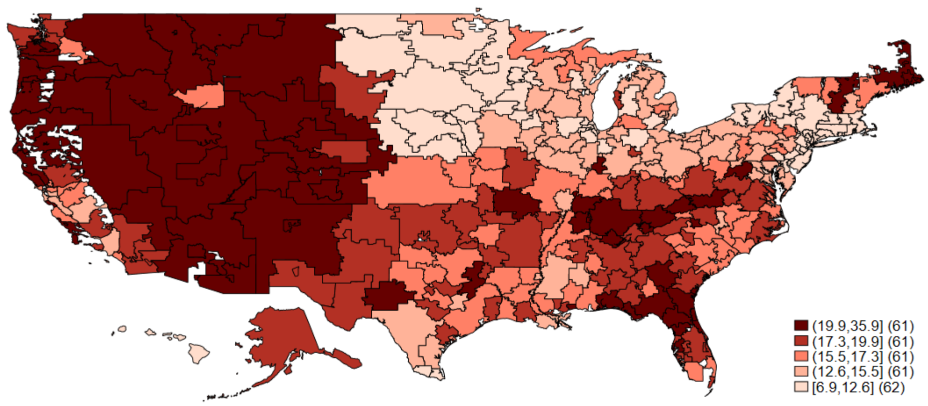
(f) Drug - HSA



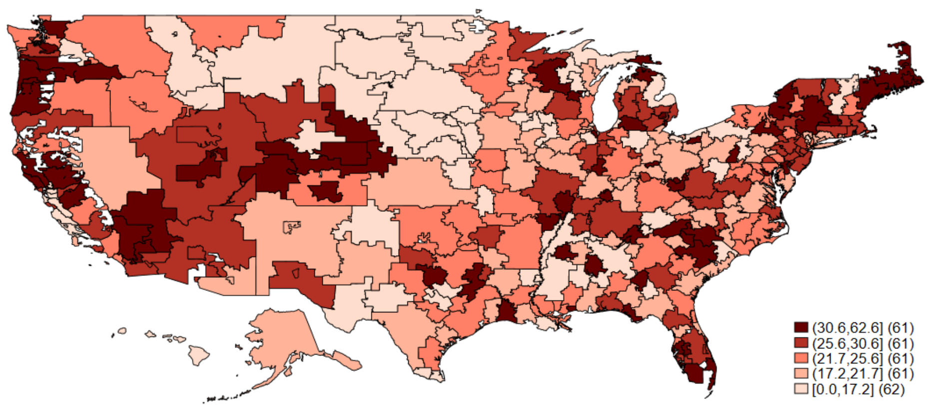
Notes: These figures replicate the event study estimation in Figure 3 using different geographic units. All estimates use movers across states (848,094 mover-year observations, 105,491 movers). Panel (a) measures the treatment utilization rate at the state level. Panel (b) measures the treatment utilization rate at the county level. Panel (c) measures the treatment utilization rate at the Hospital Service Area (HSA) level.

Figure A9: Suicide And Self-Harm Emergency Department Visit Rate by HRR

(a) Suicide rate (per 100,000)



(b) Self-harm emergency department visit rate (per 100,000)



Notes: These figures present the distribution of suicide rate (Panel (a)) and self-harm emergency department visit rate (Panel (b)) by Hospital Referral Region (HRR). The suicide rate for the population above age 65 comes from the CDC Underlying Cause of Death database, 1999-2019. Death counts are at the county level, which are aggregated to the HRR level based on a zip code crosswalk and population share. The self-harm emergency department visit rate is calculated using the baseline sample of Medicare Fee-For-Service (FFS) beneficiaries aged 65-99 with full coverage of Part A, B, and D in each year during 2010-2018. Both rates are adjusted for age and gender.

Appendix Tables

Table A1: Mental Illness Category and ICD codes

	ICD-9	ICD-10
Anxiety disorders	293.84, 300.0/10/2/3/5/89/9, 308, 309.81	F06.4, F40-F42, F43.0/1, F48.8/9
Mood disorders	293.83, 296, 300.4, 311	F06.3, F30-F39
Schizophrenia	293.81/82, 295, 297, 298	F06.0/2, F20-F29
Other mental illnesses	293.89/9, 299, 300.11-19/6/7/81/82, 301, 302, 306, 307, 309.0/1/2/3/4/82/83/89/9, 312-319	F06.1/8, F43.2/8/9, F44, F45, F48.1, F50-F99
All mental illnesses	290-319 except cognitive disorders (290, 293.0/1, 294, 310) and substance-related disorders (291-292, 303-305)	F01-F99 except cognitive disorders (F01-F05, F07, F09, F48.2) and substance-related disorders (F10-F19)

Notes: This table presents the ICD codes used for identifying (different types of) mental health claims data. ICD codes included are from "Mental Disorders" section in ICD-9 and correspondingly "Mental, Behavioral and Neurodevelopmental disorders" section in ICD-10. Classification is based on the Clinical Classifications Software (CCS) by the Agency for Healthcare Research and Quality (AHRQ). Other disorders in row 5 include adjustment disorders, attention-deficit conduct and disruptive behavior disorders, developmental disorders, impulse control disorders, personality disorders, disorders during childhood, and other miscellaneous disorders. Cognitive disorders, alcohol- and substance-related disorders are not included since related claims are not included in the main analysis. ICD codes can be expanded to two digits after decimal points, but folded in the table if they are all included in one category.

Table A2: Correlation between Moving Direction and Life Events

	(1)	(2)	(3)	(4)	(5)	(6)
	Destination-Origin Difference in Utilization Rate					
	Service			Drug		
Divorce	-0.000191			0.00196		
	(0.000972)			(0.00119)		
Widow		-0.000438			-0.000680	
		(0.00108)			(0.000975)	
Retire			-5.90e-05			0.00116
			(0.000384)			(0.000548)
Observations	57,077	57,092	69,420	57,077	57,092	69,420
Mean of Dep. Var	-0.00125	-0.00126	-0.00154	0.00348	0.00347	0.00349
S.D. of Dep. Var	0.0216	0.0216	0.0216	0.0301	0.0301	0.0303
Age group X Gender FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Origin State FEs	X	X	X	X	X	X

Notes: This table presents the correlation between the direction of moving and the life events experienced in the last year. Observations are individuals above age 65 who moved across states in the ACS data from 2006 to 2018. Divorce and death of a spouse are identified based on survey questions, "did you get divorced in the past 12 months?" and "did you become a widow/widower in the past 12 months?" Retirement is identified if the interviewee reported working in the past 12 months but is not currently employed. The outcome variable is the difference in the mental health service/drug utilization rate between the destination and origin states, calculated using non-movers in all years. Fixed effects for gender by 5-year age group, interview year, and origin state are controlled. Robust standard errors are clustered by destination and origin states. All regressions are weighted by the ACS person weight.

Table A3: Place Effect of Mental Health Treatment Utilization, by Mental Illness

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Service Use				Drug	
	Anxiety	Mood Disorder	Schizophrenia	Other	Antidepressants	Antipsychotics
$\delta_i * Post_{it}$	0.468	0.508	0.279	0.637	0.148	0.224
	(0.0717)	(0.0393)	(0.0474)	(0.0671)	(0.0298)	(0.0444)
Observations	1,008,027	1,008,027	1,008,027	1,008,027	1,008,027	1,008,027
Dep. Mean	0.0358	0.0662	0.0173	0.0265	0.246	0.0435

Notes: This table presents the place effect of mental health service/drug utilization estimated using the movers sample, excluding the year of the move, for specific types of mental health conditions. The dependent variable in each column is a binary variable indicating whether patient i, in year t, had any mental health service claim with a diagnosis of anxiety, mood disorder, schizophrenia, other mental illnesses, any claims for antidepressants, or antipsychotics, respectively. The main independent variable is the difference between the destination and origin in the corresponding service/drug utilization rate (δ_i), interacting with the indicator for the post-moving period. All the regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors, clustered at the beneficiary level, are reported in parentheses.

Table A4: Place Effect of Mental Health Service Utilization by Provider and Mental Health Treatment Spending

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Service Use				Log Payment (conditional on use)	
	Hospital Inpatient	Hospital outpatient	Mental health professionals	Primary care physicians	Service	Drug
$\delta_i * Post_{it}$	0.685	1.061	0.595	0.818	0.592	0.293
	(0.0614)	(0.0454)	(0.0306)	(0.0593)	(0.0548)	(0.0453)
Observations	1,008,027	1,008,027	1,008,027	1,008,027	92,767	246,484
Dep. Mean	0.0117	0.0212	0.0582	0.0391	5.934	4.770

Notes: This table presents the place effect of mental health service utilization by different providers and treatment spending estimated using the movers sample, excluding the year of the move. The dependent variables in Columns (1)-(4) are binary variables indicating whether patient i, in year t, had any mental health service claim provided by the hospital inpatient department, hospital outpatient department, mental health professionals (i.e., psychiatrist, psychologist, and clinical social worker), and primary care physicians, respectively. The dependent variables in Columns (5)-(6) are payments for mental health service or drugs, given utilization, in log terms. The main independent variable is the difference between the destination and origin in the corresponding service utilization rate or log payment (δ_i), interacting with the indicator for the post-moving period. All the regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors, clustered at the beneficiary level, are reported in parentheses.

Table A5: Place Effect of Mental Health Treatment Utilization, Other measurements

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Service Use (based on all diagnoses)			Any Drug Use (including anxiolytics)		
	All	Male	Female	All	Male	Female
$\delta_i * Post_{it}$	0.258	0.152	0.318	0.116	0.0249	0.168
	(0.0298)	(0.0478)	(0.0379)	(0.0287)	(0.0451)	(0.0368)
Observations	1,008,027	336,129	671,897	1,008,027	336,129	671,897
Dep. Mean	0.273	0.200	0.310	0.293	0.207	0.336

Notes: This table presents the place effect of mental health service/drug utilization with other definitions, estimated using the movers sample excluding the year of the move. The dependent variable in Columns (1)-(3) is a binary variable indicating whether patient i, in year t, had any medical claim with a mental illness diagnosis in any diagnosis order. The dependent variable in Columns (4)-(6) is a binary variable indicating whether patient i, in year t, had any prescription drug claim for antidepressants, antipsychotics, and anxiolytics. The main independent variable is the difference between the destination and origin in the corresponding service/drug utilization rate (δ_i), interacting with the indicator for the post-moving period. All the regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors, clustered at the beneficiary level, are reported in parentheses.

Table A6: Place Effect of Mental Health Treatment Utilization, Excluding Patients in Nursing Facilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Service Use			Any Drug Use		
	All	Male	Female	All	Male	Female
$\delta_i * Post_{it}$	0.283	0.226	0.313	0.121	0.0711	0.150
	(0.0330)	(0.0497)	(0.0433)	(0.0291)	(0.0444)	(0.0380)
Observations	895,721	308,847	586,872	895,721	308,847	586,872
Dep. Mean	0.0899	0.0643	0.103	0.229	0.156	0.268

Notes: This table presents the place effect of mental health service/drug utilization, estimated using the movers sample excluding the year of move and years with nursing facility claims. The dependent variable is a binary variable indicating whether patient i had any mental health service claim (Columns (1)-(3)) or any mental health drug claim (Columns (4)-(6)) in year t. The main independent variable is the difference in the service/drug utilization rate between the destination and origin (δ_i), interacting with the indicator for the post-moving period. All the regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors, clustered at the beneficiary level, are reported in parentheses.

Table A7: Geographic Variation in Provider Capacity and Perception towards Mental Illness, Distribution at HRR Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	S.D.	Min	P25	Median	P75	Max
Average annual temperature (N = 303)	56.2	8.9	34.2	49.6	55.1	63.1	77.5
# Days w/ min. temp. below 32°F annually (N = 303)	94.2	56.1	0.1	45.6	97.9	140.9	199.9
# Days w/ max. temp. above 90°F annually (N = 303)	43.9	38.5	0.1	12.5	29.9	72.9	180.7
Average monthly precipitation (N = 298)	68.5	21.3	8.8	52.2	74.7	81.8	123.4
Average daily PM2.5 level (N = 294)	6.2	2.9	0.0	4.2	6.1	8.0	16.7
# Psychiatrists per 1k MCR pop	0.85	0.50	0.18	0.50	0.70	1.03	2.97
# Psychologists per 1k MCR pop	0.76	0.50	0.04	0.38	0.66	0.96	3.17
# Clinical social workers per 1k MCR pop	0.94	0.72	0.02	0.41	0.79	1.21	5.25
# Psychiatric hospitals	1.72	1.97	0.00	0.15	1.00	2.23	10.92
# Psychiatric units	4.53	4.63	0.00	1.46	3.00	5.69	26.00
# Psychiatric beds per 1k MCR pop	3.65	2.98	0.00	1.86	2.94	4.69	25.95
# Primary care physicians per 1k MCR pop	6.6	2.5	2.7	5.0	6.0	7.4	21.2
# Nurse practitioners per 1k MCR pop	4.9	2.3	1.0	3.3	4.4	6.0	16.2
# Other specialists per 1k MCR pop	18.6	7.5	7.1	13.3	17.2	21.6	67.6
# Other hospital beds per 1k MCR pop	14.5	9.4	0.0	8.5	13.7	18.9	71.1
People are sympathetic to mental illness patients (1-Agree strongly to 5-Disagree strongly, N = 240)	2.9	0.2	2.3	2.8	2.9	3.0	4.3
Treatment can lead to normal life (1-Agree strongly to 5-Disagree strongly, N = 240)	1.7	0.2	1.2	1.5	1.6	1.8	2.9
Average age	75.7	0.6	74.0	75.3	75.7	76.2	77.2
Male	0.43	0.02	0.38	0.42	0.43	0.44	0.48
White	0.89	0.10	0.31	0.84	0.92	0.96	0.99
Medicare-Medicaid dual eligible	0.12	0.06	0.02	0.08	0.11	0.14	0.48
Medican household income (age 65+)	49,273	9,081	29,987	43,154	47,948	52,725	96,941
% w/ high school degree and above (age 65+)	78.2	6.9	42.1	74.8	79.4	83.0	91.7

Notes: This table presents the distribution of Hospital Referral Region (HRR) characteristics, including climate, provider capacity, societal attitudes towards mental illness, and demographic and economic conditions of the population. The number of physicians is calculated using the Medicare Data on Provider Practice and Specialty (MD-PPAS) from 2008-2018. The number of Medicare Fee-for-Service (FFS) recipients is estimated using the baseline sample of this analysis, multiplied by 5 to project estimates for 100% of the Medicare population. Demographic measures (i.e., age, gender, race) are based on the sample used in estimating HRR fixed effects. Data sources and methods for constructing other measurements are detailed in Appendix A. Climate information and societal attitude measures are only available for a subset of HRRs, the number of which is listed in parentheses.

Table A8: Place Effect by Treatment Use Rate in Origin HRR, Move-Up vs. Move-Down

	(1)	(2)	(3)	(4)	(5)
	Q1	Q2	Q3	Q4	Q5
	Panel A: Any Service Use				
$Post_{it} \times \delta_i \times \mathbb{1}(\delta_i \geq 0)$	0.725	0.630	0.408	0.386	0.398
	(0.125)	(0.145)	(0.174)	(0.184)	(0.172)
$Post_{it} \times \delta_i \times \mathbb{1}(\delta_i < 0)$	1.251	1.246	1.150	0.938	0.488
	(0.458)	(0.303)	(0.218)	(0.171)	(0.0776)
Observations	202,146	204,624	199,633	202,791	198,833
Dep. Mean	0.104	0.115	0.116	0.121	0.137
p-value for equal coefficient test	0.308	0.107	0.0241	0.0602	0.664
	Panel B: Any Drug Use				
$Post_{it} \times \delta_i \times \mathbb{1}(\delta_i \geq 0)$	0.0415	0.137	0.261	0.263	0.0138
	(0.0855)	(0.121)	(0.142)	(0.218)	(0.314)
$Post_{it} \times \delta_i \times \mathbb{1}(\delta_i < 0)$	-0.0224	0.635	0.390	0.215	0.443
	(0.394)	(0.251)	(0.161)	(0.154)	(0.0842)
Observations	202,693	201,679	211,274	194,633	197,748
Dep. Mean	0.224	0.253	0.261	0.279	0.296
p-value for equal coefficient test	0.881	0.122	0.611	0.881	0.221

Notes: This table presents regression results from equation (3), separately for five subsets of movers, grouped by the quintile of the treatment utilization rate in their original HRRs. The dependent variable is a dummy indicator denoting whether patient i had any mental health service (Panel (a)) or drug (Panel (b)) claim in year t. θ^{up} is the coefficient for the interaction term between the post-moving indicator ($Post_i t$) and the destination-origin differences in the HRR mental health treatment utilization rate (δ_i) when $\delta_i > 0$, while θ^{down} is the coefficient when $\delta_i \leq 0$. The regression includes individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors clustered at the beneficiary level are reported in parentheses.

Table A9: Effect of Mental Health Treatment Utilization on Self-Harm Emergency Department Visit, Excluding Patients in Nursing Facilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Any Self-Harm Emergency Department Visit					
	All	Male	Female	All	Male	Female
$\delta_i^{Service} * Post_{it}$	-0.00505	-0.00707	-0.00391			
	(0.00264)	(0.00350)	(0.00366)			
$\delta_i^{Drug} * Post_{it}$				-0.000969	-0.000124	-0.00231
				(0.00171)	(0.00265)	(0.00223)
Observations	545,527	197,692	347,833	545,527	197,692	347,833
Dep. Mean	0.000251	0.000258	0.000247	0.000251	0.000258	0.000247

Notes: This table presents the effect of changes in the local mental health treatment utilization rate on an individual's emergency department visits due to self-harm. The sample consists of patient-year observations from 2010-2018 for all individuals who changed their residential Hospital Referral Region (HRR) after 2010, excluding the year of moving and any years with nursing home claims. The dependent variable is a binary indicator indicating whether patient i had any self-harm emergency department visit in year t. The main independent variable is the difference in the mental health care service ($\delta_i^{Service}$) or drug (δ_i^{Drug}) utilization rate between the destination and origin, interacted with an indicator for the post-move period. All regressions include individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects. Standard errors clustered at the beneficiary level are reported in parentheses.