Geographic Variation in Mental Health Treatment Utilization: Evidence from Migration

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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 self-harm-related emergency department visits. (*JEL* H51, I11, I12, I14)

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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 widely 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 in an average year, and 26.2% have drug claims for antidepressants and antipsychotics. In contrast, in Arizona, the rates are 7.5% and 21.6% respectively. 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.[4] Other factors, such as the accessibility of mental health treatment and the propensity to seek mental health care, might also contribute 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] The direct spending on mental health treatment is $179 billion in 2014 and more than 60% is paid by public payers (APA, 2013). This is before counting in hundreds of billions dollars indirect cost in additional medical spending by mental health patients (Figueroa et al., 2020; Montz et al., 2016), 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). Many economic studies also document the positive effects of psychotherapy and mental health medications on health and labor market outcomes (Angelucci and Bennett, 2021; Baranov et al., 2020; Biasi et al., 2021; Bütikofer et al., 2020; Shapiro, 2022), while some studies report no discernible result (Duggan, 2005; Haushofer et al., 2020). Focusing on low- and middle-income counties, Lund et al. (2020) provide a systematic review of the impacts of mental health interventions and factors associated with program effectiveness.

[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. Suicide rates are among population above age 65, from the CDC Underlying Cause of Death database, 1999–2019. See Section 2.2 for details.

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. The impact of changes in place-side factors will therefore be reflected in the observed changes in an individual's treatment utilization upon migration, shedding light on the relative importance of place effect in driving the geographic variation.[5]

In the analysis, I distinguish between mental health service use[6] (e.g., psychotherapy) and drug use (e.g., 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 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 (Driessen et al., 2016; Mojtabai and Olfson, 2011). 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, 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, leading to a potentially higher place effect in service use 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.

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

[6]Mental health service use is identified based on the primary diagnosis in claims (see Section 2.2 for details), some of which may also include a prescription.

The event-study analysis shows that, following a move to an area with a one percentage point higher service utilization rate, an individual's probability of using service increases by 0.4–0.5 percentage points. The response occurs immediately after the move and remains relatively stable for at least seven years. 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. The magnitude of this place effect is similar to the estimate found for general non-drug healthcare spending in Finkelstein et al. (2016).[7] However, when it comes to mental health drug use, place-specific factors explain only 15.1% of the variation.

While the main analysis focuses on the extensive margin (i.e., whether there is any mental health visit or medication in a given year), I also examine intensive margin outcomes such as the number of mental health service claims, total drug dosage and payments. These measurements show place effects of similar sizes to the extensive margin measurements. Baseline results are also robust to various of sensitivity checks, including the use of different sample periods, different geographic units, and adjustments for unobserved factors.

Additional analyses reveal some interesting features in individuals' response to local utilization rates. For example, excluding nursing home residents from the sample produces smaller place effects. This is partly because nursing home residents have higher mental health treatment use on average. However, even when excluding them in calculating the regional utilization rates, the estimated place effect is still lower than the baseline—0.370 for service use and 0.139 for drug use. This reflects a smaller convergence in utilization patterns within the community-based environment and suggests that nursing homes may serve as a potential channel for the place effect. Moreover, movers, especially those originally from areas with median service use rates, exhibit larger responses to a decrease in regional utilization rates than to an equivalent increase. This potentially reflects that downward moves to regions with insufficient supply of mental health specialists imposes a hard constraint on ac-

[7] Finkelstein et al. (2016) uses an earlier sample period and does not require Medicare Part D enrollment to focus on non-drug spending. Using the current sample, the place effect is 0.520 for total non-drug healthcare spending and 0.275 for total drug spending.

cess, thereby triggering larger responses. For drug use, no significant asymmetry is observed in response to different moving directions, which is consistent with the understanding that mental health medications are frequently prescribed by various physicians, not only psychiatrists, and therefore may be less influenced by the scarcity of mental health specialists in certain areas.

To further explore the place effect, I estimate area fixed effects for treatment use and correlate them with various place characteristics. Since the analysis sample is composed of individuals with the same insurance, it effectively eliminates the potential influence of insurance coverages on the observed geographic differences in treatment use. Factors remaining in consideration are i) environmental conditions, such as temperature and pollution, that might affect people's mental health status;[8] ii) local public attitudes that affect patients' willingness to seek mental health care, possibly more so than for physical health conditions (Bharadwaj et al., 2017; Cronin et al., 2020); and iii) the accessibility of mental health care providers, including mental health professionals (i.e., psychiatrists, psychologists, and clinical social workers), primary care physicians, and institutional providers such as psychiatric hospitals.

Bivariate OLS results indicate that regions with higher mental health service utilization rates tend to have colder temperatures, higher provider density, and more positive public attitudes towards mental illnesses. When it comes to drug use, all these place-side factors exhibit weaker and less significant correlations with the place effect. In the post-Lasso multivariate regression, only the density of mental health professionals remains significantly correlated with the place effect for service use. This again highlights the importance of the uneven distribution of mental health professionals. With half of U.S. counties lacking any psychiatrists, this shortage seems to be one of the main barriers to the sufficient provision of mental health services (Beck et al., 2018; Bishop et al., 2016; Thomas et al., 2009).

Finally, I investigate the health outcomes related to the observed geographic variation in mental health treatment use. The movers analysis provides suggestive evidence that relocating to areas with a one percentage point higher mental health service use rate is associated with in a 0.00446 percentage point, or 13.6%, decrease in the probability of

[8] See literature reviewed in Liu et al. (2021) and Ventriglio et al. (2021).

having a self-harm emergency department (ED) visit. Changes in local drug utilization rates, however, do not seem to affect the incidence of self-harm. At the regional level, I show that an area with a standard deviation higher HRR-level place effect in service (drug) utilization is associated with 1.956 (0.492) fewer suicide deaths per 100,000 residents, representing a reduction of 12.3% (3.1%) compared to the mean. Together, these findings indicate a positive relationship between increased mental health treatment utilization, particularly services, and improved mental health outcomes.

This paper contributes to the emerging body of economics studies on mental health, which traditionally focuses on adolescents and working-age adults (Angelucci and Bennett, 2021; Banerjee et al., 2017; Baranov et al., 2020; Biasi et al., 2021; Braghieri et al., 2022; Chatterji et al., 2011; Cuddy and Currie, 2020a,b; Haushofer et al., 2020; Persson and Rossin-Slater, 2018; Persson et al., 2021). The older population, despite facing a similar or potentially greater mental health burden, remains understudied within the economics literature.[9] Focusing on pre-retirement older adults in the U.S., Cutler and Sportiche (2022) demonstrate the adverse mental health effect of the Great Recession on homeowners.[10] Internationally, Banerjee et al. (2023) and Dias et al. (2019) highlight the prevalence of mental health issues among older population in low- and middle-income countries, and evaluate policies to mitigate depression through randomized trials. Given the rapidly aging population in the US and globally, supporting mental health of the elderly is becoming increasingly urgent.[11] By utilizing administrative claim data for older adults, this paper enriches the literature by documenting current treatment usage patterns for this crucial yet overlooked population. Moreover, this study provides insights into the potential determinants that influence the actual use of mental health treatments, thereby assisting in the development of future policies to translate effective interventions into broad application.

[9] Discussions about older adults' mental health conditions and treatment 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., Byers et al., 2012; Frost et al., 2019; Karlin et al., 2008; Klap et al., 2003).

[10] 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.

[11] 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.

This paper is also built on the important literature on geographic variation in health care (e.g., Baicker et al., 2006; Chandra and Staiger, 2007; Cutler and Sheiner, 1999; Cutler et al., 2019; Doyle, 2011; Finkelstein et al., 2016; Fisher et al., 2003a,b; Molitor, 2018; Robinson et al., 2024; Skinner, 2011). Most of these studies are in the context of health care for physical conditions, such as heart attacks and childbirth deliveries. Only a handful of papers have documented geographic variation in mental health care (Cuddy and Currie, 2020b; Golberstein et al., 2015; McConnell et al., 2023; Sturm et al., 2003). This paper compliments the literature by examining the geographic disparities of mental health treatment use, which exhibit several unique features compared to physical health care use. Firstly, while place effect for mental health service use is approximately the same as the estimates for general non-drug healthcare spending in Finkelstein et al. (2016), the place effect for drug explains less than one-fifth of the regional differences. Secondly, the observed asymmetry in mental health service use is not seen in general non-drug healthcare use. This draws attention to the even more acute shortage of psychiatrists compared to that of general physicians. Lastly, while 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). These findings indicate that health policymakers should place increased emphasis on promoting the utilization of mental health treatment, especially services like psychotherapy.

The paper is organized as follows. Section 2 introduces the setting, data, and descriptive facts about geographic variations in mental health care. Section 3 describes the movers design strategy and Section 4 presents the results. Finally, Section 5 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. Common types 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.[12] Among these, cognitive disorders may exhibit distinct care utilization behaviors since they often have limited treatment options and patients 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.[13] 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.[14] 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, medications, and various types of medical or behavioral therapy can be prescribed. Psychotherapy and

[12] 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. See Appendix Table A1 for the list of diagnoses and the categorization.

[13] 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.

[14] 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.

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.[15] Patients don't need a referral to visit psychiatrists or psychologists who accept Medicare.

Medications such as antidepressants, antipsychotics, 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.[16] 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). The data include enrollment registers and claim records for inpatient admissions, outpatient services, physician services, and prescription drugs. Besides fee-for-service Medicare (or traditional Medicare), approximately 30% of eligible beneficiaries chose Medicare Advantage (MA or Part C) plans during the study period, for whom I do not observe claim records in

[15] Medicare Advantage (MA or Part C) plans are required to cover the same mental health services as traditional Medicare, with a small share of plans offering extra benefits such as additional inpatient hospital psychiatric services. Cost-sharing structures differ, with MA plans typically requiring lower copays for in-network services but higher costs for out-of-network care. Many MA plans also employ utilization management tools such as prior authorization and referrals (Freed et al., 2023).

[16] 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.

the data.[17]

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).

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,

[17]Cabral et al. (2023) shows that there is also large geographic variation and place effect in MA enrollment. However, they also find that the vast majority of movers (85%) maintain their pre-move choice between traditional Medicare and MA. Moreover, there is no significant correlation between regional MA enrollment rates and mental health treatment use rates when controlling for demographic compositions (see Appendix Table A2). This suggest that the potential sample selection issue due to unobserved MA enrollees is not a significant problem. Lastly, the gradual adoption of the place effect in MA enrollment also cannot explain the pattern we will see in mental health treatment use, which shows an immediate response after moving.

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

[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

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). These individuals move across a total of 32,853 origin-destination HRR pairs, with an average moving distance of 597 miles. Appendix A presents additional summary of the moving behavior. 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] Claim that has one of the ICD codes in Appendix Table A1 as the primary diagnosis are identified as mental health service claim.[23] As mentioned above, cognitive disorders and substance-related disorders are not included in the list. Patients with these disorders can still appear in the sample, but these claims (i.e., those with cognitive disorder as the primary diagnosis and those related to substance disorders according to Medicare Substance Abuse Confidentiality Regulations) are not identified as mental health service visits.

One potential limitation of using Medicare data to measure mental health service use is that visits are not observed if the service is not covered by Medicare or if the provider does not accept Medicare patients. This is especially relevant for mental health professionals, given their high Medicare opt-out rate.[24] Based on self-reported visits from the Medical Expenditure Panel Survey (MEPS), 10.3% of Medicare-covered individuals who have at least

their origin or destination HRRs. The average change in this destination claim share among the the movers sample is reported in Appendix Figure A2.

[22]During the sample period, Medicare claims use ICD-9 code to record diagnoses in 2006–2015Q3, and switched to ICD-10 in 2015Q4.

[23]Providers are required to report the condition that is primarily responsible for the admission or service as the primary diagnosis, while other coexisting conditions are listed in secondary or higher-order diagnoses (CMS, 2024). When a mental health disorder is recorded as a secondary or higher-order diagnosis, 64.8% of cases also have a primary diagnosis related to a mental health disorder. The remainder have primary diagnoses such as hypertension or diabetes, reflecting health services for these conditions with mental health as comorbidities. See Appendix B for a more detailed discussion.

[24]Yu et al. (2019) reports that 7.0% of psychiatrists opted out of Medicare in 2017, compared to only 0.7% of all physicians.

one visit to psychiatrist in a year do not have any of those visits paid by Medicare and, thus, would not be identified in Medicare claims data.[25] This is less of a concern for inpatient services and for services provided by primary care physicians. As a result, the variable used in the main analysis—an indicator of whether an individual has at least one mental health visit (based on diagnosis) from any providers—can mitigate the missing-data issue to some degree. Extended analyses that further explore service use with different providers and places of service, as well as measurements at the intensive margin, are more exposed to the missing-data issues and should therefore be interpreted with greater caution.

Measurements for mental health drug use are constructed using prescription drug claims, which include information on patient ID, 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 health-care use, health outcomes are harder to observe. Suicide, one of the most severe and negative mental health outcomes, is only observable at the regional level as suicide rates from the CDC Underlying Cause of Death database (1999–2019). Individual-level suicide deaths cannot be directly observed because cause of death information is not available in our current Medicare sample. Therefore, I use emergency department visits due to self-harm injury as another adverse outcome of 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 and outpatient records since 2009 and 2010.[26] When using this measurement, the analysis sample is restricted to 2010–2018.

[25] This calculation is based on MEPS data from 2006–2018, consistent with the sample used in the main analysis. The sample is also restricted to individuals with traditional Medicare and Medicare Part D. Among all office-based or outpatient visits to psychiatrists, 17.9% have zero Medicare payments. Based on these records, 5.8% of individuals have at least one psychiatrist visit in a year. This figure drops to 5.2% if only visits with non-zero Medicare payments are counted.

[26] 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.

Summary Statistics Table 1 presents summary statistics on demographic characteristics, patients' mental health treatment 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 spending for movers over all the observed years is very similar to that for non-movers. However, accounting for the difference in average age, movers tend to be healthier and have lower medical spending. Such differences will not affect the empirical design, which compares movers across different moving directions, but should be taken into consideration when generalizing the findings to the broader non-moving population.

In terms of mental health treatment (service and 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 treatment use 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 treatment utilization rates, defined as the share of patient-year observations with any mental health treatment 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 C.

2.3 Geographic Disparities in Mental Health Treatment Use

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.[27]

Mental health service and 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.[28] Over time, there is a steadily increasing trend in mental health service use, as shown in Appendix Figure A4.[29] This trend is consistent across most HRRs, resulting in the persistence of the initial differences in average utilization rates across HRR quintiles throughout the observed period.

Alongside the overall mental health service use rate, there is also significant geographic variation in the share of beneficiaries using specific types of services. For example, inpatient mental health care is utilized more frequently in the South, while hospital outpatient depart-

[27] 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 (Carton et al., 2015; Mojtabai and Olfson, 2011). 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).

[28] Similar distribution is found for service use among Medicare recipients regardless of Part D coverage, demonstrating a distribution similar to that for Part D enrollees (see Appendix Figure A3), though rates are generally lower as mental health patients are more likely to have Part D coverage.

[29] An exception is observed in 2006, when the utilization rate among beneficiaries with Part D coverage was higher compared to subsequent years. This could be attributed to the unique composition of the Part D enrollees in the initial year of the program. When not conditional on Part D coverage, mental health service use rate increases steadily over time.

ment care is utilized more often in the North (see Appendix Figure A3). Urban areas with high overall mental health service use 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 rates also show significant regional variation, and this disparity persists over time, as shown in Figure 1 Panel (b) and Appendix Figure A4 Panel (c). The highest rate is also highest in Miami, FL (33.2%), and the lowest in Honolulu, HI (11.9%). Between these two extremes, drug utilization 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. 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 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 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 Empirical Strategy

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:

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

where y_{it} is an indicator for patient i having any mental health service or 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 no-drug service or 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 the interaction terms between the difference in HRR treatment utilization rate and 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. ρ_s captures the relative year fixed effects, which control for changes in treatment use related to relocation but are uniform across all moving directions.[30] The regression model also incorporates individual fixed effects (α_i) to control for all time-invariant patient

[30]The estimated coefficients for the relative year fixed effects show increases in treatment utilization in the year prior to a move and in the subsequent years (see Appendix Figure A5). This pattern suggests that the timing of relocation may be endogenous and that moving itself may have a direct impact on individuals' mental health. This underscores the importance of controlling for these relative time fixed effects. However, this pattern applies to all movers regardless of the moving direction, and therefore does not contradict our underlying assumption that there is no differential trend in mental health treatment use among individuals who move simultaneously but in different directions.

characteristics and calendar year fixed effects (τ_t) to account for general time trends. x_{it} further includes 5-year age group 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 no other factors systematically vary with the moving direction and simultaneously affect the change in movers' mental health treatment use. Note that the model allows for potential differences in time-invariant health status across movers by controlling for individual fixed effects, as well as health shocks associated with the timing of the move by including relative time fixed effects. However, what the model does not allow for, and therefore requires the assumption, is the possibility of health shocks that not only coincide with the *timing* of the move but also with the *direction* of the move. This assumption could be violated if individuals experiencing adverse mental health shocks and increased needs for mental health treatment move to areas with higher utilization rates. In such cases, the increased utilization due to the health shock would be mistakenly attributed to the move, thereby biasing the effect of local utilization rates upwards.

Although I cannot fully rule out this possibility, the pattern of the results does not support the hypothesis that individuals with deteriorating mental health are more likely to move to areas with better access to mental health treatment. Specifically, if this were true, we would expect an upward trend in coefficients θ_s in the years preceding the move. However, as I will show in the next section, there is no such pattern in either mental health service or drug utilization, nor in multiple subgroups examined for robustness checks.

However, one might still be concerned that there may be an increasing need for mental health treatment prior to a move to a high utilization area, but it is not reflected in actual utilization before moving, possibly due to restricted access. To test this, I use the American Community Survey (ACS) data to examine whether moving direction is correlated with major life events such as divorce, death of a spouse, or retirement. These events are significant predictors of moving and mental health.[31] If they create negative shocks in mental health

[31] Using data from the Health and Retirement Study (HRS), Finkelstein et al. (2016) show that being widowed and retiring significantly predict moving across HRRs. Similar feature is also found in the ACS data (see Appendix Tables A3 and A4). Substantial research shows that losing partners negatively impacts the mental health of the older population (e.g., Mazure, 1998; Lindeboom et al., 2002; Siflinger, 2017). The effect of retirement on mental health shows mixed evidence, varying by the nature of retirement and different health indexes (Nishimura et al., 2018).

and cause individuals to move to places with more mental health treatment, we should see a positive correlation between these indicators and changes in local utilization rates. However, moving directions in terms of local mental health service or drug utilization pattern are not significantly different for movers who experienced these major life events in the past year (see Appendix Table A5).

Furthermore, as a robustness check, I follow the method developed by Oster (2019) to adjust for selection on unobservables. As I will show in the next section, the results remain relatively stable compared to the baseline. Taken together, these tests indicate that the potential concern for omitted factors correlating with both moving direction and changes in mental health treatment use is weak, supporting the plausibility of the identification assumption.

4 Empirical Results

4.1 Main Results: Place Effect for Mental Health Treatment Use

4.1.1 Event Study

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 $s = -1$. The joint test of the pre-move coefficients reports a p-value of 0.57. 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.[32] After the move year, an individual's likelihood of using mental health services increases by 0.4–0.5 percentage points in response to a one percentage point increase in the local utilization rate.[33] 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 general non-drug healthcare spending (Finkelstein et al., 2016).

The result for mental health drug use, as depicted in Figure 3 Panel (b), present a distinct pattern compared to service use. In the years prior to the move, coefficients are also close to zero (joint test p-value = 0.061), except a small bump in years -6 to -4. This is unlikely to be driven by selection in moving direction, as it 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. Instead, this observed pattern is possibly due to sample imbalance, as movers may have varying lengths of pre- and post-moving observation periods depending on their moving year. When replicating the event study with balanced samples, restricted to individuals observed over the full year ranges relative to their move ([-7,1], [-4,4], or [-2,6]), there is no bump in mental health drug use in the pre-period (see Appendix Figure A8).

In the years after the move, event coefficients are approximately 0.2 in both the baseline and balanced sample. 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 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.[34] Consequently,

[32] Appendix Figure A6 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, and therefore exhibit a larger effect size at year 0.

[33] The response is slightly larger when the sample is not restricted by Part D coverage (see Appendix Figure A7).

[34] 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.

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 the following subsections.

4.1.2 Difference-in-Differences Estimations

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 ($Post$). This indicator is interacted with the destination-origin difference in the mental health service or 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.[35] In contrast, the likelihood of taking mental health drugs increases only by 0.151 with a similar increase in the local drug use rate. This difference in the place effect estimates is highly significant (p-value$<$0.001). Across genders, females show slightly higher utilization rates for both mental health services and drugs. They also respond more to changes in local utilization rates, although the difference is not statistically significant.[36]

Given the inherent differences in the causes and treatments, the size of the place effect may vary across different mental illness categories. To check this, I replicate the analysis with the outcome variable denoting 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 separately. Changes in local utilization rate also correspond to the mental health treatment measure in use. Results show that service use for schizophrenia exhibits a relatively smaller place effect compared to anxiety and mood disorders, with both comparisons yielding p-values less than 0.05 (see Appendix Table A6). 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.,

[35] The place effect for mental health services is relatively larger when Medicare Part D coverage is not required, with a point estimate of 0.556.

[36] When conducting the gender-specific sub-analysis, regional utilization rates are calculated among the corresponding gender to account for gender differences in utilization at the baseline level.

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, the point estimate for the place effect is larger for antipsychotics use than for antidepressant use, although this difference is not statistically significant (p-value = 0.140).

Place effects may also vary when considering specific service providers, such as hospital inpatient departments, hospital outpatient departments, mental health professionals (i.e., psychiatrists, psychologists, and clinical social workers), and primary care physicians. Services from these specific providers show larger place effects than the main outcome, with all corresponding p-values being less than 0.001 (see Appendix Table A7). This may be attributed to 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.

The results above focus on extensive margin outcomes (i.e., whether having any mental health visits or medications) but do not consider the intensive margin (i.e., number of claims and spending), which can have different sizes of place effect. For example, the decision to see a psychiatrist may be more driven by patients' attitudes towards mental illness, whereas once they have seen and been diagnosed, the treatment is more influenced by the provider, leading to a larger place effect at the intensive margin. Conversely, the extensive margin may be more affected by easy access to providers and their tendency to screen and diagnose patients, while the intensity of the treatment depends more on the severity of the patient, leading to a smaller place effect at the intensive margin.

Table 3 presents results for the response to local treatment use patterns measured by the number of mental health service visits, the total dosage of psychiatric drugs,[37] and total spending on mental health service and drug. Since the outcome variables include zero values, I use Poisson regression to avoid potential issue with log-like transformation (Chen and Roth,

[37]Dosage of each prescription is calculated based on its strength (e.g., 50mg) and quantity (e.g., 30 pills). The annual total dosage for each patient is first aggregated by generic name. The total annual dosage for each type of medication is then divided by the median annual dosage across the entire sample before summing the dosages of different drugs.

2024). The coefficients are similar to those for the extensive margin response, with the place effect explaining 40–50% of the geographic disparities in mental health service use and below 20% of those in mental health drug use.[38] This suggests that place-specific factors affect not only the decision to initiate any mental health treatment but also the intensity of treatment use to a similar magnitude.

4.1.3 Robustness Checks

In this subsection, I assess the robustness of the main estimates using various sensitivity analyses. Results are graphically summarized in Figure 4, which shows that the estimated place effects remain relatively stable across different samples, regional utilization rate measures, and model specifications. Details on how these robustness checks are chosen and performed are outlined below, and the full regression results are provided in the Online Appendix.

To begin with, it is important to note that the sample period includes several major policy reforms. One policy change directly related to mental health treatment was the cost-sharing parity for outpatient mental health care services, which gradually reduced cost sharing from 50 percent before 2010 to 20 percent by 2014 and onward. However, despite this significant reduction in coinsurance, there is little evidence of increased service use from national trends (see Appendix Figure A4) or previous empirical studies (Cook et al., 2020; Fung et al., 2020).[39] Moreover, the policy applies uniformly across the country. Although regions with more mental health service supply might experience larger impacts, the relative distribution of mental health treatment rates across HRRs in fact remains stable. Another reform that could impact geographic variation in mental health treatment use is Medicaid expansion. While it did not affect the share of dual eligibles or general healthcare utilization among the Medicare population (Carey et al., 2020; CMS, 2020), there is concern that it exacerbated the shortage of mental health workers, leading to negative spillover effects on mental health (Bjoerkheim et al., 2023).

To assess whether the results are driven by these policy changes, I first split the sample

[38] Appendix Figure A9 contains corresponding event study figures, which all present flat pre-trends and immediate responses after moving.

[39] The only study finding increased use of mental health visits is among white beneficiaries receiving low-income subsidies (Fung et al., 2023).

into periods before 2009 and after 2014, reflecting years before and after the change in cost-sharing (also after the ACA). Results are roughly similar to the baseline but less significant due to the limited sample size (see Figure 4 rows 2–3 and Appendix Table A8). Row 4 further shows that using HRR average utilization rates over the sample years instead of just the year before move also produces similar results. Additionally, results remain robust when excluding dual eligibles or individuals currently living in states that have expanded Medicaid (see Figure 4 rows 5–6 and Appendix Table A9). This also indicates that potential concerns about not being able to observe claims for services only covered by Medicaid but not Medicare and claims from providers who opt out of Medicaid and/or Medicare after the expansion do not significantly affect the estimation. Finally, to account for potential bias in two-way fixed effect (TWFE) models with staggered treatment and heterogeneous effects, I apply the imputation-based method from Finkelstein et al. (2021a) and Cabral et al. (2023) following Borusyak et al. (2024). This yields findings essentially the same as the baseline (see Appendix Figure A10).

Another set of robustness checks involves issues related to the construction of geographic areas (see Appendix Table A10). While the main analysis uses HRR-level geographic areas, results shown in remain relatively stable when calculating regional utilization rates at the state, county, and health service area (HSA) levels, except for drug use at the state level (Figure 4 row 7), which produces imprecise estimates at only 0.05. This may be because much geographic variation in drug use and related place effects occurs within, rather than across, states. Additionally, rows 10–11 shows that the place effect increases moderately when the sample is restricted to individuals who moved between above-median and below-median (or top-quartile and bottom-quartile) HRRs, indicating a larger convergence in response to more significant changes in local utilization patterns. Dropping individuals moving to Florida—a group of movers seeking warm weather and retirement communities, which accounts for 10% of the sample—does not change the results. Lastly, adding additional controls for census region-by-year fixed effects also produces coefficients similar to the baseline (Figure 4 row 13), with a slightly smaller place effect for service use (0.368) and a slightly larger place effect for drug use (0.182).

Finally, to further address the concern of unobserved factors, I follow Oster (2019) to adjust for selection on unobservables. Under conservative assumption, the adjusted coefficients are only modestly reduced to 0.377 for mental health service use and 0.107 for drug use, suggesting no significant bias due to unobservables (see Appendix Table A11). Full details of the adjustments can be found in the Appendix D.

4.2 Additional Results

4.2.1 The Role of Nursing Homes

Nursing homes are a crucial setting in this analysis because a substantial proportion of older people—11.1% in the analysis sample—reside in these facilities. These residents differ from those outside in several important ways. They are generally older and require more intensive healthcare, including mental health care. The regulatory environment of nursing homes may also significantly affect mental health treatment utilization.[40] Additionally, patients moving into nursing homes may experience greater exposure to local practice styles, resulting in greater convergence to the regional level.

To examine the heterogeneous place effect related with nursing home stays, I rerun the analysis using patients outside the nursing facilities. Event study results show a similar pattern to the baseline, but the size of post-period coefficients is smaller (see Appendix Figure A11). As summarized in columns (1) and (3) of Table 4, the place effect is 0.283 for service use and 0.121 for drug use. This reduced effect size is partly due to lower utilization rates among non-nursing home residents—only 9.0% (22.9%) use any mental health service (drug) compared to 11.8% (26.2%) among all patients. When using regional utilization rates based solely on the non-nursing home residents, the place effect increases to 0.370 for service use and 0.139 for drug use, as shown in columns (2) and (4). This reflects the convergence in utilization patterns to the local community-dwelling population, yet it is still lower than the baseline result, suggesting the potential role of nursing homes in enhancing the place effect.

It should be noted that the use of nursing home is endogenous and has a large place effect (see Appendix Figure A12). More importantly, regional utilization rates of nursing home

[40]For example, the Nursing Home Reform Act of 1987 mandates regular mental health evaluations for nursing home residents, which may lead to higher mental health treatment rates among nursing home residents compared to those in the general community.

and mental health treatment are positively correlated, even when controlling for demographic composition (see Appendix Table A12). Therefore, it is possible that people moving to areas with high mental health treatment rates, which tend to have high nursing home rates, are more likely to be excluded from the sample. The correlation between regional nursing home rates and mental health treatment rates disappears when the latter is calculated using only the non-nursing home residents. This indicates that the endogenous sample selection issue is perhaps less of a concern when considering the results in Columns (2) and (4) of Table 4.

4.2.2 Heterogeneity by Moving Direction

Response may also vary between individuals moving to areas with higher ("moving-up") or lower ("moving-down") mental health treatment utilization rates. 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. 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. Such heterogeneous responses based on moving direction can also vary depending on individuals' origins. For example, people originally from low-utilization areas who move further downward may end up in regions with even more scarcer resources compared to those from high-utilization areas making similar moves.

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 ($\delta_i \leq 0$).

$$y_{it} = \alpha_i + \tau_t + \theta^{up} Post_{it} \times \delta_i \times \mathbb{1}(\delta_i \geq 0) + \theta^{down} Post_{it} \times \delta_i \times \mathbb{1}(\delta_i < 0) + x_{it}\beta + \epsilon_{it}, \quad (2)$$

The estimated coefficients are plotted in Figure 5.[41] For mental health service use (Panel (a)), movers exhibit larger responses to a decrease in regional service use rates than to an equivalent increase. 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 lower quintile HRRs shows even larger responses to downward moves but the confidence intervals also expanded as there are fewer people moving downwards. Movers from these HRRs also show larger responses in upward moves compared to those moving out from median HRRs. This likely reflects transitioning to regions with more mental health providers, thus relieving the constraints imposed by limited access. As for movers from top quintile HRRs, no significant difference is observed across moving directions. These individuals, despite moving downwards, probably still reside in HRRs with a sufficient supply of mental health providers, thereby avoiding drastic reductions in access.

In contrast to the service results, mental health drug use (Panel (b)) do not present significant asymmetric responses across the moving directions among all subgroups of movers. 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 one can typically continue to receive their prescriptions from primary care physicians, resulting in a smaller impact on mental health drug use.

4.3 HRR-level Place Effects and Local Characteristics

To explore which place-specific factors correlate with the place component of mental health treatment utilization, I estimate the HRR fixed effect for the usage of mental health service or drug using the following equation, and correlate it with a set of HRR characteristics.

$$y_{iht} = \alpha_i + \tau_t + \rho_{r(i,t)} + \eta_h + x_{it}\beta + \epsilon_{iht}. \tag{3}$$

[41] The precise values of the coefficients are reported in Appendix Table A13.

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 or 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 move indicators ($\rho_{r(i,t)}$) are set to zero. The HRR-level place effects (η_h) are only identified through the movers, while the inclusion of the non-movers helps to better control for calendar year and age fixed effects.

The set of HRR characteristics considered include environmental conditions, such as temperature, precipitation, and pollution, 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 the number of mental health specialists (i.e., psychiatrists, psychologists, and clinical social workers) and the capacity of institutional providers (i.e., psychiatric hospitals, psychiatric units in general hospitals). I also include providers not specialized in mental health, such as primary care physicians and nurse practitioners.[42] The distribution of these factors across HRRs is detailed in Appendix Table A14. Notably, we observe substantial disparities in the availability of mental health providers, presenting a distribution more uneven than that of primary care physicians and other specialists. For instance, New York City has 2.9 psychiatrists per thousand Medicare recipients, while Oxford, MS only has 0.19. Additionally, I consider the role of local public attitudes, including sympathy towards people with mental illness and perceived effectiveness of mental health treatment. These factors also vary across geographic areas and could affect people's likelihood of seeking mental health care when needed. Finally, I take into account average demographic and economic characteristics, including age, gender, race, Medicaid-Medicare dual eligibility, household income and education level.

Figure 6 exhibits the correlation between these HRR characteristics and the estimated

[42]The number of physicians is calculated using Medicare claims data and Medicare Data on Provider Practice and Specialty (MD-PPAS). A physician's practicing HRR is determined as the HRR where she provided the most claims in a given year. The number of physicians is first counted by HRR-year and then averaged across years. Thus, these measures include only providers who accept Medicare patients. Institutional providers capacity measures come from Provider of Services (POS) Files (2006–2018). See Appendix C for more details.

HRR-level 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.[43] 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.[44] All regressions are weighted by the number of Medicare patients in each HRR used in estimating HRR fixed effects.

For mental health service use, bivariate OLS regression results indicate that the estimated HRR-level place effects are higher in HRRs with colder temperatures, a higher supply of all types of mental health professionals and institutions, and less prevalent negative attitudes towards mental illness. The estimated place effects is also positively associated with the average Medicare population being older and comprising a larger share of females. In the post-Lasso multivariate OLS estimation, coefficients remain significant and positive for 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 estimated place effects.

As for mental health drug use, correlations with the estimated HRR-level place effects are not as strong for almost all the place-specific characteristics considered. Bivariate OLS coefficients are only marginally significant for the number of psychiatric units, share of male, and the level of population income. Only the number of psychiatric units and median household income are selected in the Lasso regression, and both are positively correlated with the estimated HRR-level place effects.

These findings suggest that the uneven distribution of mental health professionals is more closely tied to the geographic disparities in mental health service use than to mental health drug use. This also aligns with the fact that many mental health drugs are not prescribed by psychiatrists. However, it should be noted that these correlations are cross-sectional and are

[43] 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.

[44] Bivariate OLS regressions with all possible HRRs for each HRR characteristic report similar coefficients, with slightly higher significance levels for some factors (see Appendix Figure A13).

likely to capture long-term endogenous responses that have shaped the current equilibrium between the demand and supply. For instance, areas with more vulnerable populations and high demand for mental health treatment attract more providers. This is perhaps why some patient composition measures also show significant correlation with the estimated HRR-level place effect. Therefore, the relationships presented here should not be viewed as causal. For example, these findings do not necessarily mean that an increased supply of mental health specialists leads to more mental health service use.

4.4 Health Outcomes

Does increased utilization of mental health treatment improve patients' mental health status? Table 5 replicates the difference-in-difference estimation of the movers analysis using the indicator for having any self-harm emergency department (ED) visits as the outcome. There is suggestive evidence that people moving to places with a one percentage point higher mental health service utilization rate is associated with a 0.00446 percentage point lower likelihood of self-harm ED visits, or 13.6% compared to the average incidence rate. Since the movers analysis controls for individual characteristics, the observed changes reflect the impact of changes in place-specific factors, but it remains challenging to pinpoint whether it is entirely driven by the increased service use. Meanwhile, there is no consistent and significant evidence when considering changes in local drug utilization rate, potentially due to the smaller first-stage effect on individuals' drug use behavior.

Due to data limitations, I cannot directly observe suicide at the individual level. However, I show that at the regional level, there is huge geographic differences in age- and gender-adjusted suicide rate, ranging from 35.9 per 100,000 in Reno, NV to 6.9 in Bronx, NY (see Appendix Figure A14). Moreover, HRRs with higher place effects for either mental health service use or drug use tend to have lower suicide rates. A standard deviation higher in the place effect of service utilization is associated with 1.956 fewer suicide deaths per 100,000 residents—a 12.3% reduction relative to the mean (see Appendix Table A15). The link between drug use and suicide rates is less pronounced, with a standard deviation higher in drug use place effect correlating to a reduction of 0.490 suicide deaths per 100,000, or 3.1% relative to the mean. Note that the previous section shows that local population characteristics could endogenously shape place-specific factors related to mental health treatment use, potentially affecting the estimated place effect and its correlation with the suicide rate. Therefore, although the analysis suggests a positive association between mental health treatment use and mental health status, more work is needed to establish a strong causal conclusion.

5 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. Heterogeneity analyses suggests that nursing home plays an important role in the convergence of local treatment use pattern. Regional correlation further indicates that the number of mental health specialists is an important component in the place effect of service use, but not drug use, which relies 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. Initiatives such as incentivizing medical students to specialize in psychiatry and encouraging providers to underserved regions could offer solutions to achieve this goal. Telemedicine offers an additional solution for addressing the uneven distribution of providers and promoting mental health service use. Finally, there is suggestive evidence that moving to places with more mental health service use is associated with a lower likelihood of self-harm ED visits, highlighting its potential marginal benefit. Compared to many other types of medical care on the “flat-of-the-curve”, mental health care warrants greater attention and resource allocation.

Several limitations should be noted when interpreting the results of this study. The analysis is based on a sample of individuals who moved, representing a small proportion of the older population. Although it is shown that migrations occur in a representative set of origin and destination areas in terms of average treatment utilization rates, movers tend to be younger and healthier in the pre-moving period compared to non-movers. They may also be more adaptable to changes in local utilization patterns. Consequently, there may be concern to extend the findings to the broader population of the elderly. Moreover, although the exploration of specific place-side factors includes a wide range of local characteristics, it does not account for all potential mechanisms, such as regional differences in physician prescribing behaviors and diagnostic practices, which are critical determinants in mental health care delivery (Barnett et al., 2020; Currie and MacLeod, 2020; Marquardt, 2021). More future work is needed to understand these potential sources of geographic variation in treatment utilization patterns.

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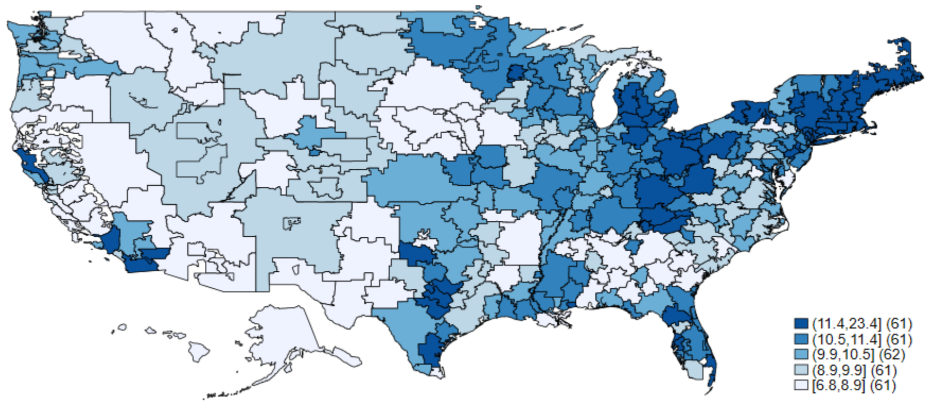
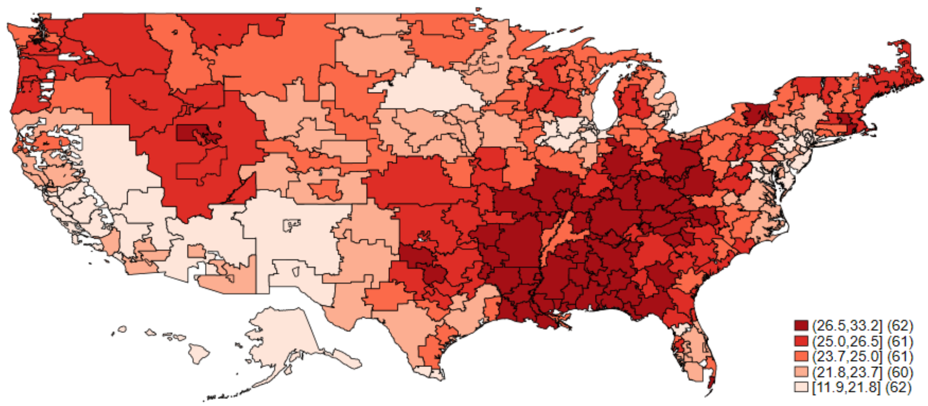
Figures

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

(a) Mental health service use rate (%)



(b) Mental health drug use rate (%)

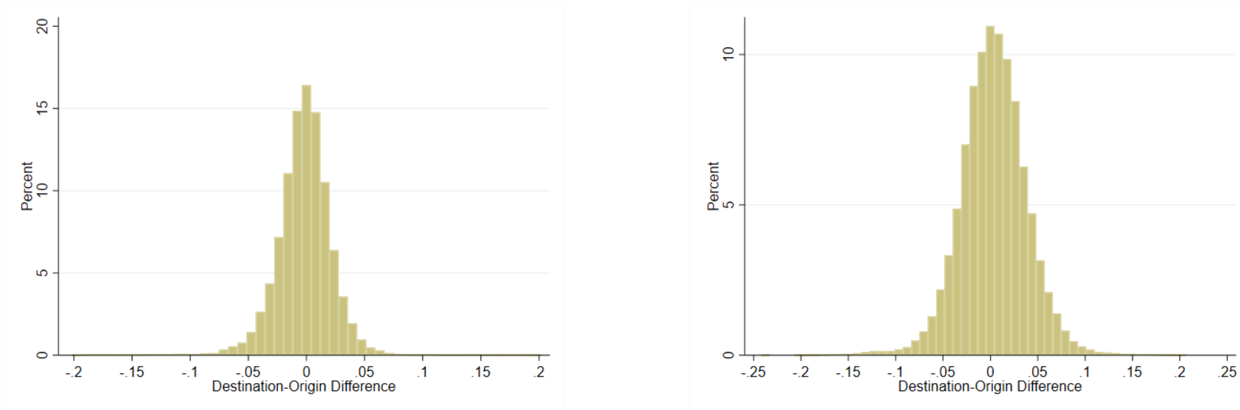


Notes: These figures illustrate the distribution of mental health treatment utilization rates by Hospital Referral Region (HRR). The sample comprises Medicare FFS beneficiaries aged 65–99, with full-year coverage for FFS Part A, B, and D in each year, drawn from the 20% Medicare FFS claims data, 2006–2018. 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

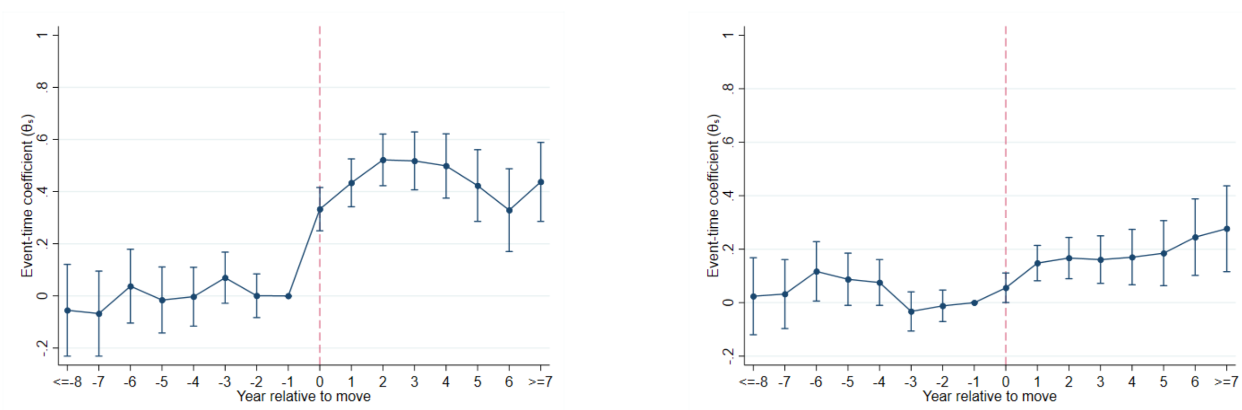


Notes: These figures show the distribution of the difference in mental health service (Panel (a)) and drug (Panel (b)) utilization rates between destination and origin HRRs (δ_i) among all movers. HRR utilization rates are calculated each year using the non-mover sample and are then merged with each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

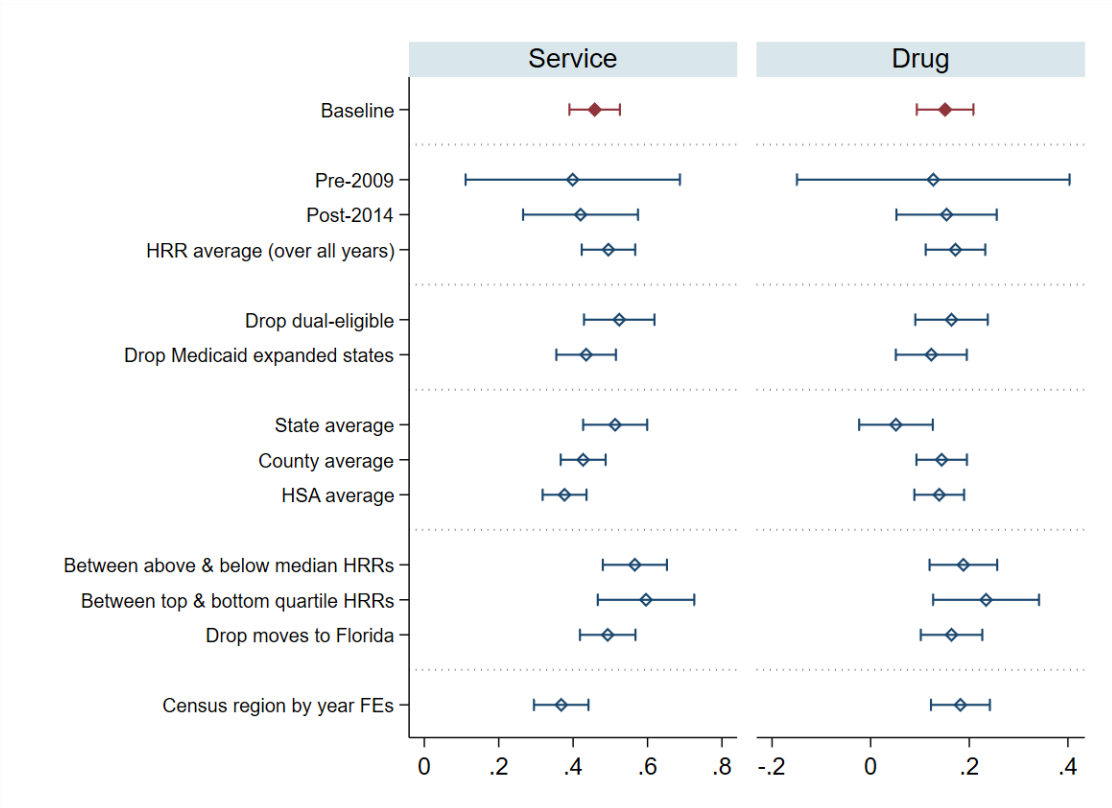
(a) Service

(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 or 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.

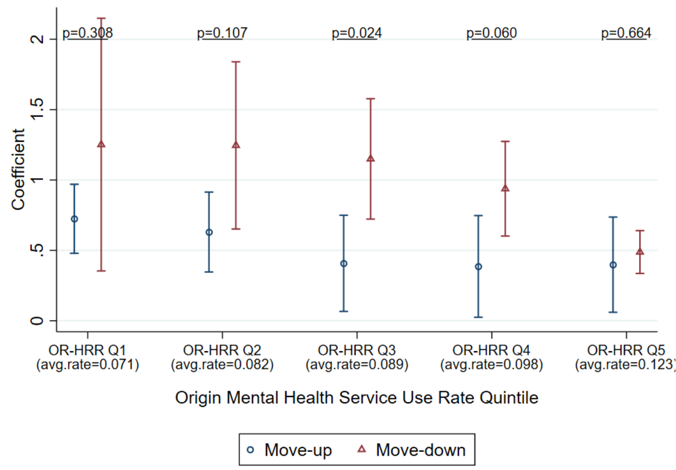
Figure 4: Robustness Checks



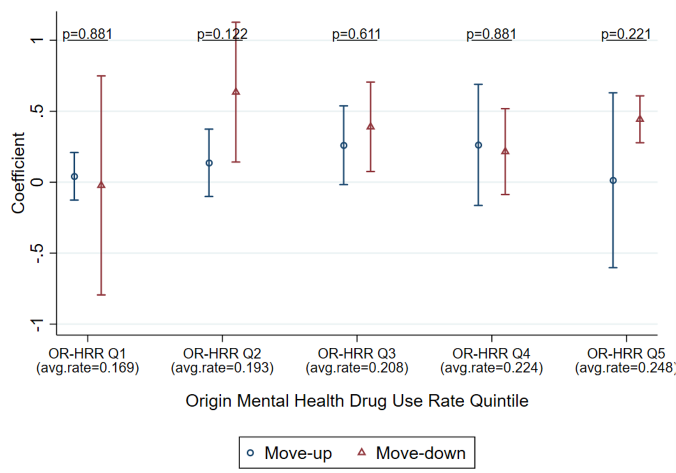
Notes: This figure plots the coefficients and 95% confidence intervals for the place effects of mental health service use (left panel) and drug use (right panel) estimated from different specifications. Baseline results from Table 2 are shown in the top row. The 2nd and 3rd rows restrict the sample to 2006–2009 (with moves in 2008–2009) and 2014–2018 (with moves in 2016–2018), respectively. The 4th row uses the full sample but calculates the difference in service or drug utilization rates between the destination and origin (δ_i) based on the HRR average utilization rate over the entire sample period, instead of the year before individual i moves. Row 5 excludes beneficiaries with both Medicare and Medicaid coverage, while row 6 drops individuals residing in states that have already expanded Medicaid as of the given year. Rows 7–9 includes movers across states and calculate treatment utilization rates at the state, county, and Hospital Service Area (HSA) levels, respectively. Rows 10–11 focus on movers across HRRs with treatment utilization rates above and below the median, or in the top and bottom quartiles. Row 12 drops individuals who moved into Florida from other states. The last row uses the same movers sample as the baseline but includes additional census region by year fixed effects. The coefficients and confidence intervals are derived from exported regression tables in Appendix Table A8-A10 and may have minor rounding errors.

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

(a) Service



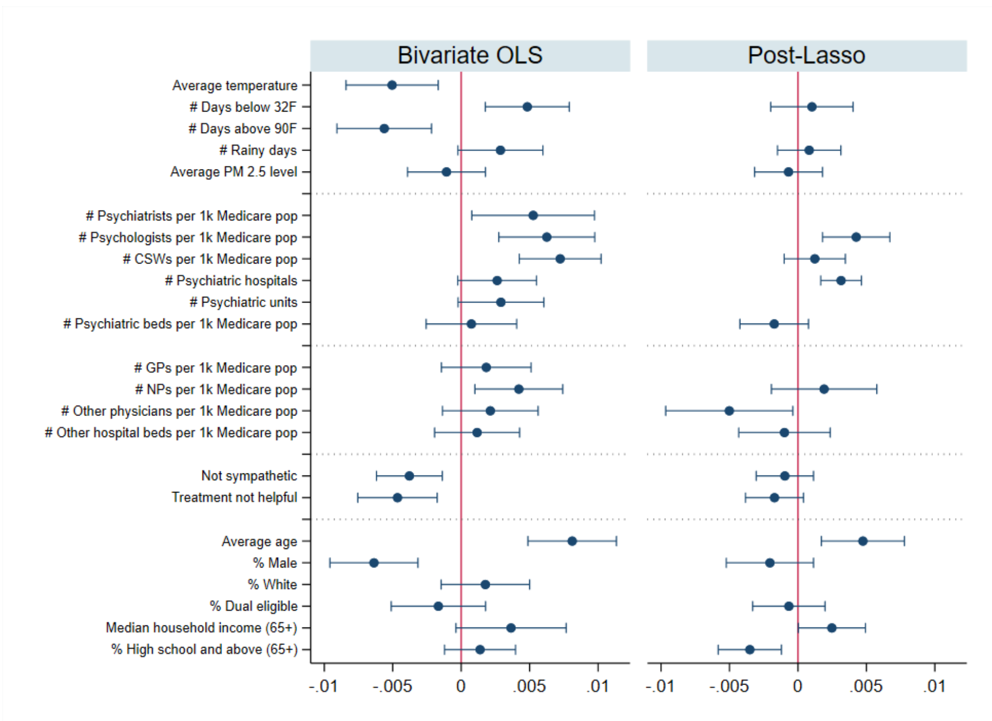
(b) Drug



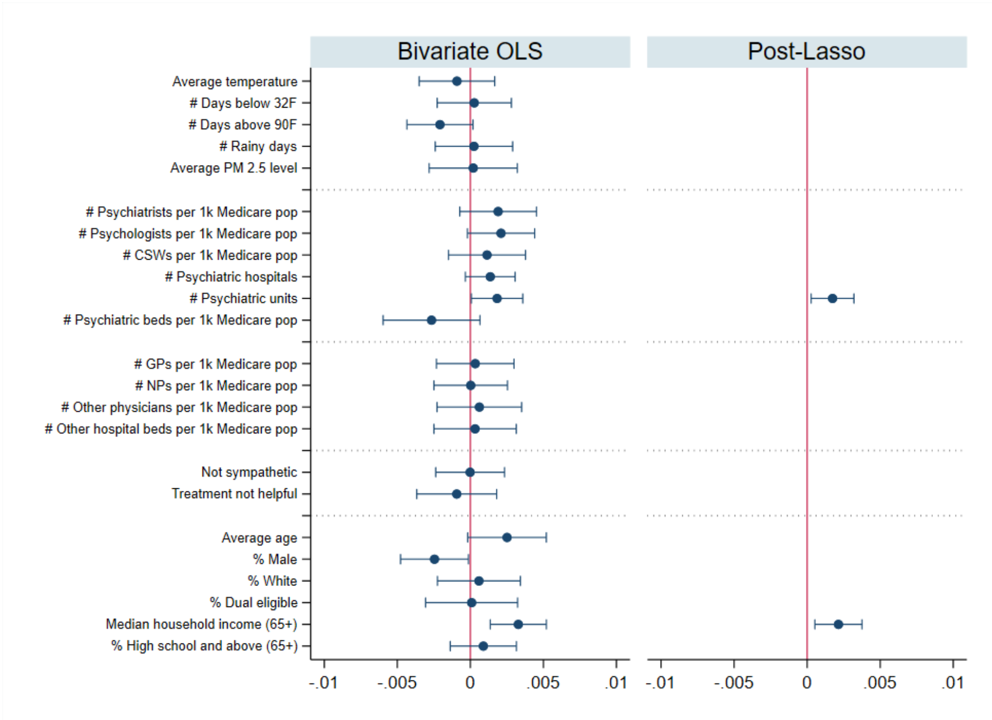
Notes: This figure shows the coefficients θ^{up} and θ^{down} estimated from equation (2), separately for five subsets of movers, grouped by the quintile of the treatment utilization rate in their original HRRs. The dependent variable is a dummy indicator denoting whether patient i had any mental health 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 ($Post_{it}$) 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. The p-values displayed above the coefficient pairs test for the equality of θ^{up} and θ^{down} within each origin HRR quintile. The average utilization rate of the origin HRRs in each quintile are listed beneath the x-axis in parenthesis.

Figure 6: Correlation between the Estimated HRR-level Place Effects and HRR Characteristics

(a) Service



(b) Drug



Notes: These figures show the correlation between HRR characteristics and the estimated HRR-level 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 (3) 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 C. 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.

Tables

Table 1: Summary Statistics for Mover and Non-Mover Samples

	Mover			Non-Mover
	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	12,188	9,083	15,394	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	0.394	0.456	0.151	0.119	0.157
	(0.0346)	(0.0595)	(0.0412)	(0.0293)	(0.0600)	(0.0322)
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 or 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 or drug utilization rate between the destination and origin (δ_i), interacting with the indicator for the post-moving period. For gender-specific sub-analysis, regional utilization rates are also calculated among the corresponding gender. 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: Place Effect of Mental Health Treatment Utilization — Intensive Measures

	(1)	(2)	(3)	(4)
	# Service Claims	Service Spending	Drug Dosage	Drug Spending
$\delta_i * Post_{it}$	0.500	0.408	0.185	0.189
	(0.0323)	(0.0538)	(0.0283)	(0.0491)
Observations	1,008,027	1,008,027	1,008,027	1,008,027
Dep. Mean	0.709	169.0	0.502	125.8

Notes: This table presents the place effect of mental health service or drug utilization, estimated using the movers sample, excluding the year of the move. All regressions are estimated using Poisson pseudo-likelihood regression with multiple levels of fixed effects ('ppmlhdfe'). The dependent variable is the number of mental health service claims, total spending on mental health service, total dosage of mental health medications (relative to the national median), and total spending on mental health medications (Columns (1)–(4) respectively) in year t. The main independent variable is the difference in the corresponding average treatment use intensity (in logs) 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 4: Place Effect of Mental Health Treatment Utilization, Excluding Nursing Home Patients

	(1)	(2)	(3)	(4)
	Any Service Use		Any Drug Use	
$\delta_i * Post_{it}$	0.283		0.121	
	(0.0330)		(0.0291)	
$\delta_i^{nNF} * Post_{it}$		0.370		0.139
		(0.0439)		(0.0314)
Observations	895,721	895,721	895,721	895,721
Dep. Mean	0.0899	0.0899	0.229	0.229

Notes: This table presents the place effect of mental health service or drug utilization, estimated using the movers sample, excluding the year of the move and years when patients having any claim from nursing facilities. The dependent variable is a binary variable indicating whether patient i had any mental health service claim (Columns (1)–(2)) or any mental health drug claim (Columns (3)–(4)) in year t. The main independent variable is the difference in the service or drug utilization rate between the destination and origin measured using all non-movers (δ_i) or non-movers outside nursing facilities (δ_i^{nNF}), 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 5: 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 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 Movers and Moving Patterns

The movers sample used in the analysis consists of 141,740 individuals, covering all 306 Hospital Referral Regions (HRRs) as both origins and destinations, and a total of 32,853 origin-destination HRR pairs. Appendix Figure A15 shows the distribution of the number and share of movers across HRRs. The top three most popular moving routes are from East Long Island, NY to Fort Lauderdale, FL; from Newark, NJ to Camden, NJ; and from Houston, TX to Austin, TX. At the state level, Florida, California, and New York see the most people moving out, while Florida, Texas, and North Carolina see the most people moving in. Appendix Figure A16 shows the distribution of moving distances, with an average distance of 597 miles.

Table 1 presents summary statistics for movers and non-movers in terms of basic demographics and healthcare utilization levels. Additionally, Table A3 shows further characteristics among people aged 65 and older from the American Community Survey (ACS) during 2006–2018. Movers tend to have higher education levels, higher household incomes, and are more likely to be divorced, widowed, and out of the labor force. This is consistent with findings by Finkelstein et al. (2016) using data from the Health and Retirement Study (HRS). In particular, Appendix Table A4 indicates that being divorced, losing a partner, and retiring in the last year are strong predictors of moving.

Although these major life events predict the decision and timing to move, they do not significantly correlate with the direction of moving in terms of mental health treatment utilization rates. Using the cross-state movers sample from the ACS, Appendix Table A5 shows that differences in mental health service and drug utilization rates between destination and origin states are not significantly different among people who have recently experienced divorce, the death of a spouse, or retirement. This is likely because the majority of elderly individuals move to be closer to children or relatives or due to living cost considerations, while only a small share move and choose destinations for health reasons Finkelstein et al. (2016).

B Mental Health Service Use in Claim Data

Mental health service use is identified in claims data for inpatient, outpatient, and physician services based on the diagnosis code. These diagnosis codes are recorded using ICD-9 codes during 2006–2015Q3 and ICD-10 codes since 2015Q4. ICD codes for different types of mental health conditions are reported in Appendix Table A1.

When identifying claims related to mental health services, only the primary diagnosis code is considered. According to the Medicare Coding Manual, the primary diagnosis should reflect the condition chiefly responsible for the admission or service (CMS, 2024). In addition to the primary code, inpatient and outpatient claim data can include up to 24 additional conditions, and physician claim data can include up to 12. These secondary codes record conditions that coexist with the primary one.

When a mental health disorder is recorded as the second-order diagnosis, 43.1% of cases also have the primary diagnosis related to a mental health disorder (see Appendix Figure

A17). The share decreases further as the diagnosis order increases. Among claims that list mental illness as non-primary diagnosis, common primary diagnoses include essential hypertension (13.4%), diabetes mellitus (6.2%), and general symptoms (6.1%). These claims likely reflect healthcare visits for other conditions with mental health recorded as a comorbidity, rather than involving mental health treatment. This is supported by Appendix Figure A18 panel (a), which shows that 99.3% of claims with the primary mental health diagnosis involve mental health-related procedures, whereas fewer than 5% of claims with only non-primary mental health diagnoses involve such services.[45] Panel (b) shows that around 45% of claims with a primary mental health diagnosis involve psychotherapy, compared to 2.3% of claims with only a second-order mental health diagnosis or even lower in higher-order diagnoses.

Taken together, including all diagnoses will capture services for other conditions where mental health is only coded as a comorbidity, rather than true mental health service use. Moreover, the variability in coding practices for comorbidities among providers can introduce additional measurement error, further supporting the decision to focus on primary diagnoses.

For completeness, I replicated the main result for service use by identifying services using two or more diagnosis codes. As shown in Appendix Figure A19, the estimated place effect decreases when higher-order diagnoses are considered. One explanation, following the reasoning above, is that the measurement focuses more on mental illness as comorbidities rather than its treatment, so patient-side factors, such as health status, can play a more significant role. However, given the measurement error related to higher-order diagnosis codes, it is not recommended to draw any definitive conclusions from these results.

Another issue to notice when constructing mental health service use measurements is that cognitive disorders, such as dementia, are not included. Although they are listed under "Mental Disorders" section in the ICD, they are generally considered neurological disorders rather than mental illnesses. Moreover, treatment differs significantly from that of typical mental illnesses such as mood disorders, focusing mainly on pharmacological management of symptoms. Therefore, I do not consider visits for cognitive disorders as mental health care visits. However, since service use is identified based on the primary diagnosis, there might be a concern if patients with dementia are more likely to have dementia as the primary diagnosis and other mental illnesses as secondary diagnoses when the visit is actually for those other mental conditions. To address this, I tested the sensitivity of the results using two alternative definitions of mental health service visits: 1) claims with primary diagnoses of cognitive disorders or the current list of mental illnesses; 2) claims with primary diagnoses in the current list of mental illnesses and no cognitive disorders as secondary diagnoses. Appendix Table A16 shows that both measurements produce essentially the same place effect, similar to the baseline. Moreover, when patients with cognitive disorders are entirely excluded from the sample (both the movers sample and the baseline sample for calculating the regional utilization rates), the results are only moderately reduced. This could be because people with cognitive disorders are more likely to rely on caregivers for healthcare decisions. When they move to new places and are cared for by local caregivers, they may converge more to the local utilization pattern.

[45] Procedures related to mental health can be identified in Medicare physician service data, which report all procedures provided during each visit and the diagnosis supporting each procedure. This level of detail is not available in inpatient and outpatient claims, so these types of claims are not included in this analysis.

C 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.

D Selection on unobservables

In this section, I follow the method developed by Oster (2019) to adjust for selection on unobservables. The intuition of this empirical analysis is to use the sensitivity of the treatment effects when including observed controls to infer the bias due to omitted unobserved controls. In this specific setting, selection on unobservables may come from time-varying factors correlated with both changes in local utilization rates and changes in individual treatment use behavior upon moving, while all time-invariant individual characteristics are controlled by fixed effects.

This method is further developed by Finkelstein et al. (2021b) in the use of movers design in identifying the place effect on mortality. However, unlike Finkelstein et al. (2021b), who examines an outcome that cannot be measured repeatedly (i.e., death) and therefore can only use the selection on the observables and unobservables of the origin to infer those of the destination, the outcome measures in this paper are recorded annually. This enables me to include individual fixed effects to control for all individual-level time-invariant characteristics and use this as a way to bound the potential selection on other unobservables.

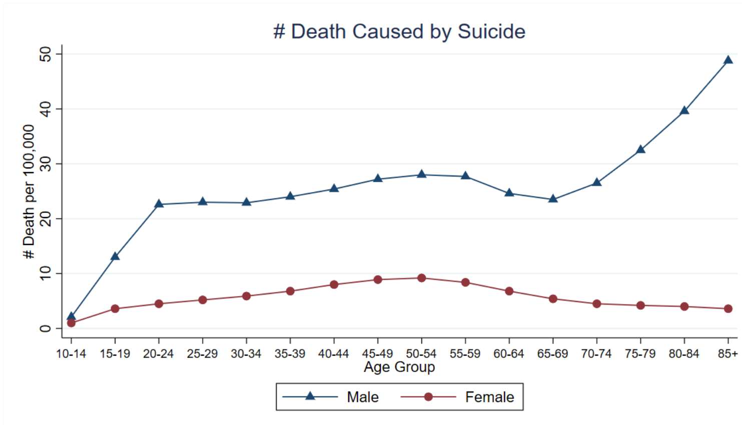
Appendix Table A11 presents the results of the adjustment. Column (1) reports the coefficient and R-squared estimated in models without individual fixed effects. What remains controlled are the origin HRR fixed effects, year relative to move fixed effects, calendar year fixed effects, and age-group fixed effects. It is essentially the same if we first residualize all outcomes, as well as the change in local utilization rate, by regressing them on these fixed effects and then run the regression using these residuals. Column (2) reports the coefficient and R-squared with individual fixed effects, which is also the baseline result in the main text.

Column (3) reports the adjusted coefficient under two benchmark assumptions suggested by Oster (2019): i) $R_{max} = 1.3 * R2_c$, where $R2_c$ is the R-squared of the model with the full set of controls (i.e., the model in column (2)); and ii) $\delta = 1$, which implies that the observed and unobserved variables have the same relative degree of selection. The adjusted coefficients are only modestly lower than the baseline result (e.g., 0.377 for service use and 0.107 for prescription drugs).

Note that these two assumptions are quite conservative. The R_{max} assumption assumes that with a hypothetical full set of unobservables controlled, we can explain 56% of the variation in mental health service use (82% for drugs). However, models controlled for the past year mental health treatment usage, including whether there is any claim and total payment in log for both service and drugs, together with all the fixed effects, only has an R-squared of 46% (69% for drugs). If we use the latter R-squared as the R_{max}, the adjusted coefficient, as shown in Column (4), is even closer to the baseline (0.439 for service and 0.138 for drugs).

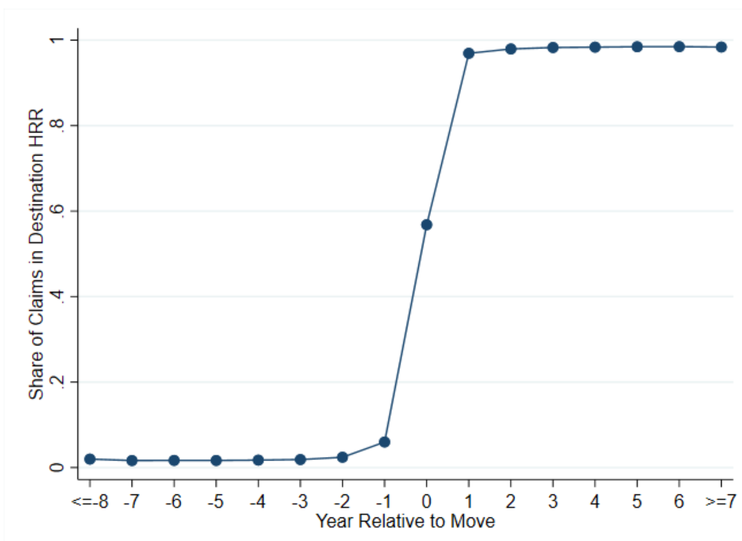
Appendix Figures

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.

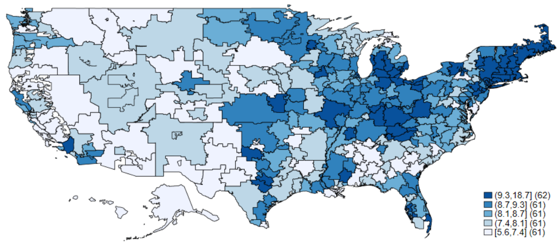
Figure A2: Share of Claims in Destination HRR by Years Relative to Moving



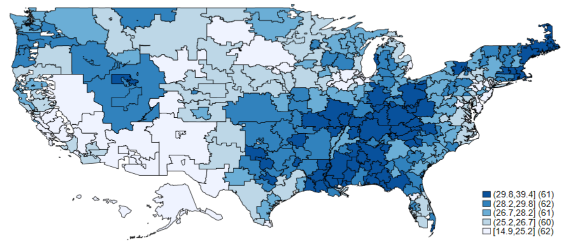
Notes: This figure shows the average share of medical claims from movers' destination HRRs out of all medical claims from either their origin or destination HRRs, by number of years relative to moving.

Figure A3: Mental Health Treatment Utilization Rate and Average Spending by HRR

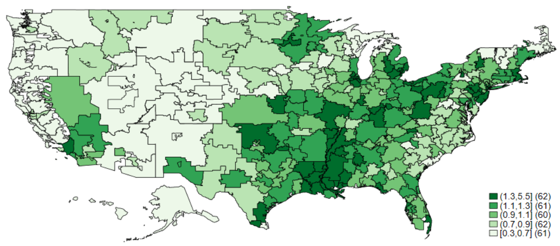
(a) Service (%, including people not covered by Part D)



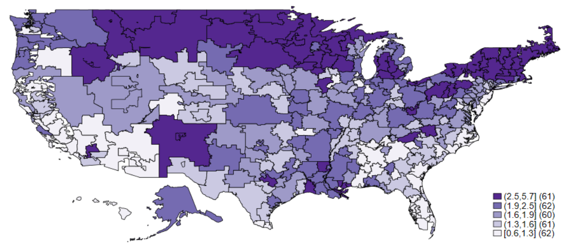
(b) Service or Drug (%)



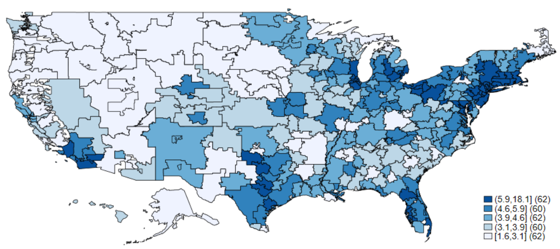
(c) Service — Inpatient (%)



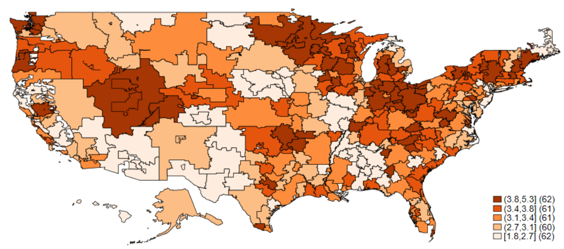
(d) Service — Outpatient (%)



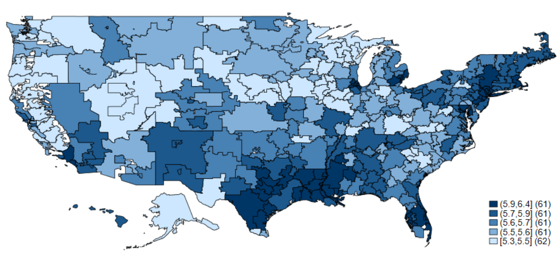
(e) Service — Mental Health Professionals (%)



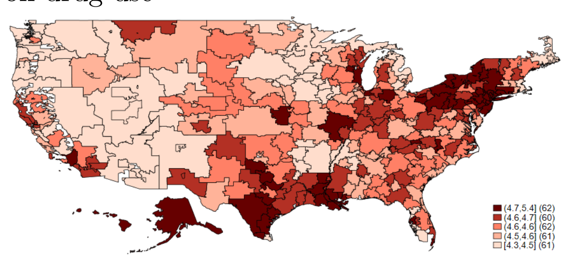
(f) Service — Primary Care Providers (%)



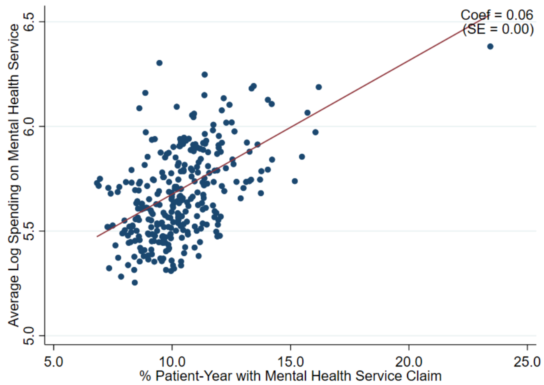
(g) Mental health service spending conditional on service use



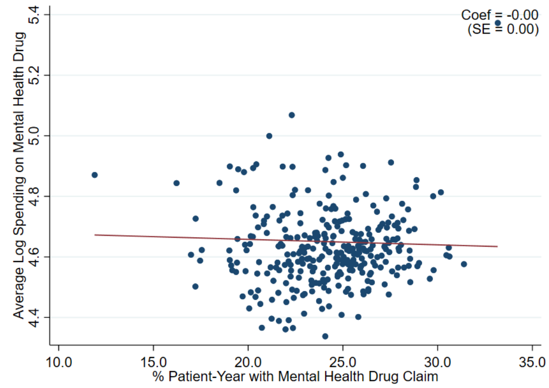
(h) Mental health drug spending conditional on drug use



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



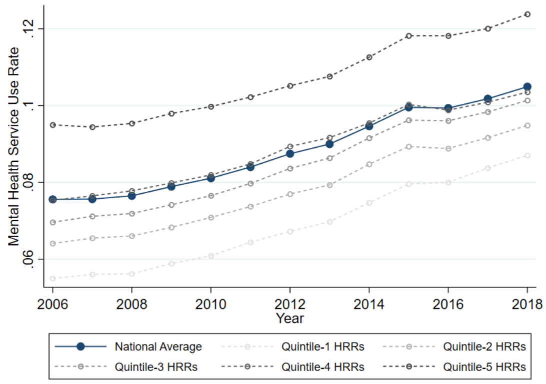
(j) Correlation between mental health drug use rate and average spending conditional on use



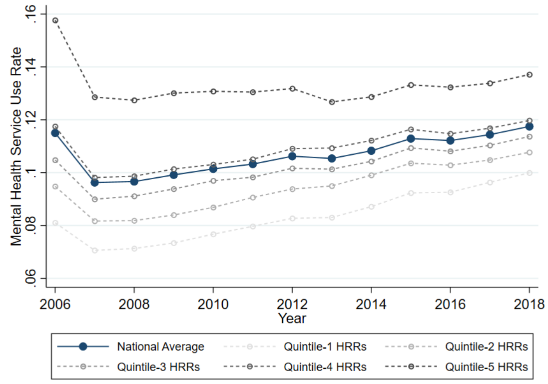
Notes: These figures plot the distributions of mental health treatment utilization rates by HRR. The sample includes Medicare Fee-for-Service (FFS) beneficiaries aged 65–99, with full coverage under Parts A, B, and D (except in Panel (a) where Part D coverage is not required) in each year, drawn from 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 use, and Panel (h) plots average mental health drug spending conditional on use. Panel (i) and (j) show scatter plots for HRR mental health service or drug utilization rate and average 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 A4: Mental Health Treatment Utilization Rate over Time

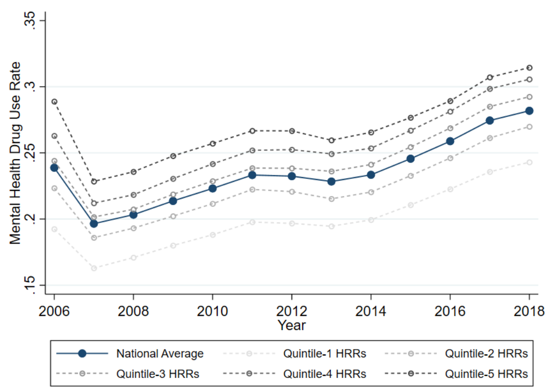
(a) Service (%, including people not covered by Part D)



(b) Service (%, only people covered by Part D)



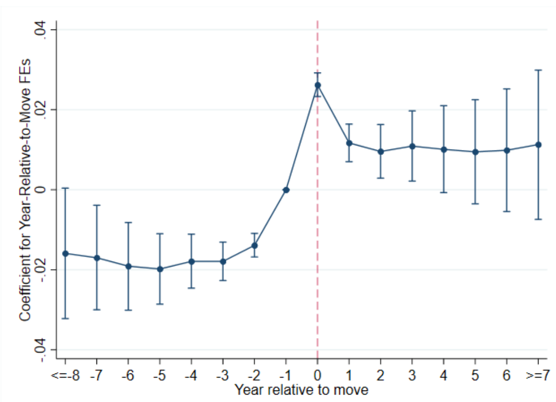
(c) Drug (%, only people covered by Part D)



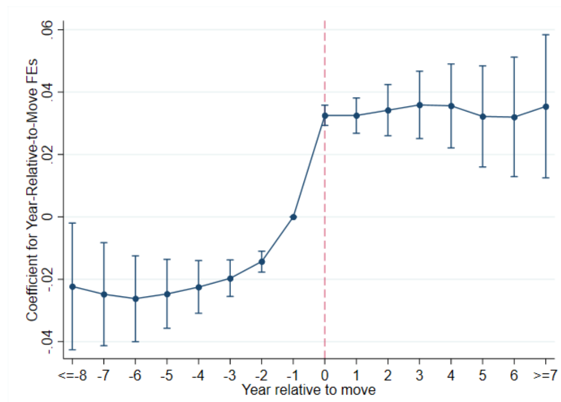
Notes: These figures show the change in mental health treatment rates over time. The sample includes Medicare Fee-for-Service (FFS) beneficiaries aged 65–99, with full coverage under Parts A, B, and D (except in Panel (a) where Part D coverage is not required), drawn from 20% Medicare FFS claims data, 2006–2018. Panels (a) and (b) show rates of mental health service use, and Panel (c) shows rates of mental health drug use. In each panel, the solid line displays the population-weighted average utilization rate at the national level. The dashed lines display the averages among five fixed groups of HRRs, categorized based on their 2006 utilization rates.

Figure A5: Year-Relative-to-Move Fixed Effects

(a) Service



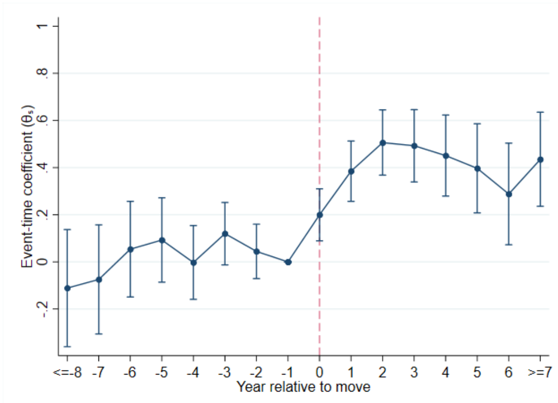
(b) Drug



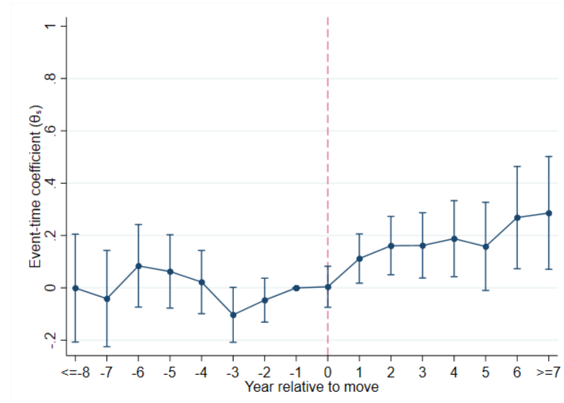
Notes: These figures show coefficients for the year-relative-to-move fixed effects (ρ_s) estimated from Equation (1). The sample includes 1,150,872 patient-year observations. The dependent variable is a binary indicator for whether patient i had any mental health service claim in year t (Panel (a)) or any mental health drug claim (Panel (b)). The dashed lines represent the upper and lower bounds of the 95% confidence interval, based on standard errors clustered at the individual level.

Figure A6: Place Effect by the Share of Claims from Destination HRRs in Year 0

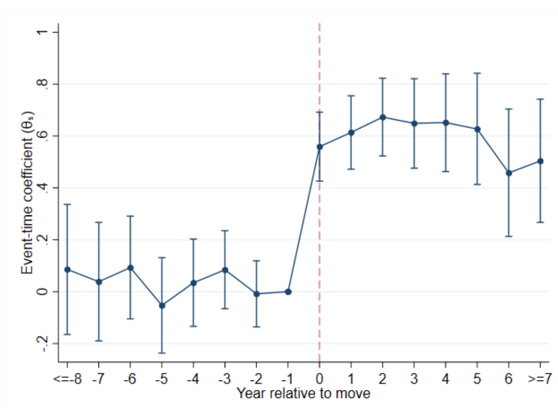
(a) Service — Below Median



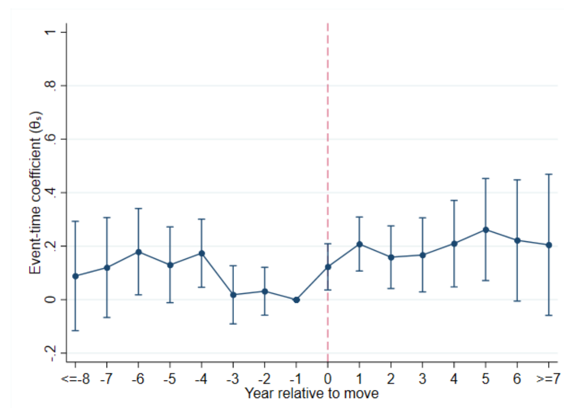
(b) Drug — Below Median



(c) Service — Above Median

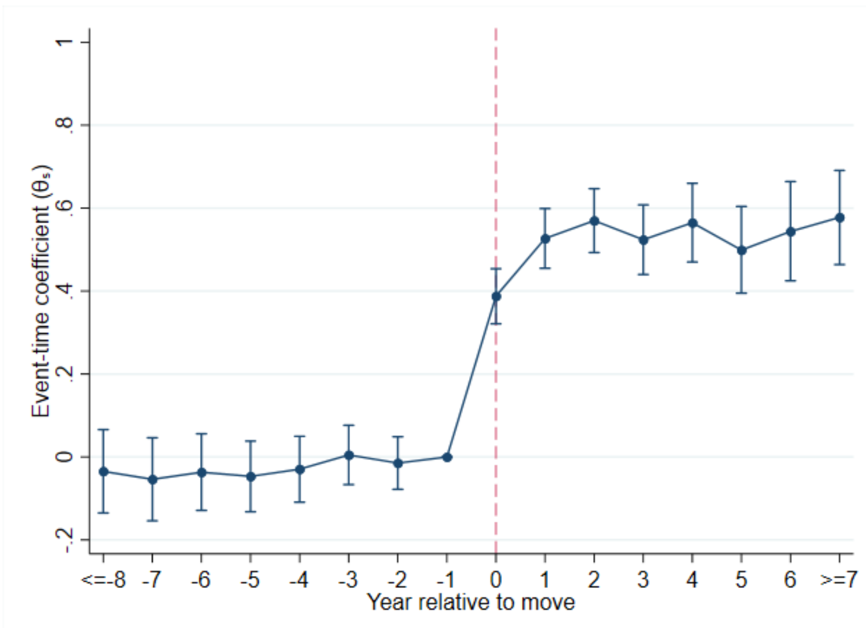


(d) Drug — Above Median



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).

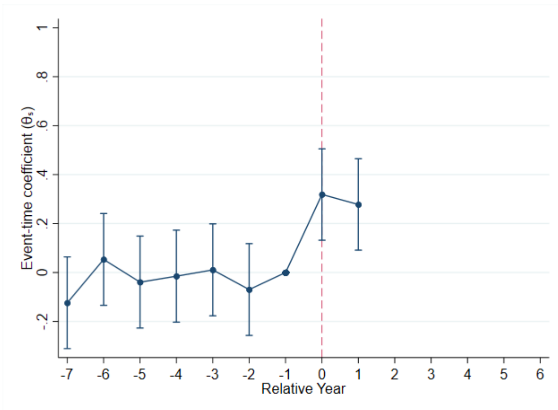
Figure A7: Place Effect: Mental Health Service Use (not conditional on Part D coverage)



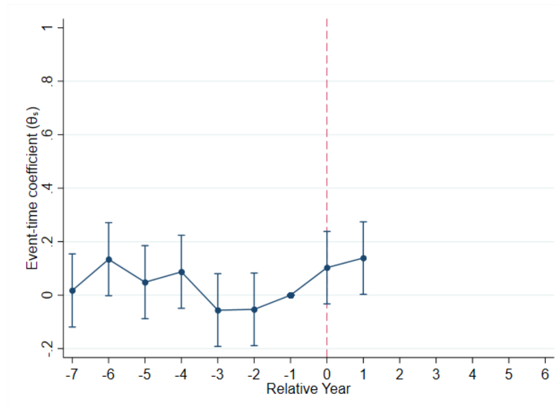
Notes: This figure replicates the event study estimation in Figure 3. The sample does not require Part D coverage and includes 2,840,919 patient-year observations. The dependent variable is a binary indicator for whether patient i had any mental health service claim in year t. The HRR mental health service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

Figure A8: Place Effect: Balanced Panel

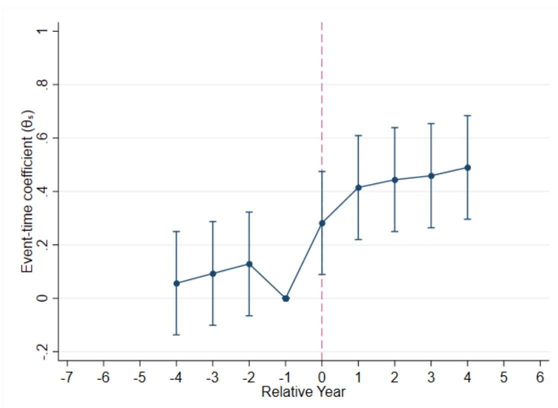
(a) Service — Relative year [-7,1]



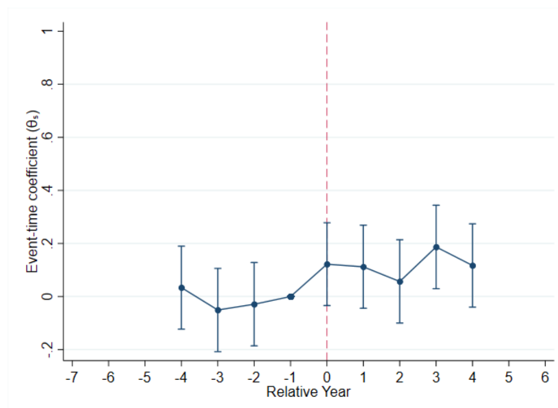
(b) Drug — Relative year [-7,1]



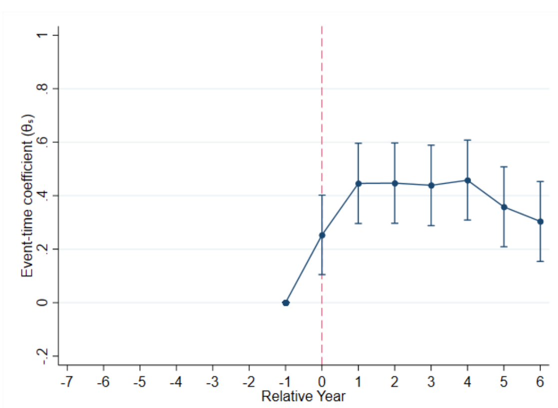
(c) Service — Relative year [-4,4]



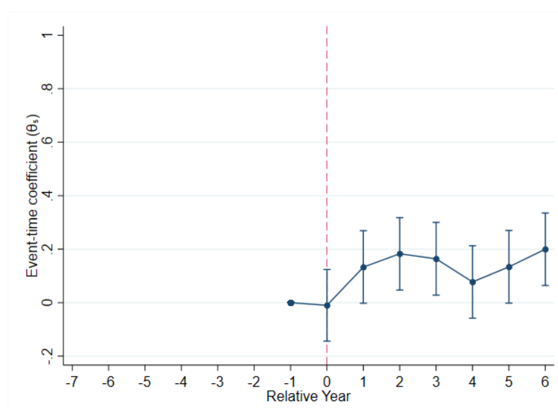
(d) Drug - Relative year [-4,4]



(e) Service — Relative year [-2,6]



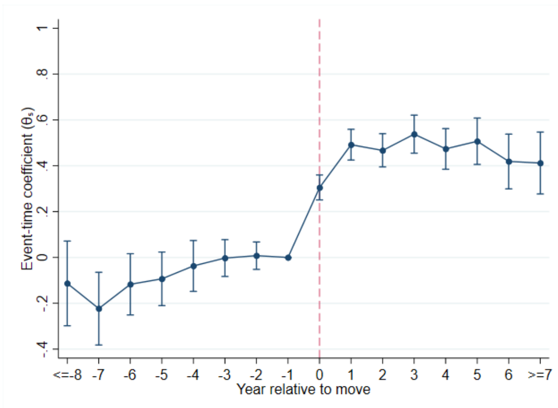
(f) Drug — Relative year [-2,6]



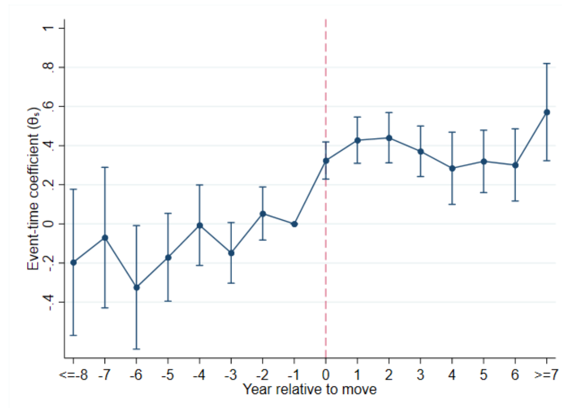
Notes: These figures replicate the event study estimation in Figure 3 using different sets of balanced samples. Panels (a) and (b) use a balanced panel in relative years [-7,1], which includes 224,491 mover-year observations (25,289 movers). Panels (c) and (d) use a balanced panel in relative years [-4,4], which includes 181,302 mover-year observations (20,351 movers). Panels (e) and (f) use a balanced panel in relative years [-1,6], which includes 213,601 mover-year observations (27,220 movers).

Figure A9: Place Effect: Intensive Margin

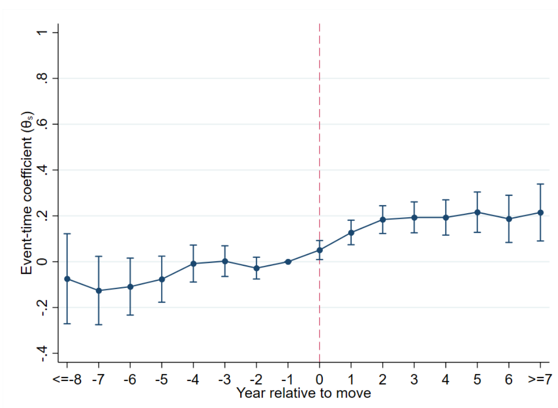
(a) Number of Service Claims



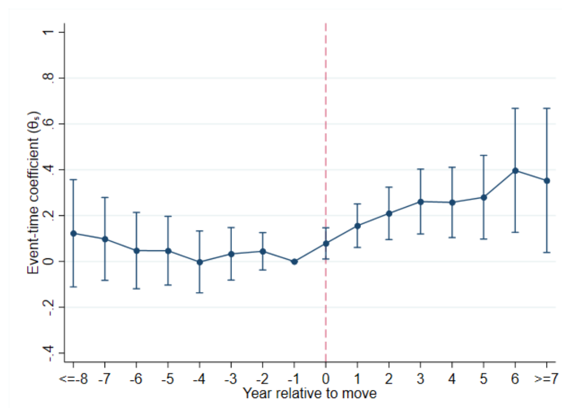
(b) Service Spending



(c) Drug Dosage



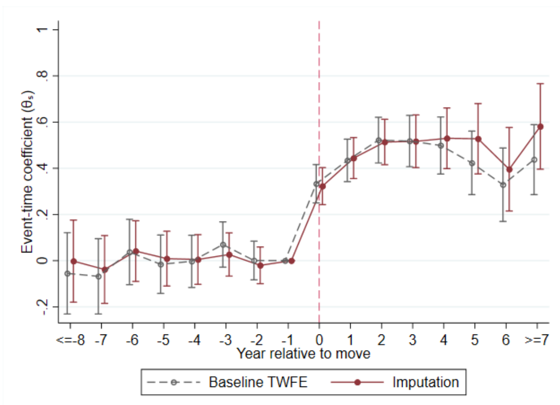
(d) Drug Spending



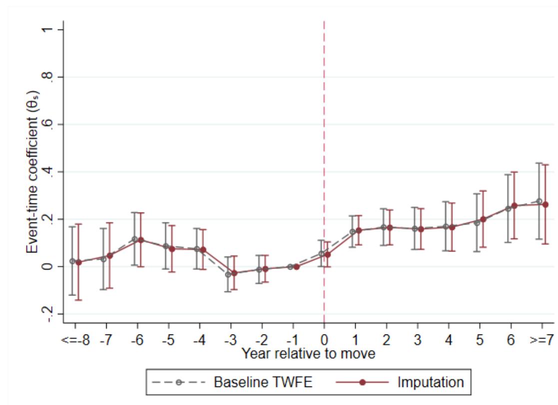
Notes: These figures show the event study estimation corresponding to Table 3. Panel (a) shows result for the number of mental health service claims. Panel (b) shows result for total spending on mental health service claims. Panel (c) shows result for the total dosage of mental health medications (relative to the national median). Panel (d) shows result for total spending on mental health medications. The main independent variable is the difference in the corresponding average treatment use intensity (in logs) between the destination and origin (δ_i), interacting with the indicator for years relative to moving. All regressions are estimated using Poisson pseudo-likelihood regression with multiple levels of fixed effects ('ppmlhdfe') including individual fixed effects, calendar year fixed effects, relative year fixed effects, and five-year age group fixed effects.

Figure A10: Event Study using the Imputation-Based Strategy

(a) Service



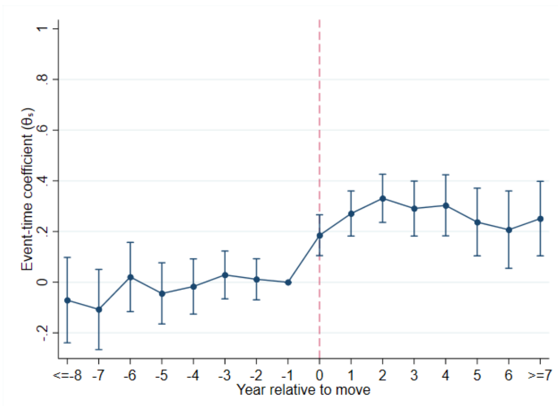
(b) Drug



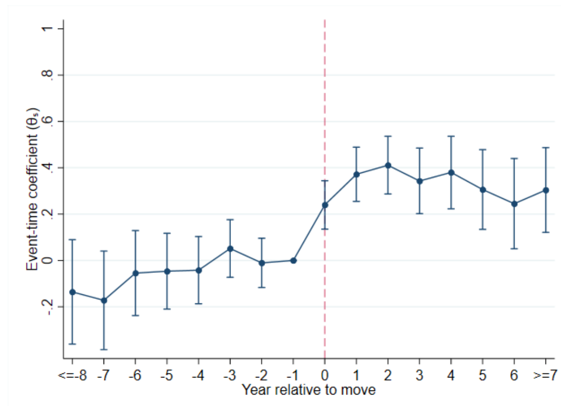
Notes: These figures show the event study results using the imputation method. The estimation is produced by first regressing mental health service or drug use on HRR-year and age-group fixed effects among the sample of all nonmovers and using these estimates to construct the residualized outcome for each mover. The residualized outcome is then used as the dependent variable in a series of event studies by the year of move. The right-hand side of each regression includes individual fixed effects, the difference in average service or drug use rates among all nonmovers between the mover's destination and origin HRR in each year, and its interaction with the year relative to move indicators. Coefficients from the interaction term are extracted and aggregated using the number of movers observed in each cell as weights. These coefficients are plotted in red, with the baseline coefficients plotted in gray. The vertical lines represent the upper and lower bounds of the 95% confidence interval, based on standard errors clustered at the individual level.

Figure A11: Place Effect: Excluding Patients in Nursing Facilities

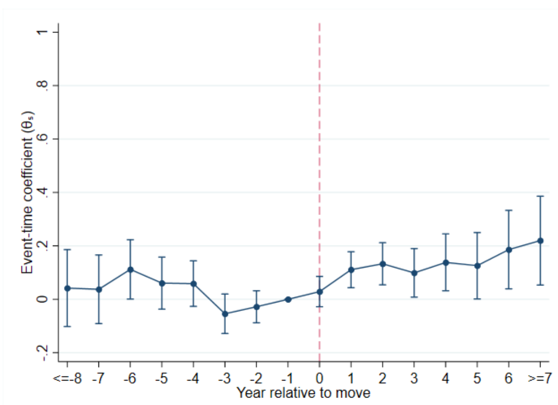
(a) Service — δ_i



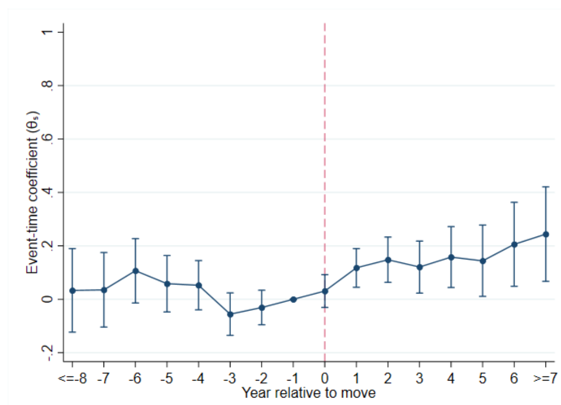
(b) Service — δ_i^{nNF}



(c) Drug — δ_i

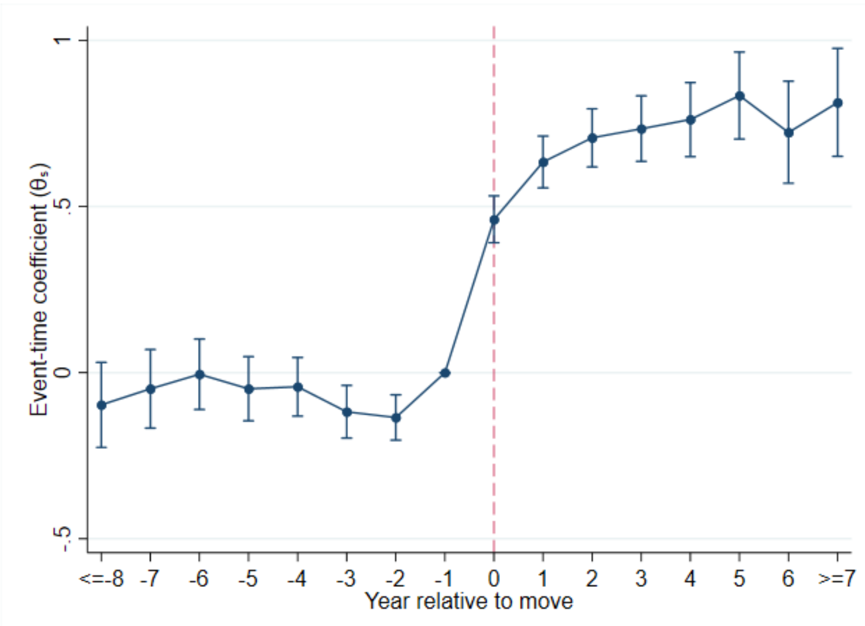


(d) Drug — δ_i^{nNF}



Notes: These figures replicate the event study estimation in Figure 3 using sample that excludes patients in years with any claim from nursing facilities. Panel (a) and (c) measures the difference in the service or drug utilization rate between the destination and origin measured using all non-movers (δ_i). Panel (b) and (d) measures the difference using non-movers outside nursing facilities (δ_i^{nNF}).

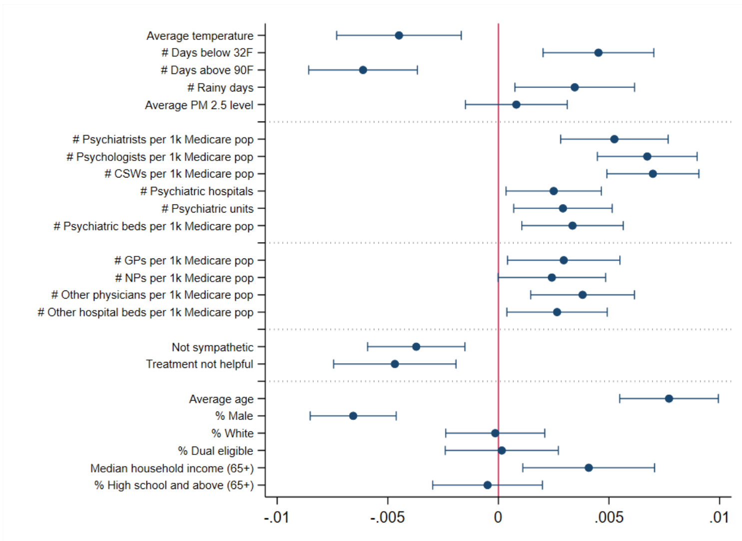
Figure A12: Place Effect of Nursing Home Use



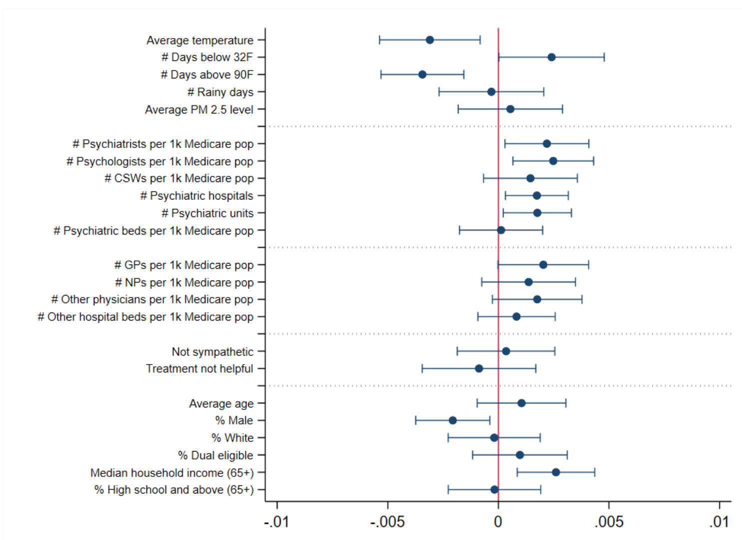
Notes: This figure show coefficients θ_s estimated from Equation (1) for nursing home use. The dependent variable is a binary indicator for whether patient i had any nursing home claim in year t. θ_s are a sequence of coefficients for the interaction terms between destination-origin differences in HRR nursing home utilization rates (δ_i) and indicators for each year relative to moving, where relative year -1 is normalized to 0. Please see the notes in Figure 3 for more details on sample and specification.

Figure A13: Correlation between the Estimated HRR-level Place Effect and HRR Characteristics — Full Set of HRRs

(a) Service

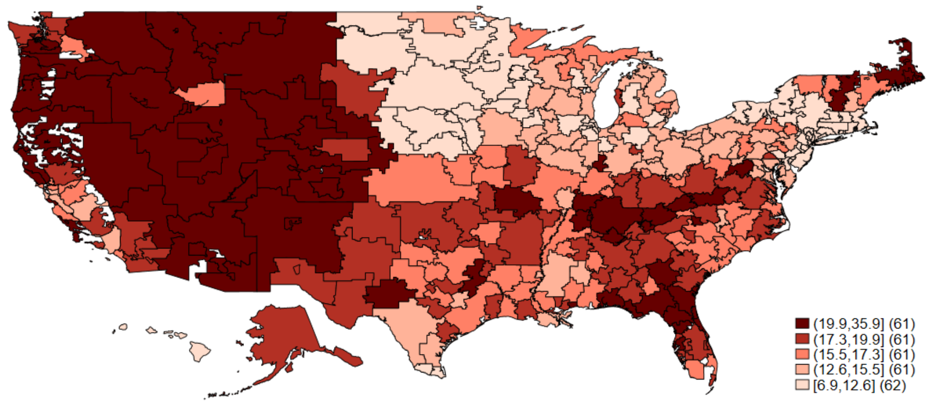


(b) Drug



Notes: These figures replicate the correlation coefficients based on bivariate OLS regressions displayed in Figure 6 using all possible HRRs for each HRR characteristic. Specifically, correlations with environmental factors are among 286 HRRs, correlations with public attitude factors are among 240 HRRs, and all others are among the full set of 306 HRRs.

Figure A14: Suicide Rate (per 100,000) by HRR

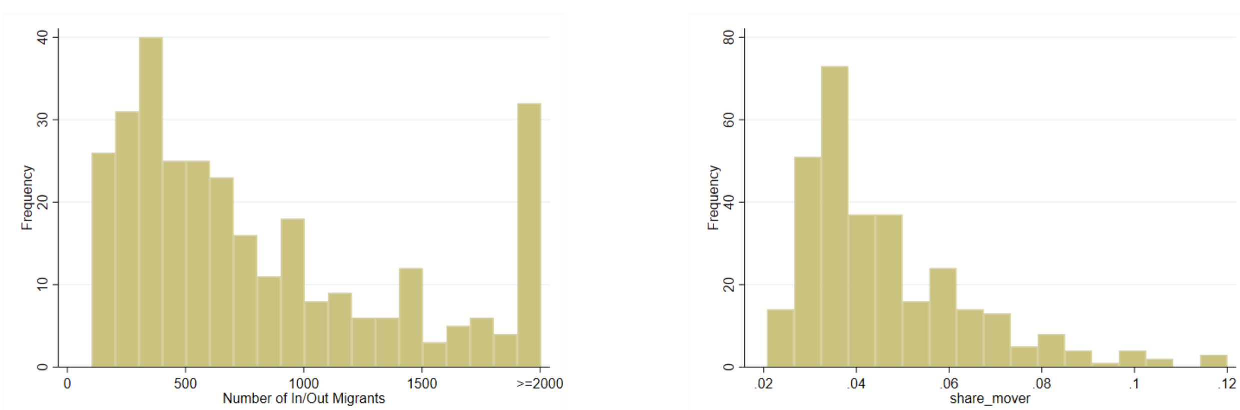


Notes: This figure present the distribution of suicide rate for the population above age 65 by HRR. The suicide rate comes from the CDC Underlying Cause of Death database, 1999–2019. Death counts are at the county level, which are aggregated to the HRR level based on a zip code crosswalk and population share.

Figure A15: Histogram of the Number and Share of Movers across HRRs

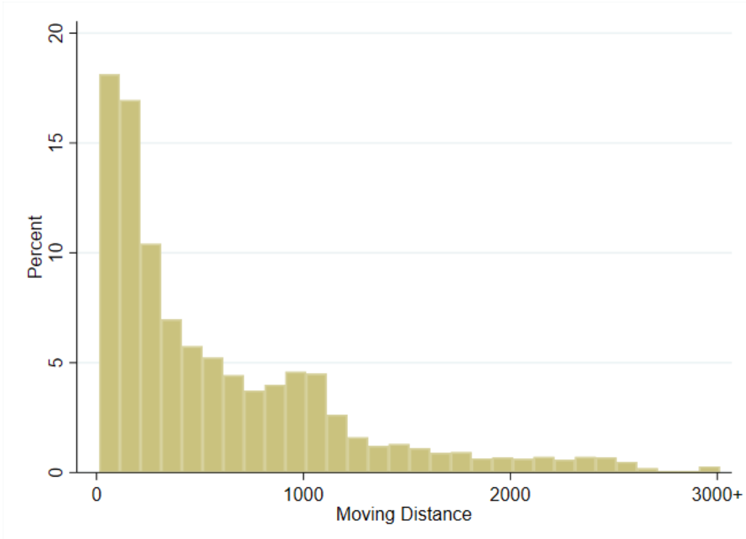
(a) Number of Movers

(b) Share of Movers



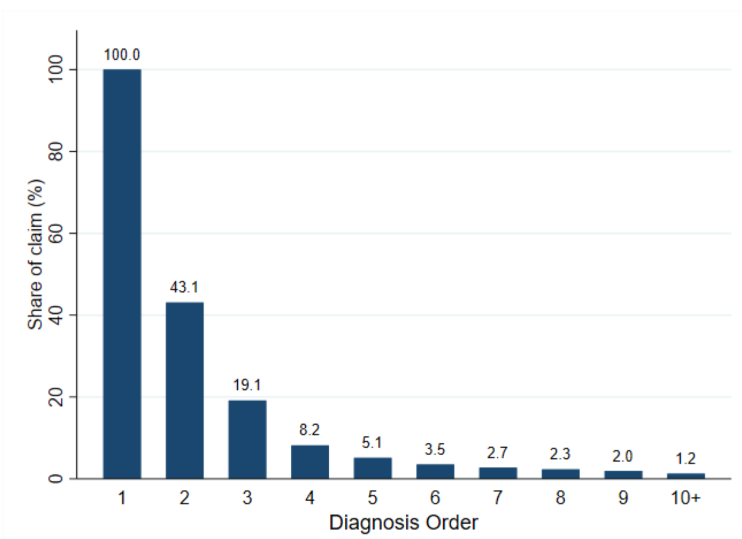
Notes: These figures plot the distribution of the number of movers (panel (a)) and the share of movers within the total population (panel (b)) in each HRR.

Figure A16: Histogram of Moving Distances (Miles)



Notes: This figure plots the distribution of moving distances in the main sample. The distance between the origin and destination HRRs is calculated as the average distance between zip codes within the two respective HRRs.

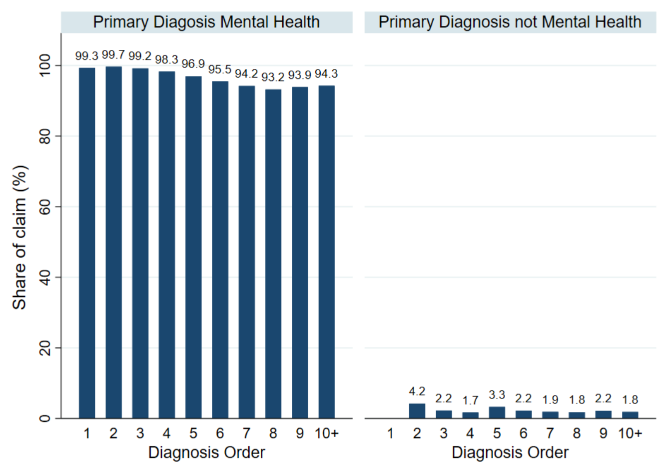
Figure A17: Share of Claims with Primary Mental Health Diagnosis Conditional on Higher Order Diagnoses



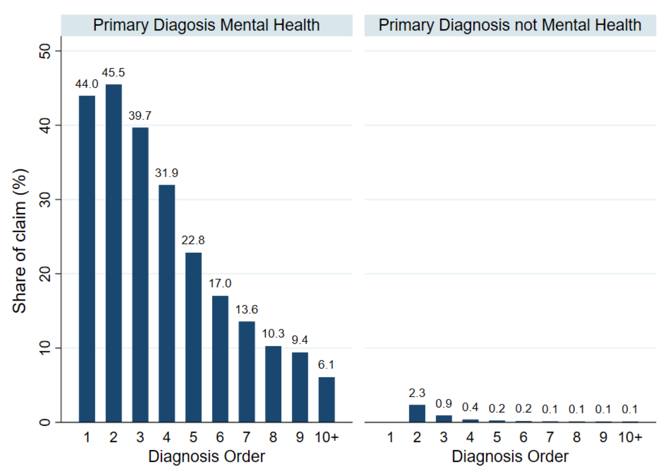
Notes: This figure presents the share of claims where mental illness is recorded as a primary diagnosis when also coded in higher orders. The claims include inpatient, outpatient, and physician service claims in Medicare 20% data from 2006–2018.

Figure A18: Share of Claims with Mental Health-Related Procedures by Diagnosis Order

(a) Mental Health-Related Procedures

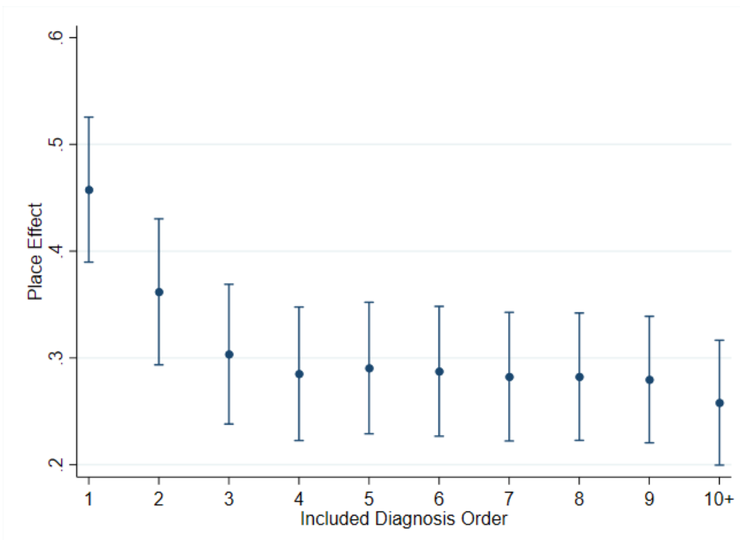


(b) Psychotherapy



Notes: These figures present the share of claims with mental health-related procedures (panel (a)) and specifically psychotherapy (panel (b)). The data include physician service claims in Medicare 20% data from 2006–2018. Mental health-related procedures are identified based on diagnosis codes supporting each procedure (i.e., line diagnosis codes), and psychotherapy is identified based on line procedure codes. In each panel, the left graph shows claims with mental illness recorded in both the primary diagnosis and in each order specified on the x-axis, while the right graph shows claims with mental illness recorded in each order but not in the primary diagnosis.

Figure A19: Place Effect — Mental Health-Related Visits Identified using Higher Order Diagnoses



Notes: This figure presents the difference-in-difference coefficients for changes in mental health-related visits when moving across regions with different average rates. Mental health-related visits are identified using diagnoses ranging from only the primary diagnosis to all diagnosis codes, as indicated on the x-axis. When using only the primary diagnosis, the estimation is the same as the main result shown in column (1) of Table 2. See the notes in Table 2 for more details on the specification. Regional diagnosis rates are calculated using the corresponding definition of mental health-related visits.

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 Regional Medicare Advantage Enrollment and Mental Health Treatment Use Rates

	(1)	(2)	(3)	(4)
	Medicare Advantage Rate			
MH Rate — Service	1.426	0.520		
	(0.505)	(0.336)		
MH Rate — Drug			-0.0887	0.356
			(0.383)	(0.254)
Demo. Controls		Yes		Yes
Observations	306	306	306	306
Dep. Mean	0.282	0.282	0.282	0.282

Notes: This table presents the correlation between HRR's Medicare Advantage (MA) enrollment rate and mental health service or drug use rate. MA enrollment rates are calculated using Medicare beneficiaries aged 65–99 years with full-year Medicare enrollment. Mental health service drug use rates are calculated among beneficiaries with fee-for-service Medicare Part A, B and Part D coverage. Columns (1) and (3) regress the HRR's MA enrollment and mental health treatment rates directly. Columns (2) and (4) regress the residualized HRR rates from regressions controlling for the share of females, whites, dual-eligible, Part D enrollment, and the average age of the corresponding sample. All regressions are weighted by the number of individual-year observations in each HRR. Robust standard errors are reported in parentheses.

Table A3: Summary Statistics for Mover and Non-Mover, ACS Data

	(1) Mover	(2) Non-Mover
Male	0.430	0.436
Age	74.5	74.7
White	0.870	0.843
Black	0.067	0.087
Education		
Less than high school	0.131	0.175
High school	0.381	0.417
Some college	0.190	0.172
College and above	0.142	0.106
Household income (median)	49,900	44,160
Marital status		
Married	0.479	0.557
Divorced or separated	0.182	0.130
Widowed	0.296	0.263
Single/Never married	0.043	0.050
In labor force	0.114	0.169
Observations	70,133	6,528,275

Notes: This table presents the summary statistics for movers and non-movers aged 65 and above from the American Community Survey (ACS) data, 2006–2018. Movers are defined as individuals who moved across state lines in the past year, while non-movers are those who stayed in the same residential address.

Table A4: Correlation between Moving Decision and Life Events

	(1)	(2)	(3)
		Move	
Divorced last year	0.0290		
	(0.00217)		
Spouse died last year		0.00867	
		(0.000546)	
Retired last year			0.0131
			(0.000471)
Observations	5,462,460	5,462,460	5,462,460
Dep. Mean	0.0106	0.0106	0.0106

Notes: This table presents the correlation between the indicator of moving and the life events experienced in the last year. Observations are individuals above age 65 in the ACS data from 2006 to 2018. Movers are defined as individuals who moved across state lines in the past year, while non-movers are those who stayed in the same residential address. 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. All regressions control for gender, age, race, education level, household income, as well as interview year fixed effects, and origin state fixed effects. Robust standard errors are reported in the parenthesis. All regressions are weighted by the ACS person weight.

Table A5: Correlation between Moving Direction and Life Events

	(1)	(2)	(3)	(4)	(5)	(6)
	Destination-Origin Difference in Utilization Rate					
	Service			Drug		
Divorced last year	-0.000199			0.00160		
	(0.00104)			(0.00117)		
Spouse died last year		-0.000319			-0.000547	
		(0.00114)			(0.00100)	
Retired last year			-0.000112			0.00136
			(0.000460)			(0.000677)
Observations	57,077	57,077	57,077	57,077	57,077	57,077
Mean of Dep. Var	-0.00156	-0.00156	-0.00156	0.00338	0.00338	0.00338
S.D. of Dep. Var	0.0224	0.0224	0.0224	0.0310	0.0310	0.0310

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. All regressions control for gender, age, race, education level, household income, as well as interview year fixed effects, and origin state fixed effects. Robust standard errors are clustered by destination and origin states. All regressions are weighted by the ACS person weight.

Table A6: 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 or 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 treatment 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 A7: Place Effect of Mental Health Service Utilization by Provider

	(1)	(2)	(3)	(4)	(5)	(6)
	Hospital Inpatient	Hospital outpatient	Primary care physicians	Mental health professionals	Psychoterapy	Any service (no Part D restriction)
$\delta_i * Post_{it}$	0.685	1.061	0.818	0.595	0.663	0.556
	(0.0614)	(0.0454)	(0.0593)	(0.0306)	(0.0365)	(0.0271)
Observations	1,008,027	1,008,027	1,008,027	1,008,027	1,008,027	2,547,786
Dep. Mean	0.0117	0.0212	0.0391	0.0582	0.0396	0.0995

Notes: This table presents the place effect of mental health service utilization by different providers 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 variable in Columns (5) is the indicator for any psychotherapy. The dependent variable in Column (6) is the indicator for any mental health service use (same as the baseline), but using sample not restricted by Part D coverage. The main independent variable is the difference between the destination and origin in the corresponding treatment 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 A8: Robustness Checks — Heterogeneity Across Time

	(1)	(2)	(3)	(4)	(5)	(6)
	Before 2009		After 2014		HRR Average Over All Years	
	Service	Drug	Service	Drug	Service	Drug
$\delta_i * Post_{it}$	0.399	0.127	0.420	0.154	0.495	0.172
	(0.147)	(0.141)	(0.0788)	(0.0519)	(0.0367)	(0.0308)
Observations	44,417	44,417	135,620	135,620	1,008,027	1,008,027
Dep. Mean	0.116	0.238	0.126	0.283	0.118	0.262

Notes: This table replicates Columns (1) and (4) from Table 2. Columns (1) and (2) restrict the sample to the years 2006–2009, with moves taking place in 2008–2009. Columns (3) and (4) restrict the sample to the years 2014–2018, with moves taking place in 2016–2018. Columns (5) and (6) use the full sample but calculate the difference in service or drug utilization rates between the destination and origin (δ_i) based on the HRR average utilization rate over the entire sample period, instead of the year before individual i moves. 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 A9: Robustness Checks — Medicaid Expansion and Dual Eligibles

	(1)	(2)	(3)	(4)
	Drop dual eligibles		Drop expanded states	
	Service	Drug	Service	Drug
$\delta_i * Post_{it}$	0.524	0.164	0.435	0.123
	(0.0483)	(0.0375)	(0.0409)	(0.0367)
Observations	826,118	826,118	771,583	771,583
Dep. Mean	0.103	0.244	0.112	0.252

Notes: This table replicates Columns (1) and (4) from Table 2. Columns (1) and (2) exclude beneficiary with both Medicare and Medicaid coverage from the sample. Columns (3) and (4) exclude individuals who currently live in states that have already expanded Medicaid as of the given year. The difference in service drug utilization rates between the destination and origin (δ_i) is calculated among the baseline sample of nonmovers in Columns (3) and (4), but restrict to those not having Medicaid coverage in Columns (1) and (2). 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 A10: Robustness Checks — Geographic Area Level, Sample, and Additional Geographic Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Geographic Level			Between above & below median HRRs	Between top & bottom quartile HRRs	Drop moves to Florida	Census region by year FEs
	State	County	HSA				
	Penal A: Any Service Use						
$\delta_i * Post_{it}$	0.513	0.427	0.377	0.566	0.596	0.493	0.368
	(0.0439)	(0.0308)	(0.0301)	(0.0440)	(0.0662)	(0.0381)	(0.0374)
Observations	741,619	741,601	739,520	427,117	93,406	912,605	1,006,262
Dep. Mean	0.116	0.116	0.116	0.113	0.112	0.119	0.118
	Penal B: Any Drug Use						
$\delta_i * Post_{it}$	0.0513	0.144	0.139	0.188	0.234	0.164	0.182
	(0.0381)	(0.0261)	(0.0257)	(0.0350)	(0.0548)	(0.0318)	(0.0305)
Observations	741,619	741,601	739,520	386,474	66,543	912,605	1,006,262
Dep. Mean	0.259	0.259	0.259	0.260	0.252	0.266	0.262

Notes: This table replicates Columns (1) and (4) from Table 2 with mental health service use in Panel A and drug use in Panel B. Columns (1)–(3) use movers across states and treatment utilization rates measured at the state, county, and Hospital Service Area (HSA) level respectively. Columns (4) and (5) use the movers sample across HRRs with treatment utilization rates above and below the median, or in the top and bottom quartiles. Column (6) drops individuals moved into Florida from other states. Column (7) uses the same movers sample as in the baseline, but include additional census region by year fixed effects. 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 A11: Adjustment for Selection on Unobservables

	(1) Baseline	(2) Controlled	(3) Adj. Coef. 1 ($R_{max} = 1.3 * R2_c$)	(4) Adj. Coef. 2 (Alt. R_{max})
Any service	0.720	0.458	0.377	0.439
	(0.0355)	(0.0346)		
	[0.011]	[0.432]		
Any drug	0.292	0.151	0.107	0.138
	(0.0376)	(0.293)		
	[0.023]	[0.633]		

Notes: This table presents adjustments for selection on unobservables following Oster (2019). Column (1) reports regression results of models without individual fixed effects (still includes origin HRR fixed effects, year relative to move fixed effects, calendar year fixed effects, and age-group fixed effects). Column (2) reports regression results with individual fixed effects. In both columns, standard errors are reported in parentheses, and the R-squared values are in square brackets. Column (3) reports the adjusted coefficients with R_{max} equals 1.3 times of the R-squared in column (2) and $\delta = 1$. Column (4) reports the adjusted coefficients with R_{max} from regressions with a full set of past year mental health treatment controls (i.e., whether there is any claim and total payment in log, for both service and drugs) together with controls in column (2).

Table A12: Correlation between Regional Nursing Home and Mental Health Treatment Use Rates

	(1)	(2)	(3)	(4)
	Nursing Home Use Rate			
MH Rate — Service	0.142			
	(0.0452)			
MH Rate — Service (non-NF)		-0.0340		
		(0.0568)		
MH Rate — Drug			0.127	
			(0.0338)	
MH Rate — Drug (non-NF)				0.0151
				(0.0371)
Observations	306	306	306	306
Dep. Mean	0.0889	0.0889	0.0889	0.0889

Notes: This table presents the correlation between HRR's nursing home use rate and mental health service or drug use rate. All rates are calculated using Medicare beneficiaries with Part D coverage. Mental health treatment rates are separately calculated for the full sample and for those without nursing home claims in the given year. All regressions control for the share of female, white, dual-eligible, Part-D enrollees, and the average age of the sample. Regressions are weighted by the number of individual-year observations in each HRR. Robust standard errors are reported in parentheses.

Table A13: 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 (2), 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 A14: 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	4.54	4.64	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+)	49,277	9,087	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 C. Climate information and societal attitude measures are only available for a subset of HRRs, the number of which is listed in parentheses.

Table A15: Correlation between the Estimated HRR-level Place Effects of Mental Health Treatment Use and Suicide Rates

	(1)	(2)	(3)	(4)	(5)	(6)
	Suicide Death per 100,000 Population					
	All	Male	Female	All	Male	Female
Estimated HRR-level Place Effect for Service Use	-107.7	-204.7	-34.22			
	(13.68)	(26.18)	(5.273)			
Estimated HRR-level Place Effect for Drug Use				-26.41	-46.39	-11.36
				(13.22)	(25.18)	(5.387)
Observations	306	306	306	306	306	306
Dep. Mean	15.91	31.00	4.392	15.91	31.00	4.392
Effect of 1 s.d. place effect	-1.956	-3.717	-0.622	-0.490	-0.861	-0.211
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 on the estimated HRR-level place effect of mental health service drug use. Observations are at the HRR level. The outcome 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. 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 (3) 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 A16: Robustness Checks — Service Use Related to Cognitive Disorders

	(1)	(2)	(3)	(4)
	Include claims w/ cognitive disorders as primary diag.	Exclude claims w/ cognitive disorders as secondary diag.	Exclude individuals w/ cognitive disorders (based on primary diag.)	Exclude individuals w/ cognitive disorders (based on all diag.)
	Any Service Use			
$\delta_i * Post_{it}$	0.467	0.459	0.401	0.389
	(0.0333)	(0.0348)	(0.0475)	(0.0554)
Observations	1,008,027	1,008,027	790,042	686,816
Dep. Mean	0.152	0.114	0.0881	0.0784

Notes: This table presents the place effect of mental health services, replicating Column (1) from Table 2. In Column (1), service use is defined as claims with a primary diagnosis of cognitive disorders or mental illness. In Column (2), service use is defined as claims with a primary diagnosis of mental illness and no secondary diagnosis of cognitive disorders. Columns (3) and (4) define service use as in Table 2 but exclude individuals ever diagnosed with cognitive disorders, based on either primary diagnosis alone or all diagnosis codes. In these two columns, destination-origin differences in regional utilization rates are also calculated among individuals without cognitive disorders. 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.