Geographic Variation in Mental Health Care: Evidence from Migration

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Abstract

This paper documents substantial geographic variation in mental health care utilization rate among Medicare enrollees and its negative correlation with regional suicide rate. Exploiting patient migration, I show that 60 percent of the geographic variation in care utilization is attributed to place-specific factors. Within the place effect, provider capacity explains only one tenth of it, while local public attitudes toward mental health can play an important role. In terms of health consequences, I find that moving to high utilization areas is associated with a lower risk 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). Although treatments such as psychotherapy and medication have been shown to be effective for many mental health conditions,[2] the use of such treatments varies widely across geographic areas.

For example, among individuals above age 65 enrolled in Medicare, 16.5% of people in Massachusetts have medical claims related to mental illness in an average year, while only 8.0% of people do in Nevada. In contrast, the suicide rate among the over-65 population is lowest in Massachusetts (7.7 per 100,000) and highest in Nevada (31.8 per 100,000).[3] The large and opposing differences in mental health care and suicide rates can be explained by two possible scenarios: (i) the rates of underlying mental illness are similar in the two states, but people in NV do not get adequate care which leads to a higher suicide propensity, and (ii) people in MA have better baseline mental health and thus have fewer suicide deaths, but use too much unnecessary mental health care. Disentangling the underlying causes of the geographic variation in mental health care use is important for designing policies to promote the efficient delivery of care and improve mental health.

In this paper, I analyze the geographic variation in mental health care utilization using administrative claims and enrollment data for a random 20% sample of traditional Medicare enrollees from 2006-2018.[4] Following the patient migration design pioneered by Finkelstein

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

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

[3] For both mental health care utilization and suicide rates, see Section 2 for details.

[4] 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). Apart from traditional Medicare (or fee-for-service Medicare), about 30% of eligible beneficiaries chose Medicare

et al. (2016), I estimate the relative importance of place and patient-specific factors in the geographic distribution of mental health care use. Within the place effect, I further analyze the roles of provider capacity and local public attitudes. Lastly, I investigate the health consequences of the geographic variation in mental health care use, focusing on the incidence of self-harm-related emergency department visits as an outcome.

By analyzing the Medicare data, this study focuses on mental health care use among the elderly population. This group carries a particularly heavy burden of mental illness,[5] but is less studied in the existing literature, which has focused more on the mental health of youth and prime-age adults (e.g., Banerjee et al., 2017; Persson and Rossin-Slater, 2018; Cuddy and Currie, 2020a). Moreover, by restricting to people covered by the same insurance, I isolate potential differences in insurance coverage on mental health care (e.g., Baicker et al., 2013). Still, I document substantial geographic variation – a three-fold difference in mental health care utilization rates at the hospital referral region (HRR) level.[6]

Geographic variation in health care utilization is not unique to mental health, and has been much more extensively studied in the context of health care for physical conditions, such as heart attacks and childbirth deliveries (see Skinner (2011) and cites therein).[7] However, lots of the literature on geographic variation in physical health care find zero correlation between the intensity of care and health outcomes (Baicker et al., 2006; Moscone et al., 2019), which does not hold in mental health care. Figure 1 Panel (c) shows a strong and negative correlation between mental health care utilization and suicide rates – HRRs with a one percentage point lower care use rate have on average 1.16 more suicide deaths per 100,000 residents.[8] This implies that more mental health care is correlated with better mental health outcomes, which makes it different from many other types of health care on the "flat-of-the-

Advantage (or Part C) plans during the study period, for whom I do not observe claim records in the data.

[5]For instance, the suicide rate among elderly men increases sharply with age after 65 years old and is much higher than that for non-elderly adults and adolescents (shown in Appendix Figure A1).

[6]The ratio of the standard deviation to the mean of HRR mental health care use rate is 0.15, similar to that for price-adjusted Medicare spending (Skinner, 2011).

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

[8]This correlation remains after controlling for gender and age composition, socioeconomic factors and gun control policies. A More detailed discussion on the descriptive evidence is in Section 2.3.

curve" (Enthoven, 1978; Fuchs, 2004).[9] However, as in the example of MA versus NV, we still need to understand whether this is driven by differences in patient-side factors, such as baseline health, or place-side factors that affect care use conditional on health status.

Using an event-study model with individual fixed effects, I analyze how an individual's mental health care use - measured as having any medical claim with a mental health diagnosis in a given year - changes in response to moving across areas with different mental health care utilization rates. I find that after moving to a place with one percentage point higher utilization rate, individual's care use probability increases by 0.672 percentage points. This result indicates that place-specific factors explain 67.2% of the geographic variation in mental health care utilization. Notably, this magnitude of place effect is higher than the corresponding estimates for general health care spending (Finkelstein et al., 2016). Large place effects are also found among different types of mental health conditions and care services, except mental health drug use, for which only 18.3% of the difference is attributable to place-specific factors.

Within the place component of mental health care utilization, I explore two sets of place characteristics, (i) provider capacity, such as the number of psychiatrists, psychologists, and other related providers per capita, and (ii) local public attitudes, measured as sympathy for mental illness patients and perceived effectiveness of mental illness treatment using Behavioral Risk Factor Surveillance System (BRFSS) survey data. Both sets of factors vary across geographic areas,[10] and can be critically important in affecting the use of mental health care. First, the shortage of mental health care professionals is often viewed as the key factor constraining adequate use of care (Thomas et al., 2009; Bishop et al., 2016).[11] Second, demand-side factors such as the awareness about mental health (care) and stigma associated with mental illness may play more decisive roles in whether patients seek help for mental health conditions compared to physical health conditions (Bharadwaj et al., 2017). These demand-side factors can be persistent when people move across different areas. They

[9] It is also consistent with mental illness being under-diagnosed and under-treated, as argued in public health and psychiatry literature (Garrido et al., 2011), although causal evidence on the health impacts of local area mental health care use is limited.

[10] For example, New York, NY has 5.52 psychiatrists/psychologists per thousand Medicare enrollees, while Oxford, MS only has 0.34.

[11] Psychiatrists also have low acceptance rate for Medicare, compared to their acceptance rate for private insurance, and also compared to Medicare acceptance rates of other physicians.

can also be affected by the local environment. For example, local public outreach initiatives may change people's perceptions and information, thus changing their care-seeking behavior after moving.

To test these two sets of factors, I first estimate area fixed effects using a broader sample consisting of both movers and non-movers, and correlate the area fixed effects with these place characteristics. Results show that places with higher mental health care utilization rates tend to have higher psychiatric provider capacity and more positive public attitudes towards mental illnesses.

Looking specifically at local provider capacity, I show that when added as control variables to the initial specification in testing movers' responses to changes in local care utilization rates, the capacity of mental health professionals explains less than 10% of the place effect. This results suggest that policy intervention focused solely on provider capacity might not be as effective as expected.[12] In the meantime, although the capacity of non-mental health professionals (e.g., primary care physicians) does not contribute to mental health care use directly, movers with more interaction with these health care providers are more affected by the changes in local care use level. Therefore, cooperation with other health care providers and integrated care-delivery can be important policy tools.

To the extent that local public attitudes as an important place-side factor, one should expect it gradually affecting individuals' care use behavior after moving. Moreover, place effect should be more pronounced for those moving from low to high utilization areas ("move-up") than those moving from high to low utilization areas ("move-down"). This is because people from high-utilization areas already accumulate knowledge about mental illnesses and treatment options, which is unlikely to forget even after moving to low-utilization areas. Such asymmetric responses should not be seen among movers who have been diagnosed with mental illnesses before moving, since all of them already have such knowledge no matter whether they are from high or low utilization areas. To test these hypotheses, I perform a series of heterogeneity tests that show results consistent with the predictions.

In the last part of the paper, I analyze the health outcome of moving to places with

[12] Such policy interventions can include directing more psychiatrists to low-capacity areas through financial support, such as student loan repayment, and expanding medical training programs.

different mental health care utilization rates. I show that moving to a place with a one percentage point higher care use rate reduces an individual's likelihood of having a self-harm emergency department (ED) visit by 14.2% relative to the average rate.[13] This result suggests that the negative correlation between regional mental health care utilization and suicide rates is partly causal, and that mental health care can improve patient mental health.

This paper contributes to a small but growing literature on mental health in economics by analyzing the mental health care use among the elderly. While adolescents and working-age adults are significantly affected by mental illnesses (Chatterji et al., 2011; Banerjee et al., 2017; Persson and Rossin-Slater, 2018; Cuddy and Currie, 2020a,b; Biasi et al., 2021; Persson et al., 2021), elderly adults bear similar, if not heavier, disease burden.[14] Moreover, because of the rapidly aging population in the US, it is becoming increasingly urgent to support the mental health of the elderly and promote efficient utilization of mental health care.[15]

Second, this paper examines potential drivers of mental health care utilization. Apart from evidence on the effect of insurance coverage(Baicker et al., 2013; Cowan and Hao, 2020), access to providers, and social stigma on mental are commonly mentioned as barriers to mental health care use, but empirical evidence has been mixed and limited (Bharadwaj et al., 2017; McClellan et al., 2020; Cuddy and Currie, 2020b; Cronin et al., 2020). In this paper, I evaluate the relative importance of the mental health care workforce in determining mental health care use and provide evidence that public attitudes is a place-specific component that can play an important role in affecting mental health care utilization.

Third, this study builds on the important literature on geographic variation in health care (Cutler and Sheiner, 1999; Baicker et al., 2006; Skinner, 2011; Chandra and Staiger, 2007;

[13] Unfortunately, I cannot observe suicide death in the current dataset. Therefore, I use self-harm ED visit as a proxy. It is valuable in future studies to obtain the cause-of-death records in the Medicare data and evaluate the consequence of mental health care use in terms of suicide deaths.

[14] More discussion concerning elderly adults mental health conditions and care use can be found in public health and psychiatric literature, which often points to the under-diagnosis and insufficient treatment of senior mental illness patients (e.g., Klap et al., 2003; Karlin et al., 2008; Byers et al., 2012; Frost et al., 2019). Most of these studies use survey data with limited size and subjective recall of service use.

[15] 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.

Doyle, 2011; Finkelstein et al., 2016; Molitor, 2018; Cutler et al., 2019). This paper fills the gap in literature by investigating the geographic variation in mental health care. I document several unique features in mental health care: the potentially positive marginal benefit of mental health care, a slightly larger place effect at 60%, the gradual change and asymmetric responses when people adopt the local utilization pattern.[16] These findings point to the importance of local public attitudes as a potential mechanism in affecting patients' care use behavior. Understanding this process is valuable for future policy in effectively promoting the uptake of mental health care, and may also be relevant for other health care settings which involve more active engagement from the patient, such as preventive care and chronic diseases management.

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

2 Background and Data

2.1 Mental Illnesses and Treatment

Mental illnesses are health conditions involving changes in emotion, thinking or behavior. These conditions may be occasional or long-lasting, and can impair an individual's ability to perform daily activities and maintain healthy relationships with others.[17] 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, schizophrenia and other psychotic disorders.[18]

[16]Some of these features, such as gradual post-moving convergence, have been seen in movers' consumption choices of brand-name commodities (Bronnenberg et al., 2012) and opioid abuse (Finkelstein et al., 2021), but is not found for general health care spending.

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

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

Patients with mental health concerns or symptoms can visit psychiatrists, psychologists, and primary care physicians (PCPs) for diagnosis and treatment. To gather information for diagnosis, physicians perform psychological evaluations asking about patients' thoughts, feelings, and behaviors.[19] The criteria for diagnoses are established by the American Psychiatric Association (APA) as published in *The Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5).* Following a diagnosis, patients can be prescribed treatments including psychotherapy/counseling, medications, and other types of medical or behavioral therapy. Diagnosis and treatments can take place in physicians' offices, hospital psychiatric units, specialized psychiatric hospitals, and community mental health centers, involving PCPs, mental health specialists, nurse practitioners and clinical social workers.[20]

2.2 Data

The primary data source for this project 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). Apart from traditional Medicare (or fee-for-service Medicare), about 30% of eligible beneficiaries chose Medicare Advantage (or Part C) plans during the study period, for whom I do not observe claim records in the data.

Mental health care is covered in Medicare Part A for inpatient services, Part B for outpatient and physician services, and Part D for prescription drugs.[21] No referral is needed for visits to psychiatrists or psychologists who accept Medicare patients. Prescription drug coverage for beneficiaries enrolled in Part D varies by plans, but all plans are required to cover all antidepressants, and antipsychotics. These drugs are not only prescribed to treat

disorders, impulse control disorders, and personality disorders.

[19] Physicians often use questionnaires to gather 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 problems that could cause the symptoms.

[20] While psychiatrists and PCPs can prescribe medications, psychologists do not have the authority to prescribe and focus extensively on psychotherapy and behavioral intervention. Nurse practitioners are sometimes also allowed, under state law, to prescribe medication. Clinical social workers are involved in evaluation, case management, and therapeutic training programs.

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

depression, psychotic disorders, but also anxiety and bipolar disorders.

The data include enrollment registers and claim records for inpatient admissions, outpatient services, physician services, and prescription drugs. The enrollment register is at patient by year level, and includes information on patients' gender, age, race, zipcode of residence, and enrollment status in each month. Focusing on the elder population, I restrict the sample to Medicare recipients between age 65 and 99 years old who are continuously enrolled in Medicare Part A and B.[22]

Claim datasets for inpatient, outpatient, and physician services 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.[23] ICD codes for different types of mental health conditions are reported in Appendix Table A1. Claims with mental illness as the primary diagnosis are identified as mental health care claims.[24] Due to regulations on substance abuse confidentiality, claims for alcohol- and substance-related disorders are redacted and therefore are not included in the analysis.[25] Prescription drug claims include information on patient and prescriber IDs, filling date, National Drug Code (NDC), and payments. Based on NDC and drug classification by the United States Pharmacopeial Convention (USP),[26]

[22]Included beneficiaries have to be covered under both Part A and B for all 12 months in each year, except in the initial year at age 65 or in the year of death. They also have to be enrolled in each year continuously without any gap year.

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

[24]The reason for only considering the primary diagnosis when identifying mental health claims is to exclude claims for other diseases with a mental health condition recorded as a comorbidity. When a mental health disorder is recorded as a secondary or further diagnosis in physician claims before 2015 (when ICD-9 is used), 59.0% also have a primary diagnosis related to a mental health disorder. Among claims that do not list mental illness in the primary diagnosis but do list one in a subsequent diagnosis, the most common types of primary diagnoses (collapsed to 3-digit ICD code) are essential hypertension (5.3%), general symptoms (2.6%), diabetes mellitus (2.4%), disorders of lipoid metabolism (1.4%), and symptoms involving the respiratory system and other chest symptoms (1.3%).

[25]See `https://www.samhsa.gov/about-us/who-we-are/laws-regulations/confidentiality-regulations-faqs` for more details. The regulations were updated in 2017, which permitted Medicare to include substance use disorder claims for research use. To be consistent, I delete these claims in all of the sample years.

[26]According to the Medicare Prescription Drug Improvement and Modernization Act of 2003 (MMA), USP is responsible for developing and revising the USP Medicare Model Guidelines (`https://www.usp.org/health-quality-safety/usp-medicare-model-guidelines`), which serve as a default classification system for the Part D formulary. More details from the Medicare Prescription Drug Benefit Manual, Chapter 6 Part D Drugs and Formulary Requirements (`https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Part-D-Benefits-Manual-Chapter-6.pdf`).

claims for antidepressants and antipsychotics are identified as mental health drug claims.[27] Patients with only mental health drug claims but no medical claim with a mental health diagnosis are not classified as diagnosed patients.

Apart from Medicare data, I also use several public datasets on regional characteristics to supplement the analysis, for example, CDC Underlying Cause of Death database, 1999-2019; CMS Provider of Services (POS) Files, 2006-2018; Behavioral Risk Factor Surveillance System (BRFSS) survey data, 2007. Detailed descriptions for each data source and variable construction are presented in Appendix A.

2.3 Geographic Disparities in Mental Health Care Utilization

Over the ten-year sample period, 31.2% of Medicare beneficiaries have been diagnosed with mental illnesses at least once. This rate is potentially higher, if we account for the fact that not all individuals are observed throughout the full sample period. Within an average year, 11.4% of the beneficiaries have medical claims with a mental health diagnosis. This includes both newly diagnosed patients and those who seek for follow-up care from hospitals or physicians' offices, while patients with only prescription drug claims are again not included.[28]

This annual mental health care utilization rate varies substantially across the United States, as shown in Figure 1 Panel (a). The geographic unit used in the analysis is Hospital Referral Region (HRR), as defined by the Dartmouth Atlas of Health Care.[29] There are 306 HRRs nationwide, grouped based on patients' residential zip codes. HRRs are designed to approximate markets for tertiary hospital care, and in the non-hospital setting, 73% of the mental health claims were made within the residential HRR of Medicare patients.[30] As shown in the plot, mental health care utilization is higher in the Northeastern region, part of the Midwest, and in Florida and Texas. HRRs in the West have much lower utilization

[27] Drugs that target only anxiety, bipolar or other types of mental disorders, such as Benzodiazepines, are not included in the main analysis to avoid any difference in plan coverage.

[28] Diagnosis and care utilization rates for different types of mental illnesses are reported in Appendix Table A2.

[29] See `https://data.dartmouthatlas.org/downloads/methods/geogappdx.pdf` and `https://data.dartmouthatlas.org/supplemental/#boundaries` for more details on the definition of HRR and crosswalk files from zip codes to HRRs.

[30] As comparisons, 55% of the mental health claims with physicians were made within the residential county, and 93% within the residential state. These geographic units will be used as robustness checks for the estimation of place effect.

rate. While 20.5% of the senior population in Miami, FL has a mental health claim in an average year, only 7.8% of their counterparts in Las Vegas, NV have a mental health claim.

Panel (b) of Figure 1 presents the number of deaths by suicide among 100,000 residents above age 65.[31] The suicide rate is also unevenly distributed across geographic areas, ranging from 36.3 in Reno, NV to 6.4 in Bronx, NY. In contrast to to the distribution of the mental health care utilization rate, the suicide rate is highest in the West and lower in the Midwest and Northeastern areas. Figure 1 Panel (c) presents the correlation between the suicide rate and the mental health care utilization rate – a one percentage point higher utilization rate is associated with 1.16 fewer suicides per 100,000 population among the elderly.

One explanation for the negative correlation could be differences in gender and age composition across geographic areas. Indeed, elderly men have a lower mental health care utilization rate but a much higher suicide rate than elderly women (see Appendix Figure A1 Panel (a)-(b)). The male suicide rate also increases sharply with age after 65, when the female suicide rate starts to decrease. By age 85 and above, there is a 13-fold difference in the suicide rate between gender. However, Appendix Figure A1 Panel (c) shows that the negative correlation between the regional suicide rate and the mental health care utilization rate exists for both genders, and is more pronounced among elderly men. Moreover, average geographic characteristics are relatively similar across HRRs with low, median and high utilization rates (see Appendix Table A3), and the negative correlation between the regional suicide rate and the mental health care utilization rate still holds after adjusting for age and gender composition, controlling for other demographic and socioeconomic characteristics as well as state-level gun ownership policies[32] (see Appendix Table A4).

Apart from the general utilization measure, the share of beneficiaries using specific types of mental health care, such as inpatient, outpatient, and psychiatrist/psychologist visit also varies across geographic areas. As reported in Table 1, all of these rates have at least 9-fold differences between the lowest and highest utilization areas. These differences not only re-

[31] The sample includes people aged over 65 enrolled in Medicare Advantage (MA), which is not included in the Medicare FFS claim data. However, the mental health diagnosis rate in our sample of Medicare FFS enrollees is similar to that previously reported in Medicare advantage plans (McAvay and Goetz, 2014).

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

flect the likelihood of using mental health care, but also different preferences towards each type of care. For example, as shown in Appendix Figure A2, inpatient mental health care is utilized more in the south, while outpatient care is utilized more in the north. Medication is also an important type of treatment for mental illnesses. Conditional on having Part D coverage, 23.1% of patient-year observations have at least one claim for anti-depressants or anti-psychotics. This rate is higher than the mental health care utilization rate because not all patients using mental health drug(s) have a medical claim with a mental health diagnosis.[33] Conditional on having medical claims with a mental health diagnosis, payment for mental health care (and drug) also varies across geographic areas. Places with a higher mental health care use rate also tend to have higher mental health care spending conditional on having care usage (see Appendix Figure A2 Panel (e)-(h)). This goes against the hypothesis that only patients with mild mental disorders have a different likelihood of using mental health care across places, as that would predict higher average spending among patients getting treatment in low utilization areas. On the contrary, it suggests that patients with mental health conditions of different severity have lower care use at both the intensive and extensive margin in low utilization areas, where the suicide rate is high.

3 Patient and Place Effects

3.1 Movers Design

To investigate place and patient-specific factors that contribute to the geographic disparity in mental health care utilization, I exploit exogenous changes in place-specific factors when patients move across geographic areas. The primary empirical question is whether individuals change their own likelihood of using mental health care when they move to places with higher or lower mental health care utilization rates.

The baseline sample consists of traditional Medicare recipients aged 65-99 years old with full coverage of FFS Part A and B plans in each year with no gap years. It consists of

[33] 68% of patient-year observations with mental health drug claims do not have medical claims with a mental health diagnosis in the current year, and 49.0% of them have never been diagnosed with a mental illness in current or previous years.

10,620,307 patients (68,451,915 patient-year observations), and is used to calculate HRR mental health care utilization rates. From the baseline sample, I construct the movers sample by identifying people whose residential zipcode changed across HRRs during the sample period. In order to have 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,[34] to make sure that it is an actual physical move instead of just a change in mailing address. In the end, the movers sample consists of 427,001 movers and 3,807,563 patient-year observations.

Table 2 presents summary statistics on demographic characteristics, patients' individual-level mental health care utilization and regional utilization rates in residential HRRs. Comparing 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, but it is much lower in the pre-moving period when they have relatively similar ages compared to non-movers. In terms of mental health care use, movers have a similar utilization rate in the pre-moving period comparing to non-movers, but higher utilization rate 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. Increased mental health care use rate, as well as higher overall health spending, after moving, may be partially explained by that these individuals are mechanically older in the post-moving period. However, it is also possible that the act of moving in itself has mental health impacts. To account for these factors, I control for age group fixed effects of age group and the number of years relative to moving fixed effects in my regression models.

Finally, mental health care utilization rates defined as the share of patient-year observations with any mental health claim within the residential HRR do not differ between movers

[34]This is calculated at patient-year level as the number of medical claims with provider zipcode inside the mover's destination HRR divided by the number of medical claims with provider zipcode inside either her origin or destination HRRs. If there was no claim before moving, I require the destination claim share in the post-moving period to be at least 0.95. If there was no claim after moving, I require the destination claim share in the pre-moving period to be no more than 0.05. Average change in this destination claim share among the movers sample is reported in Appendix Figure A3.

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 mental health care utilization places and to move to higher utilization places. This can also be seen in Appendix Figure A4 Panel (a) where I show the distribution of destination-origin differences in local mental health care utilization rate for all movers. Ranging from -0.127 to 0.127, the changes in local utilization rate center close to zero and are symmetrically distributed.

Using the movers sample, I test how an individual's likelihood of having any mental health care claim changes when moving to a place with a different utilization rate. This is estimated using the event-study specification,

$$y_{it} = \alpha_i + \tau_t + \sum_{s=-9}^{8} \mathbb{1}[s = r(i,t)](\rho_s + \theta_s \delta_i) + x_{it}\beta + \epsilon_{it}, \tag{1}$$

where y_{it} is an indicator for patient i having any medical claim with a primary diagnosis related to a mental illness in year t. δ_i is defined as $\bar{y}_{d(i)} - \bar{y}_{o(i)}$, representing the difference in the HRR mental health care utilization rate between the destination HRR ($d(i)$) and the origin HRR ($o(i)$). Note again that HRR utilization rates are calculated using the baseline sample including both movers and non-movers. θ_s is a set of coefficients for each year relative to moving ($r(i,t)$). Since there are much fewer cases on both tails, I keep [-9,8] years relative to moving in the regression sample, among which relative year -1 is set as the baseline year. ρ_s is a set of indicators for each relative year, which control for any changes in mental health care use related to moving that do not differ across moving directions. The regression also includes individual fixed effects (α_i) to control for all time-invariant patient characteristics, such as baseline health status, race/ethnicity, and sex, calendar year fixed effects (τ_t) to control for time trends, and 5-year age groups fixed effects (x_{it}).

The key parameter of interest θ_s can be interpreted as the response to changes in local utilization rates, if the underlying assumption is satisfied that no other factors vary systematically with the moving direction and also affect movers' mental health care utilization. This assumption can be violated if, for example, people who have increasing use of mental health conditions choose to move to places with higher utilization rates. This can be directly tested by looking at the series of relative year coefficients θ_s in the years before moving. If the assumption holds true, the set of pre-moving coefficients should be flat and close to zero.

Two additional sets of evidence also provide support for this assumption by showing that factors potentially related to mental health care use are not correlated with the moving directions of the elderly population. First, people who have been diagnosed with mental illnesses before moving have a similar moving pattern as others. Appendix Figure A4 Panel (b) plots the distribution of changes in HRR utilization rate among pre-diagnosed movers and non-yet-diagnosed movers. Both groups show a wide-spread, roughly symmetric, and mostly identical distribution of destination-origin difference in HRR mental health care utilization rates. Second, the moving direction is not correlated with factors that may negatively affect mental health status. Studies have shown that people experience worse mental health after major adverse life events such as divorce, death of a spouse, or job loss (Mazure, 1998; Lindeboom et al., 2002; Mandal and Roe, 2007; Siflinger, 2017).[35] It would be a concern if people who recently experienced an adverse life shock chose to move to places with a higher mental health utilization rate while experiencing deteriorating mental health themselves. To test this, I use American Community Survey (ACS) data from 2006 to 2018 to identify elderly adults above age 65 who moved across states.[36] Based on their state-to-state moving direction, I merge in average changes in HRR mental health care utilization rate experienced by Medicare recipients who moved in the same direction. Appendix Table A5 shows that changes in the local mental health care utilization rate are not significantly different for movers who divorced, were widowed, or retired in the past year. Taken together, these results show that there is no selection in moving direction related to mental health conditions or care use demand, and therefore, we should expect any post-moving changes in individual mental health care use behavior to be a response to changes in the local utilization pattern.

[35] The effect of retirement on mental health status of the elderly has mixed evidence in the literature, varying by voluntary and involuntary retirements, different health indexes, and strategies in addressing endogenous retirement decisions. See Nishimura et al. (2018) for more discussion.

[36] Appendix Figure A5 confirms that migration flows identified in the ACS data are similar to those identified in the Medicare sample.

3.2 Event Study Estimates

Figure 2 plots coefficients θ_s estimated from Equation (1) representing an individual's response to changes in the local mental health care utilization rate in each year relative to the move. The coefficients during the years before moving are close to zero and stay flat from $s = -9$ to $s = -1$. This result suggests that there are no differences in mental health care use among movers, either in levels or in trends, that are systematically correlated with moving directions. In other words, there is no evidence of selective moving based on people's trajectory of mental health utilization.

The change in the local mental health care utilization rate takes effect on an individual's care use immediately after moving. People who move to places with a 1 percentage point higher mental health care utilization rate increase their likelihood of using mental health care by 0.4 percentage points in $s = 0$. Note that people might move in the middle of the year and are only partially "treated" in year 0, suggesting that the $s = 0$ estimate represents an an underestimation of the response. After the year of the move, an individual's likelihood of using mental health care increases by around 0.6 percentage points in response to a 1 percentage point increase in the local care utilization rate. This result means that 60% of the difference in the mental health care use rate between destination and origin HRRs is absorbed immediately after moving. This magnitude of place effect is slightly larger than the 50% place effect found for total health care spending (Finkelstein et al., 2016).

Moreover, Figure 2 shows that post-moving coefficients gradually increase from 0.569 in year 1 to 0.835 in year 8, suggesting that a mover's mental health care use almost converges to the average utilization level in the destination HRR in the eight years after moving. Note that the sample used in Figure 2 is not balanced and there is concern that the increasing post-moving coefficients are due to changes in sample composition. For example, if early movers for whom I observe a longer post-moving period show a larger place effect than those who moved in later years, this can lead to event study coefficients increasing with post-moving years. To test this, I run a set of event studies with balanced panels for certain sub-periods. The results are shown in Appendix Figure A6, which confirm that movers respond immediately after moving and keep adopting the local utilization pattern as they stay longer in the destination area. The post-moving convergence is not found for total health care spending (Finkelstein et al., 2016), which I will discuss more in Section 4.4.

As further robustness checks, I test whether the response to the change in local utilization rates is only driven by certain migration directions, for example, from places with the most care to places with the least care. Appendix Figure A7 presents a series of event study plots that use different subsamples of movers – those who move between an HRR with above (or top quartile or top decile) care utilization rates and an HRR with below (or bottom quartile or bottom decile) care utilization rates. All these results are similar to each other and to the main results, suggesting that there is no heterogeneous effect by the size of the change. Moving from high-to-low and low-to-high utilization areas does show some asymmetric responses, which will also be discussed more in Section 4.4. Moreover, while the main analysis uses local mental health care utilization rates measured at HRR level, Appendix Table A6 presents robustness results with local utilization rates measured in different geographic units. The sample includes movers across state borders and is consistent in different columns. Again, we see similar results no matter whether the utilization rates are measured at state, county, HRR and hospital service area (HSA)[37] level.

After confirming in the event study that there are no differential pre-trends in individuals' mental health care use, and showing the post-moving pattern in response to changes in local utilization rate, Table 3 column (1) summarizes the place effects in difference-in-differences estimations. Panel A excludes the year of moving from the sample and uses one aggregated indicator for all post-moving years for each mover i ($Post$) interacting with the destination-origin difference in the mental health care utilization rate (δ_i). The coefficient for this interaction term reflects the overall response after moving – an individual's likelihood of having mental health care claim increases by 0.672 percentage points after moving to places with a 1 percentage point higher utilization rate. Panel B uses three relative year indicators, namely post-moving year 0 ($Post_0$), years 1-4 ($Post_{1-4}$), and years 5-8 ($Post_{5-8}$), each interacted with δ_i. This model allows me to isolate the partial "treatment" effect in the

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

initial year, and to test whether there is a larger response later in the post-moving period. As shown in the table, moving to places with a 1 percentage point higher utilization rate leads to an additional 0.08 percentage points increase in an individual's annual care use probability during post-moving year 5-8 compared to year 1-4, but the difference is not statistically significant.

Columns (2)-(6) in Table 3 presents the place effect for different categories of mental illness. In each regression, the outcome variable is an indicator for whether the patient have any medical claims with a primary diagnosis related to the specific type of mental illness in the year. Changes in local utilization rate are also specific to the corresponding mental illness. As shown in Panel A, cognitive disorders, such as dementia and delirium, exhibit a larger place effect than other types of mental illnesses. This is probably because the care use decision for cognitive disorder patients often involves family members and other care takers. These care takers may be more influenced by the place effect, either because they have lived in the place for a longer time period (i.e., before the patient had moved there) or because they are more aware of local resources. In the meantime, patients' own preferences for care are likely less relevant for cognitive disorders than other types of mental illness. In terms of post-moving convergence, care use for the cognitive disorders also shows largest increase between year 1-4 and year 5-8 coefficients, followed by care use for other mental health conditions. Anxiety disorders, mood disorders, and schizophrenia, however, have smaller and less significant differences in the two post-moving coefficients. Appendix Table A9 presents the results of excluding cognitive disorder from mental health conditions. Columns (1) and (2) replicates the first column of Table 3 and report similar results. Difference in the coefficients of post-moving year 5-8 and year 1-4 is 0.0754 and statistically significant at 5% level.

Table 4 presents regression results for different types of mental health care use measures. Mental health care use through psychiatrist/psychologist and inpatient visits show similar size of place effects as overall mental health care use. However, while the response to changes in psychiatrist/psychologist use shows a slight post-moving increase, the response to changes in inpatient mental health care use is immediate and remains constant in later years. Care utilization at outpatient departments (including community mental health care centers) has a larger place effect, but the use of mental health prescription drugs (conditional on having Part D coverage) is more persistent across origin to destination changes in local mental health care utilization. Moving to places with a 1 percentage point higher utilization rate of mental health drugs only leads to a 0.183 percentage points increase in an individual's likelihood of having a mental health drug claim after moving, and up to a 0.270 percentage points increase after 5-8 years of living in the destination area. Conditional on care use, spending on mental health care (and drugs) also shows a sizable place effect. This can be seen as an intensive margin response to changes in local mental health care (and drug) spending. But unlike the extensive margin, there is no larger response in year 5-8 post-moving compared to year 1-4 at the intensive margin.

Appendix Table A10 and A11 presents further robustness checks by (i) excluding patients who have ever stayed in nursing facilities, and (ii) using all diagnoses (not only the primary one) to identify mental health claims. As shown in Columns (1) in Appendix Table A10, dropping people stayed in long-term care facilities lead to only 24.9% of the geographic differences explained by the place-specific factors. One possible reason could be that nursing homes patients have a higher share of cognitive disorders, which shows the largest place effect. However, the effect is still much smaller than the effect in Appendix Table A9 when cognitive disorders are excluded. Another reason is that providers in nursing facilities are the channels through which local utilization patterns are transmitted to people who moved in. This mechanism will be discussed with more details in Section 4.3. Including second and further diagnoses in the claims data to identify mental health care use also lead to a smaller place effect. However, note that the dependent mean is about two times the average when we focus on the primary diagnosis. Therefore, this variable could include a large amount of claims where mental health issues are coded as comorbidities.

4 Mechanisms

4.1 Place-Specific Factors

The empirical results so far indicate that place effects explain a large share of the geographic disparity in mental health care utilization rates. An individual's own care use probability converges to the local care utilization rate at the destination area and more than 60% of the geographic disparities are absorbed after migration. Next, I explore the different factors that contribute to the "place effect".

One important factor that affects care utilization is the accessibility of providers. In mental health care, this is a particularly severe issue, as there has been a growing shortage and uneven distribution of mental health care specialists. Appendix Figure A8 plots the distribution of the number of psychiatrists and psychologists per thousand Medicare FFS recipients across HRRs.[38] As shown in the figure, psychiatrists and psychologists are more concentrated in the northeastern area where we also see a high mental health care utilization rate (e.g., New York, 5.5 psychiatrists/psychologists per thousand Medicare FFS recipients, 16.9% mental health care utilization rate), and also part of the west where the utilization rate is not as high (e.g., San Mateo CA, 3.4 psychiatrists/psychologists per thousand Medicare FFS recipients, 8.4% utilization rate). On the other end of the provider capacity spectrum, Oxford MS, for example, only has 0.34 psychiatrists/psychologists per thousand Medicare FFS recipients. As summarized in Appendix Table A7, the distribution of mental health care specialists is more skewed than that of general practitioners and other specialists. Institutional capacity to deliver mental health care, such as the number of psychiatric hospitals, units and beds, is also distributed unevenly.

Another possible factor is about differences in local public attitudes about mental health. Stigma against people with mental illness may prevent them from being open about their

[38]Number of physicians is counted using Medicare Data on Provider Practice and Specialty (MD-PPAS) 2008-2018. The dataset is at physician-by-year level and includes each individual provider who had a valid NPI and submitted a Medicare Part B non-institutional claim for evaluation and management services, procedures, imaging, or non-laboratory testing with a positive allowed charges amount in that year. The second restriction ensures that only psychiatrists/psychologists accepting Medicare patients are included. However, it excludes psychiatrists and psychologists who are employed by institutions and do not submit non-institutional claims. HRR is based on practice zipcode merged in from the 20% claims data.

condition and needs. Low awareness of treatment options and their clinical efficacy may reduce patients' likelihood of seeking appropriate mental health care. These social perceptions likely vary across geographic areas due to differences in culture, demographic structure, and local campaigns targeted at mental health problems. Using Behavioral Risk Factor Surveillance System (BRFSS) survey data, I construct two variables to capture the stigma level about mental illness and the perceived effectiveness of mental health treatment among people above age 65. The former is based on interviewee responses to statement that *"People are generally caring and sympathetic to people with mental illness."* The latter is based on responses to statement that *"Treatment can help people with mental illness lead normal lives."* Both answers were on a 5-point scale, with "1" representing strongly agree and "5" being strongly disagree. The last two rows in Appendix Table A7 show the distribution of HRR average attitudes. For both measures, there are about 2-fold differences between the lowest and highest HRRs, and about 0.2 point differences between 25th and 75th percentile.[39]

To test whether these place-specific factors are correlated with the place component of mental health care utilization, I first estimate the HRR fixed effect using a broader sample that consists of all movers and 25% of non-movers with the following equation,

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

where y_{iht} is the indicator of patient i living in HRR h having any mental health care 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, and for the non-movers, the year relative to moving is set to a missing indicator which is absorbed by their individual fixed effect. The key estimator is HRR fixed effect η_h, which represents the place component in determining mental health care use for each HRR. A higher η_h means this place has a higher utilization rate after controlling for a patient's individual effect.

Next I analyze the correlation between the estimated HRR fixed effect (η_h) and HRR char-

[39] Another way to see the difference is that 7% more people disagree with the sympathy statement and 3% more people disagree with the efficacy statement in the 75th percentile HRR compared to the 25th percentile HRR.

acteristics in provider capacity, social perception towards mental illness, and demographic composition. Coefficients from the multivariate OLS regression are plotted in Figure 3. All HRR characteristic measures are standardized z-scores and the regression is weighted by HRR Medicare population size.

The top set of correlates are mental health care provider capacity, among which the number of psychiatrists and psychologists per capita, as well as the number of psychiatric hospitals, are both positively correlated with the HRR fixed effect for mental health care use. The number of psychiatric beds, however, is negatively correlated with the place component when all other capacity measures are controlled. Besides mental health specialists, the number of nurse practitioners per capita is also positively correlated with a higher local mental health care use pattern, but other provider capacity measures are not statistically significant.

In terms of public attitudes towards mental illnesses, especially the perceived ineffectiveness of mental health treatment, we see negative correlations with the HRR fixed effects in mental health care use. Places where people tend not to believe that mental health treatment can bring life to normal have lower mental health care use due to the place effect. This correlation is not explained by average age, gender, or race of Medicare recipients, nor by the average household income and education level of the local senior population. Among these HRR population characteristics, older average age and lower share of male population are positively correlated with a HRR effect in a higher mental health care use.

Taken together, descriptive evidence shows that both provider capacity and social perception towards mental illness enter into the place-specific factors that explain the geographic disparities in mental health care use. While having a sufficient number of providers certainly affects access to care, knowledge and perception about mental illness and treatment cannot be ignored as factors that may prevent an individual from seeking for treatment even if there is sufficient access to care. Next, I look more closely at these two sets of factors and the potential mechanisms that they act on patient's response to changes in the local mental health care utilization rate during migration.

4.2 Provider Capacity

In this section, I focus on the effect of provider capacity on mental health care utilization and test how much does provider capacity explain the geographic difference in mental health utilization?

More specifically, I re-estimate the difference-in-differences regression in Table 3 Panel A column (1) and add a series of provider capacity measurements as controls. The coefficient for the interaction term between the post-moving indicator and the destination-origin difference in mental health care utilization rate (δ_i) is plotted in Figure 4. From the baseline regression, three sets of capacity measures are added: (1) number of psychiatrists and number of psychologists per thousand Medicare FFS recipients; (2) number of psychiatric beds per thousand Medicare FFS recipients, number of psychiatrist hospitals, and number of psychiatric units in regular hospitals; and (3) number of general practitioners, number of nurse practitioners, and number of other specialists per thousand Medicare FFS recipients. As shown in the graph, holding mental health specialist capacity constant reduces the effect magnitude of moving to places with a 1 percentage point higher mental health care use rate from 0.672 to 0.623. This means that the regional capacity of mental health specialists explains about 9.3% of the place component in mental health care utilization. Further adding the institutional capacity of mental health care and other provider capacity would in total explain less than 10% of the place component.

Note here that local provider capacity could be endogenously determined by the historical demand for mental health care in the area. Places with other characteristics that drive more mental health care use would attract more providers entering the area, leading to both a higher utilization rate and higher provider capacity. If so, the analysis will overestimate the effect of local provider capacity. Despite this, the majority of the place component remain unexplained.[40]

[40]Columns (3)-(4) in Appendix Table A9 - A11 presents robustness checks using different samples or definitions of mental health care, which shows qualitatively similar results.

4.3 Interaction with Other Providers

Although the number of other providers does not directly affect individuals' mental health care utilization, these providers may play a role in identifying symptoms of mental illness and referring patients to specialist treatment. Patients with more interaction with PCPs or those who live in nursing facilities (NF), including nursing homes or skill nursing facilities, are more exposed to this channel of effect and therefore should pick up more of the local care use pattern. To test this, I split the sample based on whether the patient in the post-moving period, and the frequency of receiving evaluation and management services (E&M) from PCPs in the pre-moving period.

Figure 5 shows the event study estimation and Table 5 presents the regression result based on difference-in-differences specification. The left side figure compares movers who have NF stays (red dashed lines) versus those who have never stayed in a NF (blue solid lines) in the post-period. With a similar pre-trend among the two groups, movers with NF stays have much larger coefficients during the post-period, which reflects a much larger response to the changes in the local care use pattern (0.270 vs 1.038 percentage points increases after moving to places with a 1 percentage point higher utilization rate). Again, we need to note that these two groups have different average utilization rates at baseline. However, even after accounting for that, the relative changes after moving are larger for the NF patients (3.2% vs 4.7% as shown in Table 5).

The right side panel in Figure 5 divides movers by average E&M visits per year with PCPs before the move in terciles. The green dashed line on the top represents coefficients estimated among movers with the most E&M visits, while the blue solid line on the bottom represents coefficients estimated among movers with the fewest E&M visits. As predicted, movers that have more interaction with PCPs have larger responses to changes in the local mental health care use rate, and such order of the effect sizes remains after adjusting for the baseline utilization rates for different groups of movers. As reported in Table 5 columns (3)-(5), after moving to a place with a 1 percentage point higher utilization rate, an individual's likelihood of using mental health care increases by 3.2%, 4.6%, and 5.4% among groups with low, median, and high frequency of E&M visits.

This suggests that these providers also serve important roles in patients' mental health care utilization decisions. With regular check-ups or even daily visits, they have the opportunity to diagnose mental illnesses that the patients themselves may not be aware of. They can also deliver basic information about mental disorders, refer patients to mental health specialists and encourage them to seek professional mental health care if needed. Through these channels, patients moving into new places adapt to the local utilization pattern more quickly and on a larger scale. This also indicates the importance of care coordination between mental health specialists and general practitioners, which is coming more into focus along with the increasing shortages in the mental health specialist workforce (Kroenke and Unutzer, 2017).

4.4 Public Attitudes

In this section, I investigate the role of public attitudes in the adoption of the local mental health care pattern after moving to a new place. The main event study presented in section 3.2 reveals a special feature in mental health care settings compared to general health care, which is the gradual convergence to the regional average during one to eight years after moving. This is consistent with a learning process, where people moving to a new area adopt new information from the local environment, update their beliefs and change their care seeking behavior. The correlation between HRR fixed effects in mental health care use and local characteristics found in section 4.1 also shows that average social perception towards mental illness and treatment can be important place factors. To further validate this hypothesis, I will look at heterogeneous effects across moving directions and between patients who have or have not been diagnosed with a mental illness before moving, compare the extensive versus intensive margin responses, and test the role of interactions with other providers within the health care system. I will discuss how these results follow the prediction of patient learning but not other alternative mechanisms.

Moving direction An individual's learning process can be asymmetric for reasons such as confirmation bias and the favorability of new information (Rabin and Schrag, 1999; Eil and Rao, 2011). In the context of people updating their perceptions towards mental health and treatment after moving to a new place, the speed and magnitude of learning might differ between people who move from high-utilization to low-utilization places ("move-down") and people who move in the opposite direction ("move-up"). Imagine an individual who originally lived in places with high care use rates, where local residents have high awareness about mental health conditions and treatment, she already had information about the importance of mental health and the benefit of seeking professional help. Such knowledge is unlikely to degenerate after moving to a low utilization place, so she would be less affected by the decrease in the local care use rate after "moving-down", compared to others "moving-up". Meanwhile, if people moving away from low utilization areas have a social stigma towards mental illness that prevents them from seeking care, and such belief is not fully updated after moving to a high utilization area, we will expect to see a smaller effect after "moving-up" than after "moving-down".

To test this hypothesis, I estimate an event study regression with sequences of coefficients specific to upward and downward migrations,

$$y_{it} = \alpha_i + \tau_t + \sum_{s=-9}^{8} \mathbb{1}[s = r(i,t)] \sum_{d=\mathbb{1}[\delta_i >= 0]} (\rho_s^d + \theta_s^d \delta_i) + x_{it}\beta + \epsilon_{it}, \tag{3}$$

where θ_s^1 represents changes in response to δ_i when moving to higher utilization places ($\delta_i > 0$), as shown in Figure 6 by the blue solid line, while θ_s^0 represents changes in response to δ_i when moving to lower utilization places ($\delta_i \leq 0$), as shown in the figure by the red dashed line. As shown in the figure, people in both moving directions respond to changes in the local utilization rate by adjusting their own likelihood of using mental health care closer to the care use rate in the destination area. For those who move-down, for instance, positive coefficients mean they are less likely to use mental health care after moving, since δ_i is negative. Comparing people across moving directions, responses are larger after moving to places with more utilization, while baseline care utilization rates among movers are similar in the pre-moving preiod (10.0% for upward movers and 10.4% for downward movers). Putting the two groups in the same difference-in-differences regression where I have moving direction indicators interacting with $POST * \delta_i$, as reported in Table 6 column (1), we see that moving to places with a 1 percentage point higher utilization rate leads to a 0.252 percentage points larger response than moving to places with a 1 percentage point lower utilization rate.

These results suggest that there is learning after moving and the learning process is asymmetric. Although I cannot separate the existence of different beliefs and their updating processes, it seems that people adapt more to those that lead to higher demand for mental health care use. It may be that the belief in the importance of one's mental health condition and the effectiveness of mental health treatment that people picked up in the high utilization place persists after moving to a low utilization place, or that perceived stigma towards mental illness is more likely to be removed after receiving corrected information than to be accumulated after exposure to a high stigma environment.

Pre-diagnosed movers Following the previous prediction, we should also see that people who have been diagnosed with mental illnesses before moving have a smaller place effect and less asymmetric responses between high-to-low versus low-to-high moves. These movers are already aware of their mental health issues, have overcome any perceived stigma around seeking help, and know about treatment options. Therefore, they should be less affected by the changes in social perception during migration, no matter whether their move involves an increasing or decreasing local care use rate.

Figure 7 shows event study results based on equation (3) among separate subgroups of movers who have been diagnosed with mental health conditions before moving (left panel) and movers who have no mental health diagnosis before moving (right panel). Table 6 shows difference-in-differences results for the two groups of movers when both separating and not separating heterogeneous moving directions. For both groups of movers, there is quick and substantial convergence to the care use rate at the destination area. Moving to a place with a 1 percentage point higher mental health care utilization rate increases the likelihood of using mental health care by 1.251 percentage points for the pre-diagnosed movers and by 0.519 percentage points for the not-yet-diagnosed movers. Note that HRR care utilization rates are calculated using the baseline sample including all residents regardless of their diagnosis history, but the rate is much larger for those who have been diagnosed before. Therefore, although the coefficients are larger in levels among the pre-diagnosed movers sample, they represent a smaller relative effect. More specifically, the 1.251 percentage points increase in mental health care use probability for pre-diagnosed movers after the 1 percentage point increase in local care use rate is about 3.6% comparing to the baseline probability, whereas for the not-yet-diagnosed movers, the increase is 9.7% relative to the mean.

More interestingly, the gap between upward and downward moving is almost zero for the pre-diagnosed movers, and the asymmetric response is only observed among those who have never used mental health care before. This rejects the alternative explanation of habit formation, which also predicts gradual post-moving convergence and asymmetric response across moving direction but should be mainly driven by those who have a habit of using mental health care. It is also against the hypothesis that people who have been diagnosed before are more likely to move intentionally to places better for their mental health condition and therefore adopt more local effects after moving.

Appendix Table A9 and A10 shows similar results when excluding cognitive disorders as mental health conditions and when excluding people ever stayed in nursing facilities from the sample. In both robustness check exercises, we see larger effect in upward movings which is mostly driven by people who have never diagnosed with mental illness before. In Appendix Table A11, however, we see larger effect in downward movings, especially for pre-diagnosed movers. Again this could be driven by claims where mental health conditions are coded as commodities, which can be largely driven by the coding pattern of providers instead of patients decision of seeking care.

4.5 Alternative Mechanisms

A recent paper by Finkelstein et al. (2021) also finds a place effect of prescription opioid abuse increasing with number of years after moving, and points to addiction as a channel that explains the post-moving convergence. In the mental health care setting, one potential reason is that an individual's mental health status is gradually affected by the local environment and therefore her care use pattern grows more and more similar to the local average over the years. If this is the case, the convergence should be more prominent in disease types that are more affected by the local environment. However, as shown in Table 3, we do not see a larger place effect for mental illnesses such as mood disorders.

Moreover, we should also expect to see intensive margin responses follow the same post-moving convergence and asymmetric pattern if the underlying health condition change is driving the response. In Table 4, I show that log mental health care spending conditional on care use responds to changes in the local average immediately after moving but stays constant afterwards. Appendix Table A8 further shows that there is no difference between upward and downward moving, for both pre-diagnosed movers and not-yet-diagnosed movers.[41]

5 Health Outcomes

As discussed earlier, there is a strong negative correlation between local area mental health care utilization and suicide rates among individuals aged 65 and older. This correlation persists even after controlling for various demographic and socio-economic characteristics, and local gun-related policies. In this section, I estimate the causal effect of mental health care using the movers design, or more precisely, the increase in the probability of having a mental health claim after moving to places with a higher mental health care utilization rate.

Lack of information about cause of death in the Medicare data prevents me from studying suicides in my analysis. Instead, I use emergency department (ED) visits due to self-harm as a proxy for suicide attempts. Self-harm incidents are identified using external cause of injury codes (E–codes) which are coded separately from the main diagnosis codes in Medicare inpatient records from 2009, and in Medicare outpatient records from the year after.[42] Before 2009, only 20% of ED visits for injury and poisoning had E-codes reported, whereas over 90% had E-codes reported after 2010. Therefore, the analysis sample is restricted to years 2010-2018. Furthermore, considering that patients in long-term care facilities can have different pattern of suicidal behavior and the likelihood of being admitted to ED when there are care providers around, I exclude patients who have ever stayed in nursing home or skill nursing

[41]Note that for the not-yet-diagnosed movers who have never used mental health care before moving, the sample only consists of their post-moving years with mental health claims. The variation is therefore only the difference in moving direction (controlling for original HRR fixed effects) with no comparison within person before and after moving.

[42]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.

facilities during the sample period from the analysis.

Table 7 presents regression results for the effect of changes in the local mental health care utilization rate due to migration on an individual's likelihood of having an ED visit due to self-harm. Due to limited time periods, I only focus on the difference-in-differences regression where all years after moving are assigned to one post-moving indicator. The results show that moving to a place with a 1 percentage point higher mental health care use rate leads to a 0.02833 fewer self-harm ED visits per thousand population. The effect is economically large in magnitude compared to the 0.200 per thousand self-harm ED visit rate. Note that while elderly men have a much higher suicide rate than women, the average rate of self-harm ED visits is similar by gender. This is consistent with other evidence indicating that men are more likely to be "successful" in their suicide attempts than women (Tsirigotis et al., 2011). Therefore, the benefit of mental health care for men is likely to be even more life-saving, and under-estimated when ED visits are analyzed as the outcome Regardless, the effect of moving to high mental health care use places is larger and more significant for men. Moreover, this analysis does not incorporate other detrimental consequences of poor mental health, such as the interaction with chronic diseases (CDC and NACDD, 2008).

6 Conclusion

In this paper, I use administrative data from Medicare to study the geographic variation in mental health care utilization among people aged 65 and above. I show that the mental health care use rate varies substantially across areas in the United States, with similar size as that documented for general Medicare spending (Skinner, 2011).

By exploiting changes in the local mental health care use pattern due to migration, I show that people moving to places with a one percentage point higher utilization rate of mental health care increase their likelihood of having mental health care claims by 0.672 percentage points. This means that place-specific factors explain about 67.2% of the geographic variation, while the remaining 32.3% is attributable to patient-side factors. Similar place effects are found across different types of mental illnesses and mental health care services, except for the use of mental health prescription drugs, which has a relatively lower place component.

Looking into the place-specific factors, I show that provider capacity, measured by the number of psychiatrists and psychologists per capita, only explains less than 10% of the place effect in mental health care utilization. In the meantime, local public attitudes towards mental illness play an important role in movers' adoption of the local care utilization pattern. This is shown by asymmetric responses for people who move from low-to-high and high-to-low care utilization areas, especially among those who were never diagnosed with any mental illness before moving. Other potential place-specific factors include regional differences in physicians' practice patterns in diagnosis and prescription (Barnett et al., 2020; Marquardt, 2021) are not studied in this paper. More future works are needed to understand this potential source of geographic variation, possibly using clinical doctor notes or changes in screening requirements and practice guidelines.

In terms of the consequences of geographic variation in mental health care, I show a strong and negative correlation between regional mental health care utilization rate have a lower suicide rate, and evidence that moving to places with more mental health care use reduces the likelihood of self-harm ED visits. This signals the marginal benefit of providing more mental health services. Compared to many other types of medical care on the "flat-of-the-curve", more attention and resources should be devoted to promoting the use of mental health care.

To achieve this goal, results on the causes of geographic disparities of mental health care use suggest that policies targeted at increasing the supply of mental health care specialists might not be effective by itself. Education campaigns that targeting at reducing social stigma and increasing awareness of mental health and treatments are needed. Moreover, interaction with PCPs and other parts of the health care system helps patients adjust their mental health care use behavior, and therefore should be more involved in delivering more integrated mental health care. Telemedicine provides an additional direction for promoting mental health care use. Not only does it increase patients' access to care, but it may also reduce the perceived stigma level compared to physical visits to psychiatrists or psychologists.

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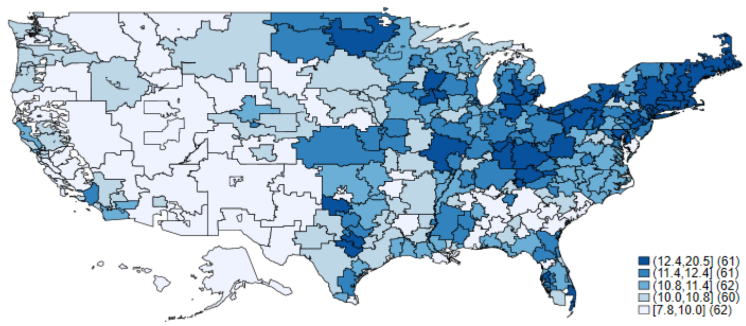
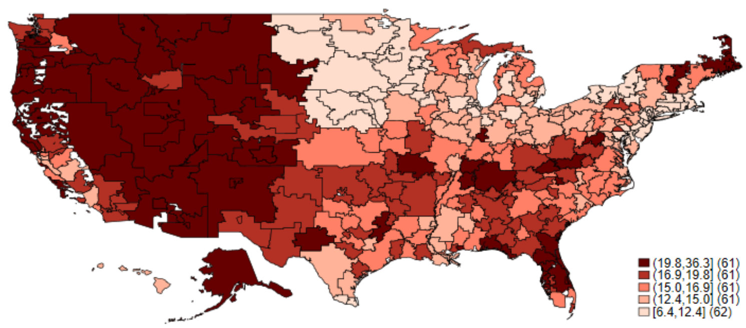
Figures

Figure 1: Suicide Rate and Mental Health Utilization Rate by HRR

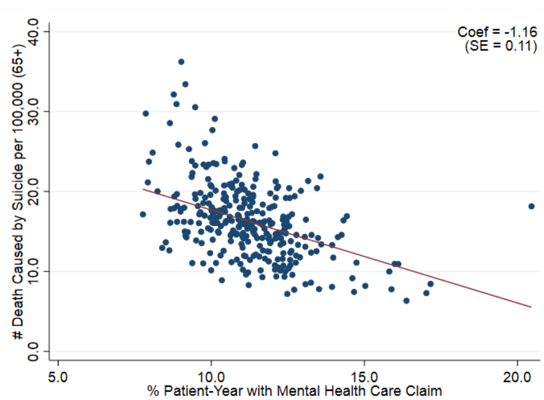
(a) Mental health diagnosis rate (%) in FFS Medicare



(b) Number of death caused by suicide per 100,000 residents (aged 65+)

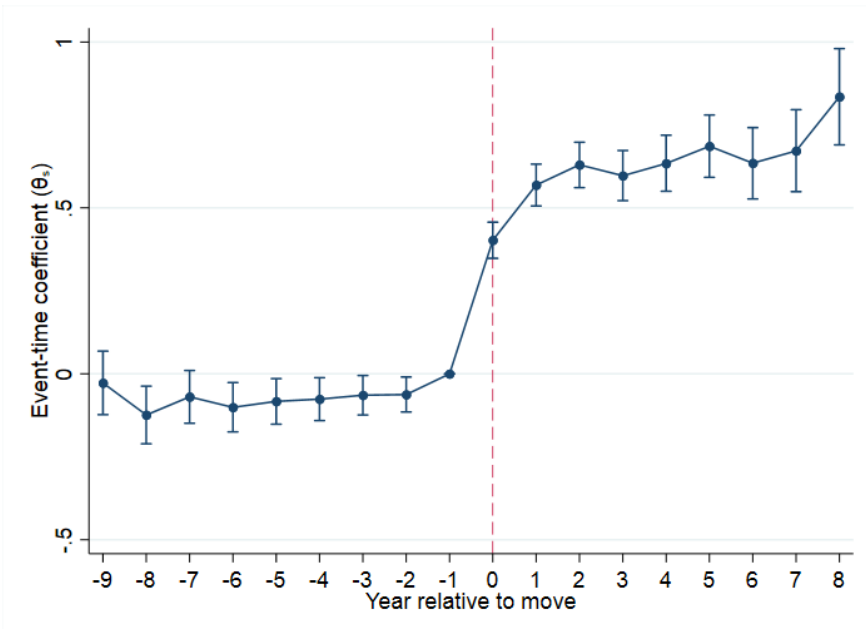


(c) Correlation at HRR Level



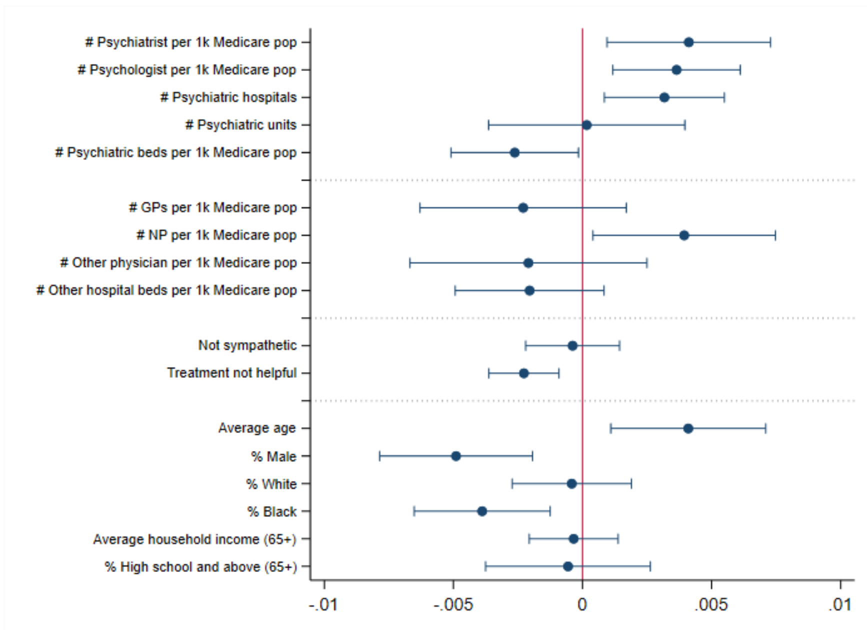
Notes: Panel (a) plots the distribution of mental health diagnosis rate by HRR among FFS Medicare beneficiaries with full coverage of Part A and B, age 65 and above in 2006-2018. Any patients that had inpatient, outpatient, or physician service claims with primary diagnosis related to mental health are identified as diagnosed patients. The 306 HRRs are grouped into quintiles based on their suicide rates. Numbers in bracket show the ranges, and the number in parathesis shows the number of HRRs included. Panel (b) plots the distribution of suicide rate by HRR. Data come from CDC Underlying Cause of Death database, 1999-2019, at county level, which are aggregated to HRR level based on zip code crosswalk and population share. Panel (c) shows the scatter plot of the two rates with each dot representing one HRR. The fitted line, coefficient and standard error are based on regression weighted by population age 65 and above.

Figure 2: Effect of Local Mental Health Care Utilization Rate on Individual's Mental Health Care Use



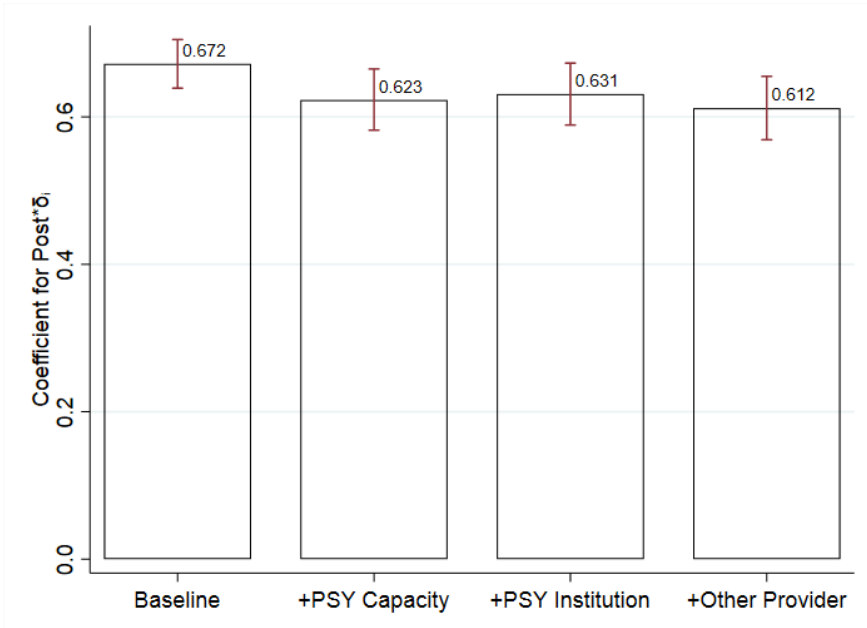
Notes: This figure shows coefficients θ_s estimated from Equation (1). The sample includes 3,653,723 patient-year observations for all movers during [-9,8] years relative to moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. θ_s are a sequence of coefficients for the interaction terms between destination-origin differences in HRR mental health care utilization rate (δ_i) and indicators for each year relative to moving, where relative year -1 is normalized to 0. The regression includes individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. The dashed lines are upper and lower bounds of the 95% confidence interval based on standard errors clustered at the individual level.

Figure 3: Correlation between HRR Fixed Effect and Characteristics



Notes: This figure shows the correlation between the HRR fixed effect in mental health care utilization and different HRR characteristics. The dependent variable is the HRR fixed effect (η_h) estimated based on Equation (2) using a sample that consists of all movers (in all years except the year of moving) and 25% non-movers. Place characteristics includes mental health care provider capacity, other provider capacity, public attitudes towards mental illness and treatment, and average demographic and socioeconomic characteristics, including age, gender, race, average household income and education level. A detailed description of the capacity and public attitudes measures is presented in Appendix Table A7. Demographic measures (i.e., age, gender, race) are based on the baseline sample of this analysis from Medicare, while socioeconomic measures (i.e., income and education) are based on ACS 5-year estimates in 2010 & 2015 for the senior population above age 65. All these measures are standardized z-scores and the multi-variate regression is weighted by HRR Medicare population size.

Figure 4: Place Effect Explained by Regional Provider Capacity

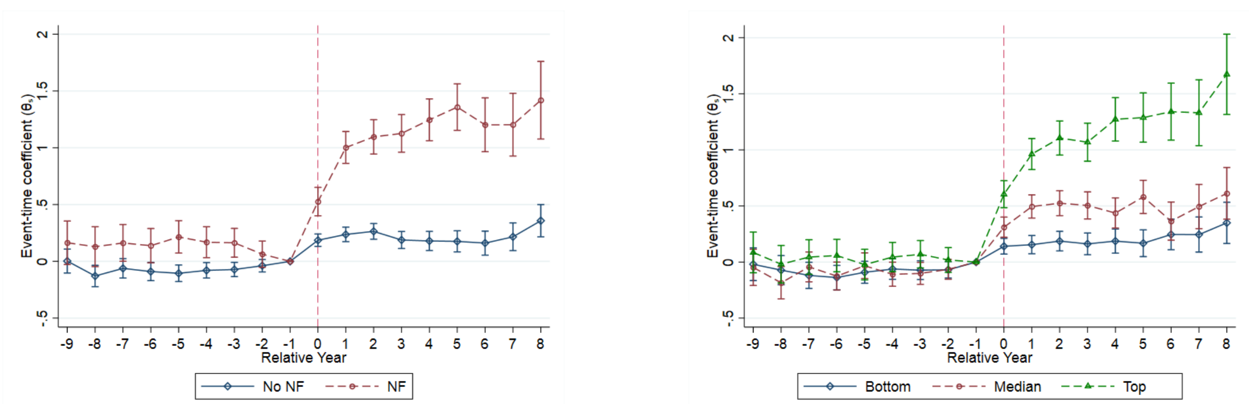


Notes: This figure shows four regression results estimating the effect of changes in the local mental health care utilization rate on an individual's care use. The sample includes 3,653,723 patient-year observations for all movers between [-9,8] years relative to moving excluding the year of moving. The baseline regression replicates the regression in Table 3 Panel A Col (1). The other bars reflect regression results after adding three sets of provider capacity measures as controls. From left to right, adding one additional set each time, the three sets of capacity measures are: (1) the number of psychiatrists and the number of psychologists per thousand Medicare FFS recipients; (2) the number of psychiatric beds per thousand Medicare FFS recipients, the number of psychiatrist hospitals, and the number of psychiatric units in regular hospitals; and (3) the number of general practitioners, the number of nurse practitioners, and the number of other specialists per thousand Medicare FFS recipients. More description of these measures can be found in Appendix Table A7. Each bar represents the coefficient for the interaction term between post-moving indicator and destination-origin difference in the mental health care utilization rate (δ_i), and the error bar represents the 95% confidence interval.

Figure 5: Place Effect: Interaction with Other Providers

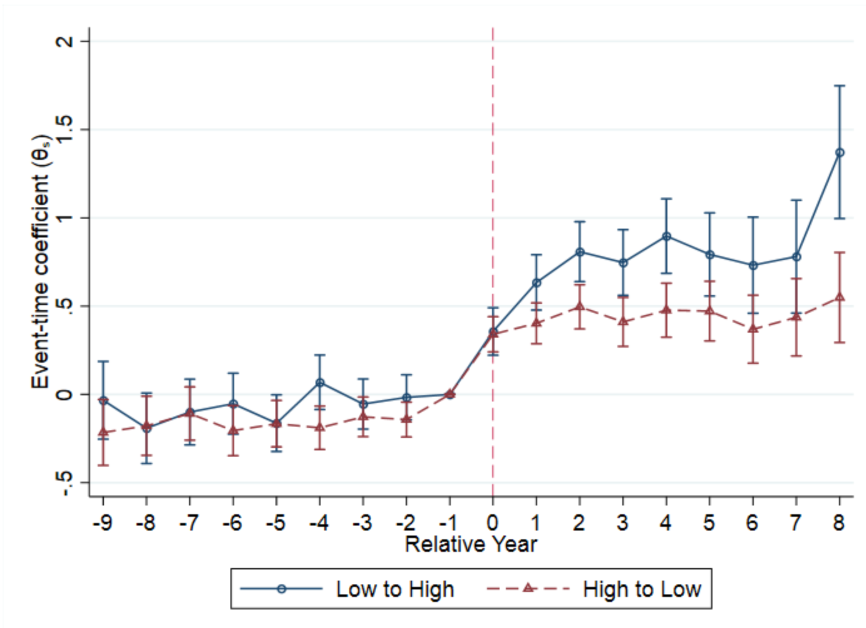
(a) By NF

(b) By E & M Visits



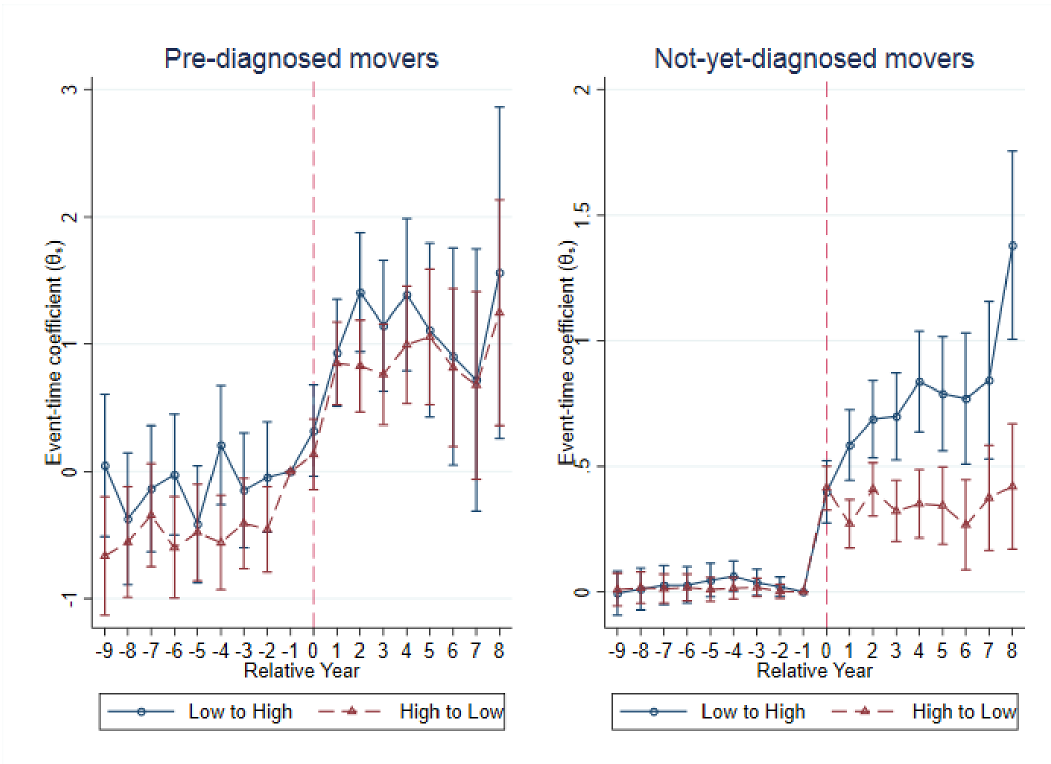
Notes: This figure shows coefficients θ_s estimated from Equation (1) for separate subgroups of movers based on their interaction with other providers. The left side panel splits the sample by whether the patient has any claims from a skilled nursing facility (SNFs) or nursing homes in the years post moving. The right side panel splits the sample by the number of E&M visits with PCPs annually in the years post moving, where Q1 has the lowest number and Q3 has the highest. The sample includes 3,653,723 patient-year observations for all movers during [-9,8] years relative to moving. θ_s are a set of coefficients for the interaction terms between destination-origin difference in HRR mental health care utilization rate (δ_i) and indicators for each year relative to moving, where relative year -1 is normalized to 0. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. Regression includes individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. The dashed lines are upper and lower bounds of the 95% confidence interval based on standard errors clustered at the individual level.

Figure 6: Place Effect: Move-Up vs. Move-Down



Notes: This figure shows coefficients θ_s^1 (blue solid line) and coefficients θ_s^1 (red dashed line) estimated from equation (3). The sample includes 3,653,723 patient-year observations for all movers during [-9,8] years relative to moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. θ_s^1 are a set of coefficients for the interaction terms between relative year indicators and destination-origin differences in the HRR mental health care utilization rate (δ_i) if $\delta_i > 0$, while θ_s^0 are coefficients if $\delta_i \leq 0$. Regression includes individual FEs, calendar year FEs, relative year FEs for upward and downward movings separately, and five-year age group FEs. The dashed lines are upper and lower bounds of the 95% confidence interval based on standard errors clustered at the individual level.

Figure 7: Place Effect: Diagnosed Movers vs. Not-yet-diagnosed Movers



Notes: This figure shows coefficients θ_s^1 (blue solid line) and coefficients θ_s^1 (red dashed line) estimated from equation (3) separately for people who have been diagnosed with a mental illness before moving (left panel) and people who have not been diagnosed before moving (right panel). The sample includes 961,700 patient-year observations for pre-diagnosed movers and 2,692,023 patient-year observations for not-yet-diagnosed movers during [-9,8] years relative to moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. θ_s^1 are a set of coefficients for the interaction terms between relative year indicators and destination-origin differences in the HRR mental health care utilization rate (δ_i) if $\delta_i > 0$, while θ_s^0 are coefficients if $\delta_i <= 0$. Regression includes individual FEs, calendar year FEs, relative year FEs for upward and downward movings separately, and five-year age group FEs. The dashed lines are upper and lower bounds of the 95% confidence interval based on standard errors clustered at the individual level.

Tables

Table 1: Geographic Variation in Mental Health Care Utilization Rates

	(1)	(2)	(3)	(4)	(5)	(6)
	National Average	Distribution of HRR Rates				
		Min	P25	P50	P75	Max
Share of patient-years w/ any mental health care use (%)	11.4	7.5	9.9	10.9	11.9	20.3
... from psychiatrists/psychologists	4.6	1.1	2.9	3.8	4.8	14.5
... from general practitioners	4.1	2.6	3.6	4.1	4.7	6.4
... from other providers	5.0	2.6	3.9	4.5	5.2	10.0
... from inpatient visits	0.5	0.1	0.3	0.4	0.6	1.4
... from outpatient visits	2.6	0.7	1.9	2.6	3.4	9.4
Share of patient-years w/ any mental health drug claims (%)	23.1	11.7	21.4	23.6	25.2	31.3
Mental health care spending conditional on care use	958.6	384.1	712.5	852.7	1076.0	3123.0
Mental health care and drug spending conditional on care use	1371.8	551.5	1082.7	1265.0	1504.0	3955.9

Notes: This table presents the distribution of the mental health care utilization rate by Hospital Referral Region (HRR). The sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Mental health care utilization rates in the first six rows are calculated as share of patient-year observations that have any inpatient, outpatient, or physician service claim with a primary diagnosis related to mental illnesses. Prescription drug use rates in row 7 is the share of patient-year observations (conditional on having Part D coverage) that have any antidepressant or antipsychotic claims. Average mental health care spending in row 8 is conditional on having any medical claim with a mental health diagnosis, while row 9 further restricts Part D coverage to include drug spending.

Table 2: Summary Statistics for Mover and Nonmover Samples

	Mover			Nonmover
	All Years	Pre	Post	
Age	76.0	73.9	78.3	74.0
Male	0.41	0.41	0.41	0.44
White	0.90	0.90	0.90	0.85
Medicare-Medicaid dual eligible	0.10	0.09	0.12	0.14
Part D coverage	0.51	0.43	0.58	0.52
Part A/B spending	10,635	7,967	17,293	11,805
Mental health care use	0.14	0.11	0.21	0.12
...from psychiatrists/psychologists	0.06	0.05	0.08	0.05
...from general practitioners	0.06	0.04	0.08	0.04
...from other providers	0.07	0.04	0.11	0.05
...from inpatient visits	0.01	0.01	0.01	0.01
...from outpatient visits	0.03	0.02	0.05	0.03
Mental health drug claim	0.27	0.21	0.32	0.24
Mental health care spending conditional on use	751.1	865.2	793.4	706.9
Mental health care and drug spending conditional on use	967.5	1259.2	964.3	949.8
HRR mental health care utilization rate	0.112	0.113	0.111	0.114
# Patients	427,001	427,001	427,001	9,699,984
# Patient-years	3,807,563	2,040,359	1,767,204	60,417,420

Notes: This table presents summary statistics on demographic characteristics and mental health care utilization pattern, regional utilization rates in residential HRRs, for the movers sample before and after moving as well as the non-movers sample. Baseline sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Non-movers are people who did not change their residential HRR throughout the sample periods, while movers are people who changed their residential HRR only once and 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 individual (by pre-/post-moving period) level and then averaged across people. Regional average is calculated at HRR level using the baseline sample including both movers and non-movers.

Table 3: Place Effect of Mental Health Care Utilization, by Mental Illness Types

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Anxiety	Cognitive Disorder	Mood Disorder	Schizophrenia	Others
Panel A: Post Moving						
$\delta_i * Post$	0.672	0.585	0.901	0.692	0.523	0.778
	(0.0248)	(0.0548)	(0.0367)	(0.0290)	(0.0363)	(0.0420)
Observations	3,213,579	3,213,579	3,213,579	3,213,579	3,213,579	3,213,579
Dep. Mean	0.131	0.0285	0.0501	0.0526	0.0142	0.0226
Panel B: Year 0, 1-4, 5-8 Post Moving						
$\delta_i * Post_0$	0.454	0.238	0.599	0.382	0.348	0.471
	(0.0260)	(0.0640)	(0.0405)	(0.0301)	(0.0486)	(0.0522)
$\delta_i * Post_{1-4}$	0.651	0.568	0.867	0.671	0.515	0.750
	(0.0247)	(0.0551)	(0.0367)	(0.0290)	(0.0376)	(0.0426)
$\delta_i * Post_{5-8}$	0.732	0.0601	1.041	0.701	0.536	0.853
	(0.0386)	(0.0899)	(0.0571)	(0.0439)	(0.0548)	(0.0662)
Observations	3,653,723	3,653,723	3,653,723	3,653,723	3,653,723	3,653,723
Dep. Mean	0.140	0.0304	0.0556	0.0559	0.0159	0.0246
Diff. btw Year 5-8 and Year 1-4	0.0811	0.0333	0.174	0.0301	0.0208	0.103
(P-value)	0.0192	0.690	0.000749	0.438	0.695	0.0936

Notes: This table presents the effect of changes in the local mental health care utilization rate on an individual's care use, for different types of mental illness. The sample includes 3,653,723 patient-year observations for all movers between [-9,8] years relative to move. Panel A further excludes the year of move from the sample. The dependent variable is a dummy variable indicating whether patient i had any mental health care claim, or any claims related to each type of mental illness in year t. The main independent variable in Panel A is the destination-origin difference in the care utilization rate of the corresponding mental illness (δ_i), interacting with the indicator for the post-moving period. The main independent variables in Panel B are the destination-origin difference in care utilization rate interacting with indicators for year 0, year 1-4 and year 5-8 post-moving. All the regressions include individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. Standard errors are clustered at beneficiary level.

Table 4: Place Effect of Mental Health Care Utilization, by Care Type and Spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Psychiatrist/ Psychologist	Psychotherapy	Inpatient	Outpatient	Prescription Drug	Log Spending (conditional on care use)	
						Care Only	Care & Drug
Panel A: Post Moving							
$\delta_i * Post$	0.760	0.733	0.924	1.124	0.183	0.713	0.580
	(0.0189)	(0.0248)	(0.0610)	(0.0235)	(0.0300)	(0.0495)	(0.0752)
Observations	3,213,579	3,213,579	3,213,579	3,213,579	1,598,370	248,612	134,264
Dep. Mean	0.0519	0.0321	0.00513	0.0290	0.249	6.328	6.799
Panel B: Year 0, 1-4, 5-8 Post Moving							
$\delta_i * Post_0$	0.368	0.342	0.504	0.566	0.00985	0.433	0.497
	(0.0199)	(0.0248)	(0.0999)	(0.0269)	(0.0253)	(0.0413)	(0.0582)
$\delta_i * Post_{1-4}$	0.740	0.717	0.892	1.097	0.169	0.716	0.620
	(0.0188)	(0.0247)	(0.0634)	(0.0236)	(0.0288)	(0.0442)	(0.0655)
$\delta_i * Post_{5-8}$	0.813	0.736	0.970	1.217	0.270	0.716	0.522
	(0.0286)	(0.0380)	(0.0959)	(0.0370)	(0.0450)	(0.0742)	(0.105)
Observations	3,653,723	3,653,723	3,653,723	3,653,723	1,833,338	310,479	166,397
Dep. Mean	0.0563	0.0342	0.00629	0.0317	0.256	6.372	6.821
Diff. btw Year 5-8 and Year 1-4	0.0732	0.0191	0.0781	0.120	0.101	0.000440	-0.0980
P-value	0.00357	0.566	0.393	0.000424	0.00690	0.995	0.258

Notes: This table presents the effect of changes in the local mental health care utilization rate on an individual's care use, for different types of care providers, prescription drug use, and spending. The sample includes 3,653,723 patient-year observations for all movers between [-9,8] years relative to move. Panel A further excludes the year of move from the sample. The dependent variable is a dummy variable indicating whether patient i in year t had any mental health care claim from a psychiatrist/psychologist, general practitioner, other physician, inpatient visit, outpatient visit, or any mental health prescription drug claim (conditional on Part D coverage), or log mental health care spending (conditional on care use), or log mental health care and drug spending (conditional on care use and Part D coverage). The main independent variable in Panel A is the destination-origin difference in the care utilization rate of the corresponding mental care use measure (δ_i), interacting with the indicator for the post-moving period. The main independent variables in Panel B are the destination-origin difference in care utilization rate interacting with indicators for year 0, year 1-4 and year 5-8 post-moving. All the regressions include individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. Standard errors are clustered at beneficiary level.

Table 5: Place Effect: Interaction with Other Providers

	(1)	(2)	(3)	(4)	(5)
	No NF	NF	By E&M Visits		
			Q1	Q2	Q3
$\delta_i * Post$	0.270	1.038	0.236	0.563	1.096
	(0.0244)	(0.0520)	(0.0316)	(0.0394)	(0.0535)
Observations	2,113,294	1,100,285	1,079,172	1,127,165	1,007,242
Dep. Mean	0.0839	0.223	0.0733	0.122	0.204
Relative effect	3.221	4.661	3.217	4.606	5.367
Indiviudal FEs	X	X	X	X	X
Year FEs	X	X	X	X	X
Relative Year FEs	X	X	X	X	X

Notes: This table presents regression results estimated from a difference-in-differences version of Equation (1) for separate subgroups of movers based on their interaction with other providers. The sample includes patient-year observations for all movers between [-9,8] years relative to move excluding the year of move. Columns (1)-(2) split the sample by whether the patient has any stay in nursing facilities (NFs) in the years post moving, while columns (3)-(5) split the sample by the number of E&M visits with PCPs annually in the years post moving, where Q1 has the lowest number and Q3 has the highest. Each sample includes patient-year observations for movers excluding the year of moving. The dependent variable is a dummy variable indicating whether patient i had any mental health care claim in year t. δ_i is the destination-origin difference in care utilization rate, which is interacted with the indicator for post-moving period ($Post$). All the regressions include beneficiary fixed effects, calendar year fixed effects, relative year fixed effects, and indicators for 5-year age groups. Standard errors clustered at beneficiary level.

Table 6: Place Effect: Moving Direction and Diagnosis History before moving

	(1)	(2)	(3)	(4)	(5)
	All movers	Pre-diagnosed movers		Not-yet-diagnosed movers	
$\delta_i * Post$		1.251		0.519	
		(0.0651)		(0.0230)	
$\delta_i * Post * Up$	0.792		1.234		0.679
	(0.0612)		(0.155)		(0.0595)
$\delta_i * Post * Down$	0.540		1.210		0.312
	(0.0454)		(0.120)		(0.0401)
Observations	3,213,579	852,248	852,248	2,361,331	2,361,331
Dep. Mean	0.131	0.347	0.347	0.0536	0.0536
Diff. btw Moving Up and Down	0.252		0.0243		0.367
P-value	0.000960		0.901		3.07e-07
Indiviudal FEs	X	X	X	X	X
Year FEs	X	X	X	X	X
Relative Year FEs		X		X	
Relative Year * Up/Down FEs	X		X		X

Notes: This table presents regression results estimated from a difference-in-differences version of equation (3). The sample in column (1) includes 3,213,579 patient-year observations for all movers between [-9,8] years relative to move excluding the year of moving. Columns (2)-(5) splits the sample by whether the movers have any mental health claims before moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. δ_i is the destination-origin difference in HRR mental health care utilization rate, which is interacted with indicator for years after moving, and indicators for whether it is an upward move ($\delta_i > 0$ or downward move ($\delta_i <= 0$). All the regressions include beneficiary fixed effects, calendar year fixed effects, relative year fixed effects, and indicators for 5-year age groups. Columns (1), (3), (5) also have fixed effects for relative year by upward/downward moving direction. Standard errors clustered at beneficiary level.

Table 7: Effect of Mental Health Care Utilization on Self-Harm ED Visit

	(1)	(2)	(3)	(4)	(5)
	All	Male	Female	Dual	Non-Dual
	Any Self-Harm ED Visit (per 1,000)				
$\delta_i * Post$	-2.833	-4.716	-1.350	-17.18	-1.780
	(1.485)	(2.029)	(2.117)	(12.87)	(1.353)
Observations	1,023,436	442,563	580,860	61,214	957,627
Dep. Mean	0.200	0.210	0.193	0.425	0.183

Notes: This table presents the effect of changes in the local mental health care utilization rate on an individual's ED visits due to self-harm. The sample includes 1,023,436 patient-year observations in 2010-2018 for all movers who changed their residential HRR after 2010, during [-4,3] years relative to move excluding the year of moving. The dependent variable is a dummy variable indicating whether patient i had any self-harm ED visit in year t. The main independent variable is the destination-origin difference in the mental health care utilization rate (δ_i) interacting with the indicator for the post-moving period. All the regressions include individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. Standard errors are clustered at beneficiary level.

Appendix

A Additional Data Sources

CDC Underlying Cause of Death database This database is used to construct the suicide rate across geographic areas, gender, and age groups. Based on death certificates for U.S. residents in 1999-2019, the dateset reports number of deaths, crude death rates or age-adjusted death rates for selected causes-of-death and for different sub-populations. To derive suicide rates at Hospital Referral Region (HRR) level, I start with number of suicides and population counts at county level, disaggregate to zipcode level based on population weights and re-aggregate to HRR level. For privacy reasons, all sub-national data representing 0-9 deaths are suppressed. To avoid too many missing values, I include all available years in deriving the suicide rate, which does not differ much if only years overlapped with the main sample are considered.

Dartmouth Atlas Physician Capacity Measures This datasest is constructed by the Dartmouth Atlas program based on American Medical Association (AMA) Master Files. To match main sample in the analysis, I use HRR level measures in 2011, specifically, number of primary care physicians, psychiatrists, and other specialists (all other physicians except psychiatrists), all denominated by 100,000 residents. Note that physicians counted in this dataset are not restricted to those accepting Medicare patients. The denominators also include residents of all ages. One might worry that this does not reflect the actual capacity available to provide health care services to the Medicare population. This might be especially problematic for psychiatrists, as many of them do not accept Medicare payments. To account for this, the main analysis uses capacity measures by counting the number of physicians that have Medicare claims and denominating it by the Medicare population. The Dartmouth Atlas measures of physician capacity are only used as robustness checks.

CMS Provider of Services (POS) Files The POS file contains data on characteristics of hospitals and other health care facilities. Taking the average across datasets in 2006-2015, I calculate the number of psychiatric hospitals, the number of psychiatric beds (including beds in psychiatric hospitals and psychiatric units of general hospitals), and the number of all hospital beds, in each HRR (identified based on facility's zip code). Both of the measurements for hospital beds are denominated by 1,000 residents using the same population estimate from the Dartmouth Atlas Physician Capacity Measures, 2011.

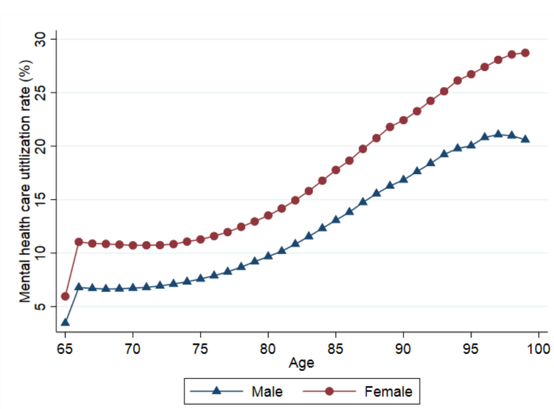
American Community Survey (ACS) The ACS dataset is used for two purposes: measuring population demographic characteristics and constructing potential moving reasons across migration flows. Population demographic characteristics drawn from ACS include median household income and share of population above age 25 with a high school degree. To compute HRR-level statistics, I use zip code level datasets (2019 ACS five-year estimates) and take the average based on population weights. Migration flows are constructed at state-to-state level using individual data from 2000-2019. 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 predicting chances of moving.

Behavioral Risk Factor Surveillance System (BRFSS) survey data This dataset is used to measure stigma towards mental illness across geographic area. Conducted via telephone, this survey collects data about U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. The questionnaire consists a fixed set of core questions and an optional module that vary by year and state. In particular, two questions related to attitude towards mental health were asked 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. Using these two sets of answers, I am able to construct average level of perceived sympathy and treatment efficacy by HRR (identified based on zip code).

B Appendix Figures

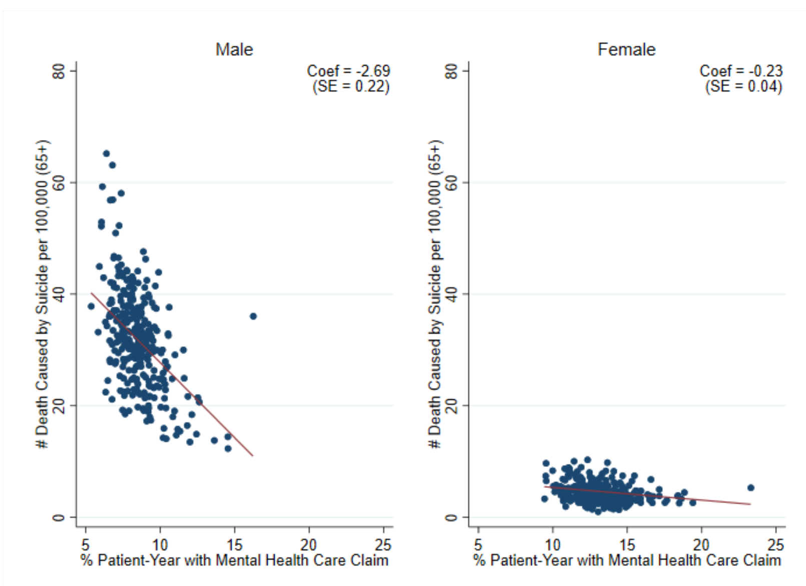
Figure A1: Mental Health Care Utilization and Suicide Rates by Gender, Age, and HRR

(a) Mental health care utilization rate by gender and age



(b) Suicide rate by gender and age

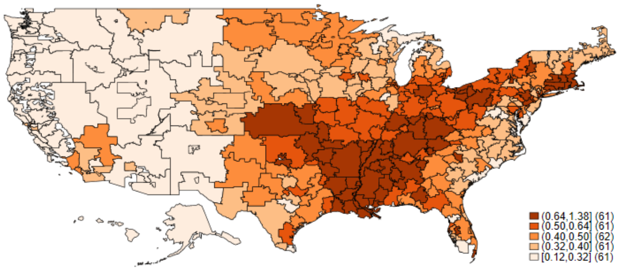
(c) Correlation between HRR mental health care utilization rate and suicide rate, by gender



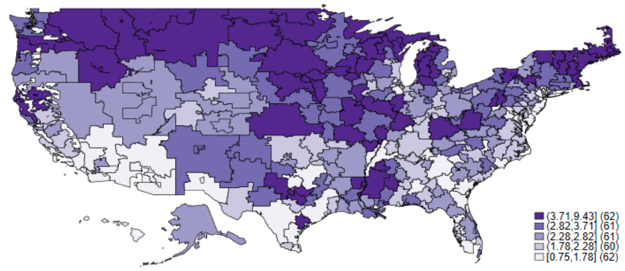
Notes: Panel (a) plots mental health care utilization rate by gender and age. Sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Mental health care utilization rate is calculated as share of patient-year observations that have any inpatient, outpatient, or physician service claim with a primary diagnosis related to mental illnesses. Panel (b) plots suicide rate by gender and 5-year age group, using CDC Underlying Cause of Death database, 1999-2019, at county level. Panel (c) shows the scatter plot of the HRR mental health care utilization rate (x-axis) and suicide rate among population age 65 (y-axis) by gender. The fitted lines, coefficients and standard errors are based on regressions weighted by population above age 65 of each gender.

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

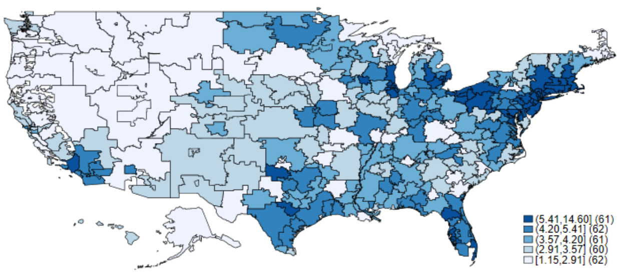
(a) Inpatient (%)



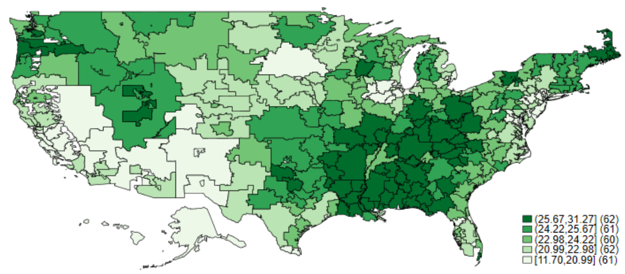
(b) Outpatient (%)



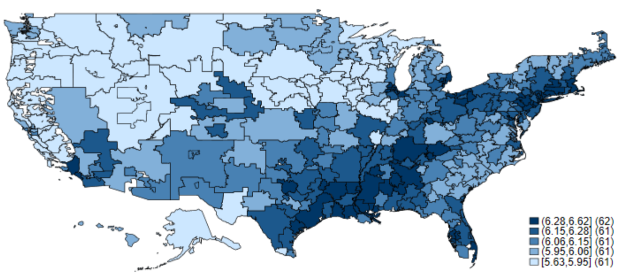
(c) Psychiatrist/Psychologist (%)



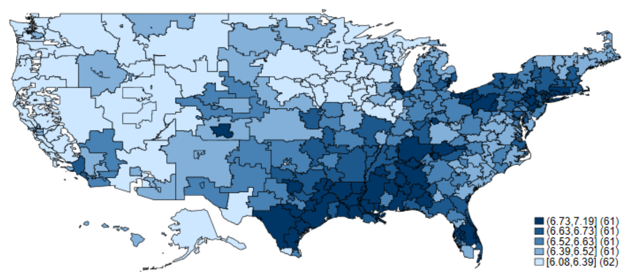
(d) Antidepressants/Antipsychotics (%)



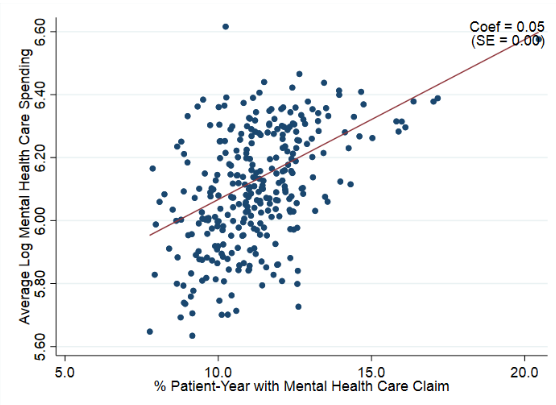
(e) Mental health care spending conditional on care use (drug excluded)



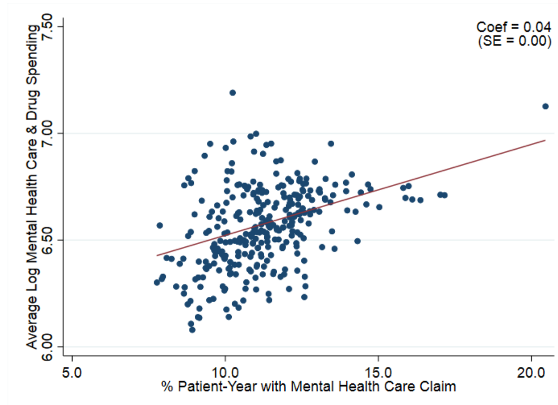
(f) Mental health care spending conditional on care use (drug included)



(g) Correlation between mental health care use and average spending conditional on use (drug excluded)

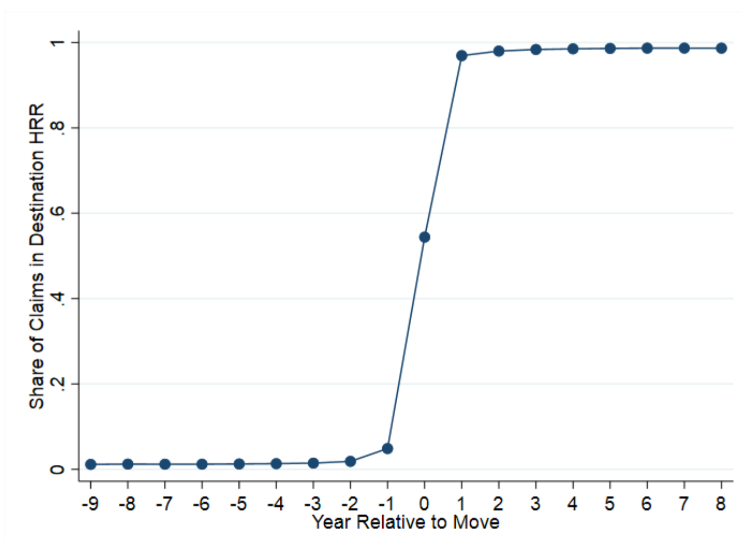


(h) Correlation between mental health care use and average spending conditional on use (drug included)



Notes: These figures present the distribution of mental health care utilization rate by Hospital Referral Region (HRR). Sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Panel (a)-(c) plots HRR mental health care utilization rates defined as share of patient-year observations that have any inpatient, outpatient, or psychiatrist/psychologist claim with a primary diagnosis related to mental illnesses. Panel (d) plots HRR prescription drug use rates defined as share of patient-year observations (conditional on having Part D coverage) that have any antidepressant or antipsychotic claims. Panel (e) plots average mental health care spending conditional on having any medical claim with a mental health diagnosis, and Panel (f) plots average mental health care and drug spending further conditional on Part D coverage. Panel (g) and (h) shows scatter plots for HRR mental health care utilization rate and average mental health care spending (drug excluded and included) conditional on care use. The fitted lines, coefficients and standard errors are based on regressions weighted by the number of patient-year observations in each HRR.

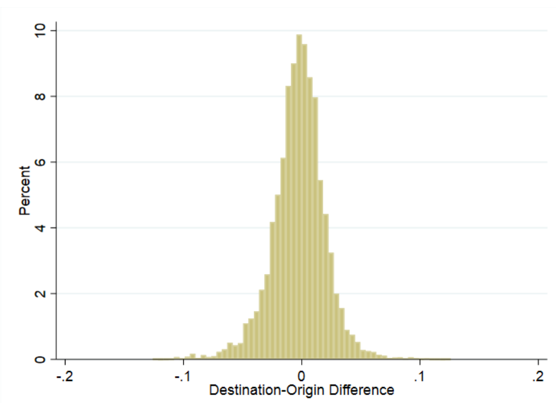
Figure A3: Share of Claims in Destination HRR by Years Relative to Moving



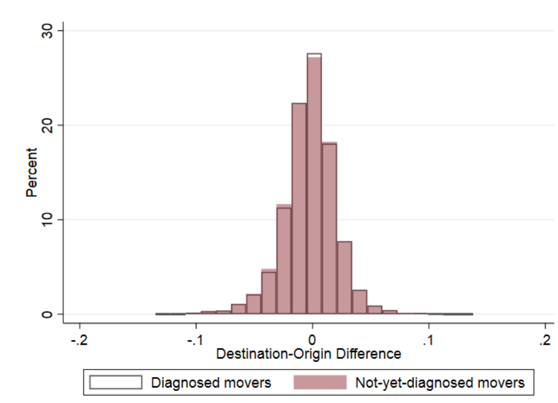
Notes: This figure shows the average share of medical claims from movers' destination HRRs among medical claims from either their origin or their destination HRRs, by number of years relative to moving.

Figure A4: Distribution of Destination-Origin Difference in Utilization Rate

(a) All movers



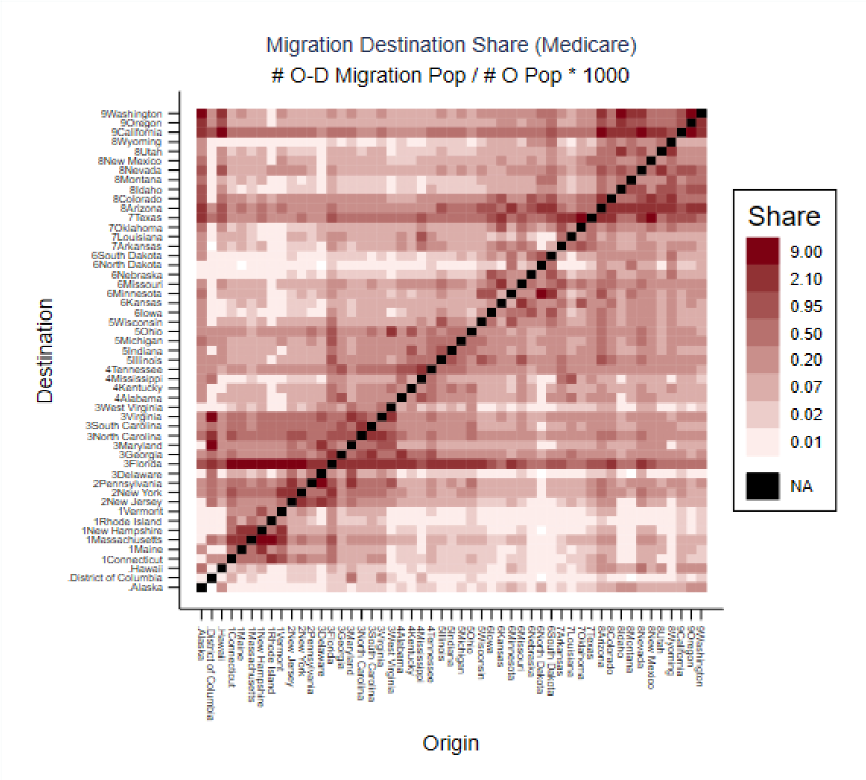
(b) Pre-diagnosed movers vs. not-yet-diagnosed movers



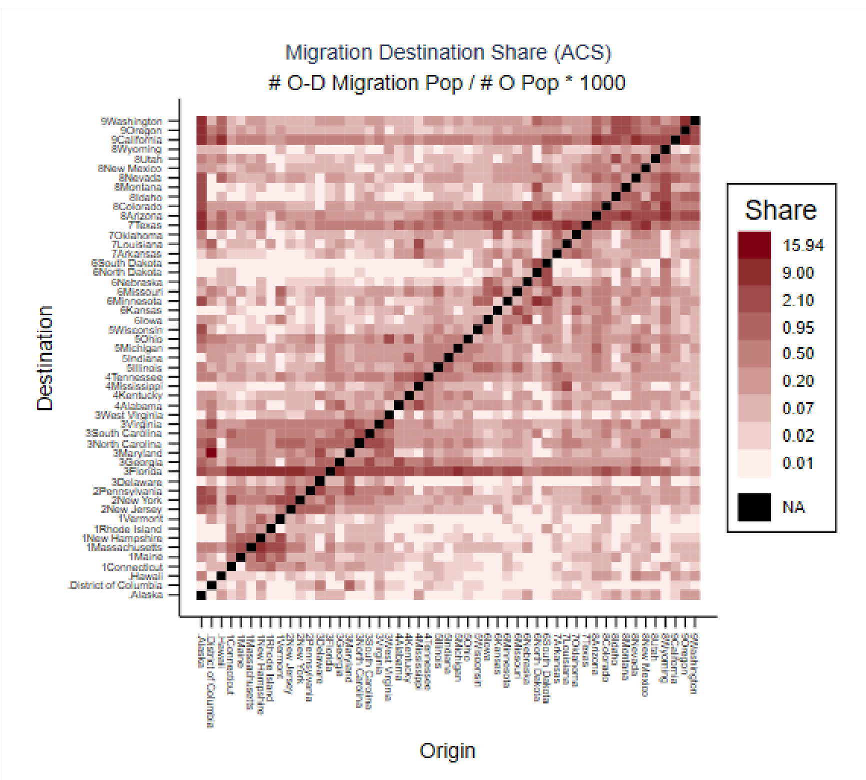
Notes: These figures show the distribution of the difference in mental health care utilization rates between destination and origin HRRs (δ_i) among all movers (Panel (a)) and among movers who have been diagnosed or have not been diagnosed with mental illnesses before moving (Panel (b)).

Figure A5: State-to-State Migration Flow in ACS and Medicare Data

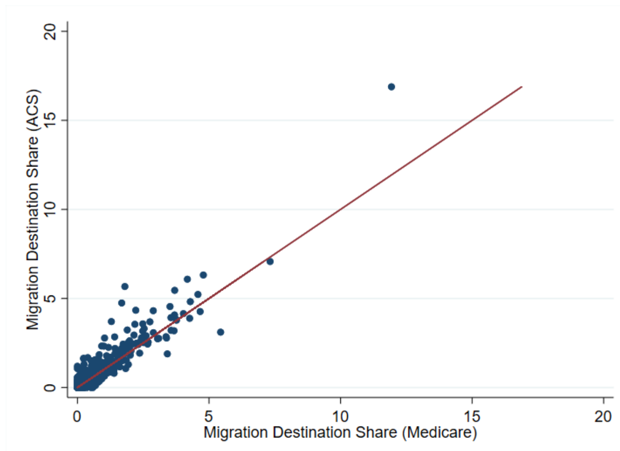
(a) Medicare



(b) ACS



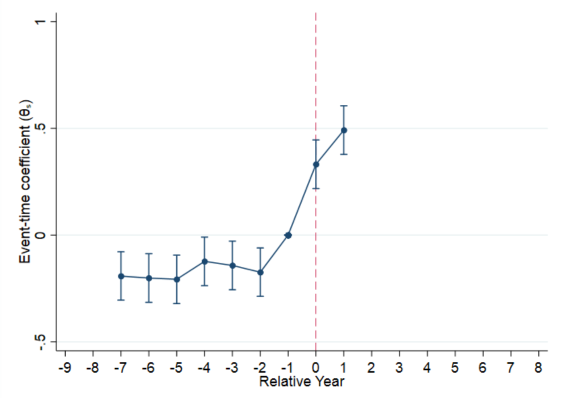
(c) Correlation between Migration Flow in ACS and Medicare Data



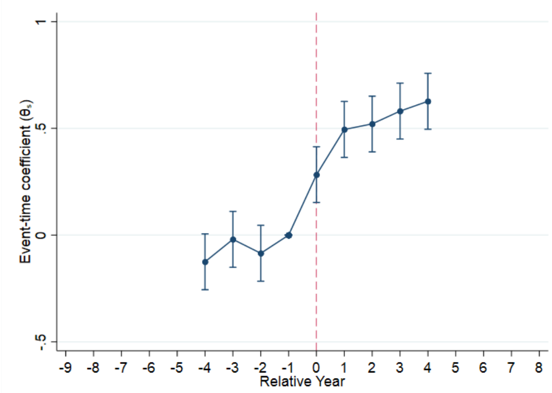
Notes: These figures plot the state-state migration flow intensity among people age above 65 in Medicare (Panel (a)) and ACS (Panel (b)) data. Each cell represents one state-to-state level migration flow, with origin state on the horizontal axis and destination state on the vertical axis. Both axes group states by census region, represented by the numerical digit in the label - New England (0), Middle Atlantic (1), South Atlantic (2), East South Central (3), East North Central (4), West North Central (5), West South Central (6), Mountain (7), Pacific (8), and Others (9). Migration flow intensity is measured as number of people moving from origin state to destination state denominated by the population of origin state (in thousands). Panel (c) shows the correlation between migration flow intensity in the two datasets, with each dot representing a state-to-state migration flow.

Figure A6: Place Effect: Balanced Panel

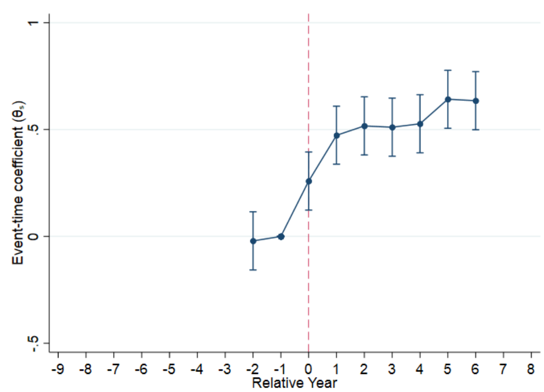
(a) Relative year [-7,1]



(b) Relative year [-4,4]



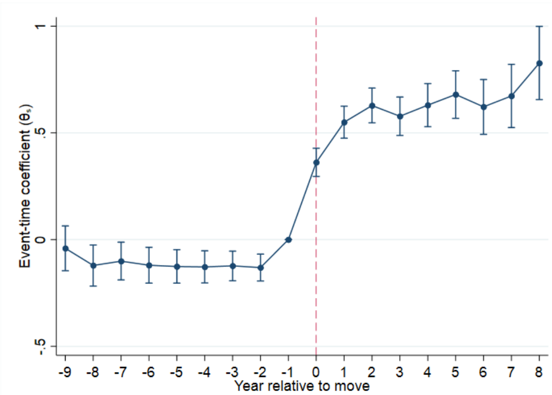
(c) Relative year [-2,6]



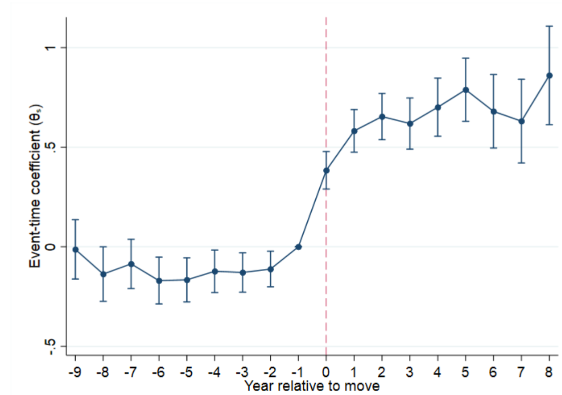
Notes: This figure replicates event study estimation in Figure 2 using different sets of balanced samples. Panel (a) uses a balance panel in relative years [-7,1] which includes 812,610 mover-year observations (90,290 movers). Panel (b) uses a balance panel in relative years [-4,4] which includes 630,378 mover-year observations (70,042 movers). Panel (c) uses a balance panel in relative years [-2,6] which includes 549,720 mover-year observations (61,080 movers).

Figure A7: Place Effect: Moving Directions

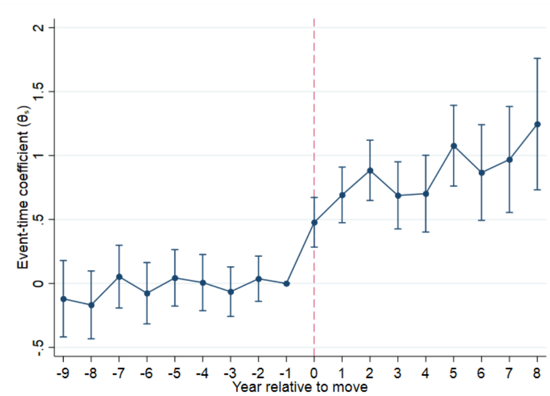
(a) Between above and below median HRRs



(b) Between top and bottom quartiles HRRs

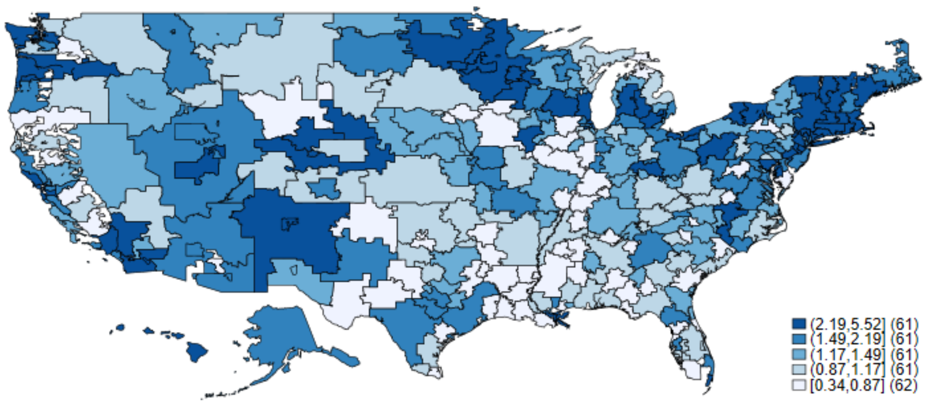


(c) Between top and bottom 10% HRRs



Notes: This figure replicates event study estimation in Figure 2 using subsamples of movers. Panel (a) includes individuals who move between HRRs that are above and below median mental health care utilization rates (1,517,203 mover-year observations, 170,406 movers). Panel (b) includes individuals who move between HRRs that are in the top and bottom quartiles of the mental health care utilization rates (344,942 mover-year observations, 39,174 movers). Panel (c) includes individuals who move between HRRs that are in the top and bottom 10% of the mental health care utilization rates (37,413 mover-year observations, 4,278 movers).

Figure A8: Number of Psychiatrists and Psychologists per 1,000 Medicare FFS Recipients by HRR



Notes: This figure presents the distribution of the number of psychiatrists and psychologists per 1,000 Medicare FFS recipients by HRR. The number of physicians is counted using Medicare Data on Provider Practice and Specialty (MD-PPAS) 2008-2018. The dataset is at physician-by-year level and includes individual providers who had a valid NPI and submitted a Medicare Part B non-institutional claim for evaluation and management services, procedures, imaging, or non-laboratory testing with a positive allowed charges amount in that year. Information on practice location is merged in using 20% claims data of each year. If a physician practiced in multiple HRRs in a given year, she will only be counted in the HRR where she submitted most of the claims. Number of Medicare FFS recipients is counted using the baseline sample of this analysis, multiplied by 5 to get estimates for 100% the Medicare population.

C Appendix Tables

Table A1: Mental Illness Category and ICD codes

	ICD-9	ICD-10
Cognitive disorders	290, 293.0/1, 294, 310	F01-F05, F07, F09, F48.2
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 291-292, 303-305)	F01-F99 (except 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). Alcohol- and substance-related disorders are not included since related claims are redacted from our Medicare data. 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. 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: Diagnosis Rate, Care Utilization Rate, and Patient Characteristics by Mental Illnesses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Share Patients	Share Patient-Years	Patients Characteristics				
			Age	Male	White	Dual Eligible	Part D Coverage
Any mental illness	0.31	0.11	78.2	0.36	0.88	0.21	0.61
Anxiety	0.10	0.03	76.2	0.28	0.90	0.20	0.64
Cognitive disorder	0.14	0.04	82.7	0.37	0.87	0.26	0.61
Mood disorder	0.14	0.05	76.9	0.32	0.89	0.23	0.63
Schizophrenia	0.06	0.01	80.4	0.38	0.87	0.30	0.62
Other mental illness	0.09	0.02	77.3	0.39	0.88	0.20	0.62
Never diagnosed mental illness	0.69	0.63	72.7	0.48	0.83	0.11	0.49

Notes: This table presents the diagnosis rate, care utilization rate and patient characteristics for different types mental health conditions, compared with patients never diagnosed with a mental illness. Sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Column (1) presents share of patients ever diagnosed with (each type of) or never diagnosed with mental illnesses. Column (2) presents share of patient-year observations with any (type of) or no mental health claim. Both the diagnosis rate and the care utilization rate are based on medical claims from inpatient, outpatient, or physician services. A prescription drug claim alone is not counted as a mental health diagnosis or care use. Columns (3)-(7) present patient characteristics, which are calculated by first averaging age and enrollment status for each patient among years with (each type of) mental health claim, and then aggregating across patients.

Table A3: Medicare Population Characteristics in HRR with Low, Median, High Mental Health Care Utilization Rates

	HRRs w/ low utilization	HRRs w/ median utilization	HRRs w/ high utilization
# HRRs	102	102	102
Mental health care utilization rate (%)	9.4	10.9	12.8
# Medicare population	30,519	35,197	47,081
Average # year observed	5.9	6.0	5.9
Age	75.3	75.5	76.0
Male	0.44	0.43	0.42
White	0.87	0.90	0.90
Dual eligible	0.12	0.11	0.11
Part D coverage	0.51	0.53	0.54

Notes: This table presents the average Medicare population characteristics in HRRs with low, median and high mental health care utilization rates. Sample includes Medicare FFS beneficiaries aged 65-99, with FFS Part A and B coverage for the full months in each year with no gap year, from 20% Medicare FFS claims data, 2006-2018. Mental health care utilization rate is calculated as share of patient-year observations in each HRR that has any inpatient, outpatient, or physician service claim with a primary diagnosis related to mental illnesses. Average patient characteristics are calculated by first averaging age and enrollment status for each patient, then aggregating at HRR level, and finally taking average across the 102 HRRs within each utilization rate tercile.

Table A4: Correlation between HRR Mental Health Care Utilization Rate and Suicide Rate

	(1)	(2)	(3)	(4)	(5)
	Suicide rate	Suicide rate (age, gender adjusted)		Suicide rate (age adjusted, by gender)	
				Male	Female
Utilization rate	-1.170				
	(0.105)				
Utilization rate (age, gender adjsted)		-1.242	-1.112		
		(0.121)	(0.124)		
Utilization rate (age adjusted)				-2.601	-0.230
				(0.255)	(0.0436)
Observations	306	306	306	306	306
Mean of dep. var	15.67	16.08	16.08	31.64	4.497
Demographic controls			X	X	X
Gun ownership controls			X	X	X

Notes: This table presents the regression results of HRR suicide rate on mental health care utilization rate. Observation is at HRR level. Definition of mental health care utilization rate and suicide rate follows Figure 1. Age adjusted rates are calculated using standardized 10-year age groups at national level. These rates are further adjusted using gender ratio at national level to derive the age and gender adjusted rates. Demographic controls include share of white patients and share of dual eligible patients among Medicare FFS population age above 65, Medicare Advantage penetration rate, median household income, share of household below poverty line, share of people graduated from high school, share of people graduated from college, and share of people living alone. The last five measures are collected from the American Community Survey (ACS) 2010 and 2015 five-year estimates for 65 and above population. Gun ownership controls include state-level universal background check law, permit to purchase law, and proportion of adults living in a household with a firearm, from RAND State-Level Estimates of Household Firearm Ownership (Schell et al., 2020).

Table A5: Correlation between Moving Direction and Life Events

	(1)	(2)	(3)
	Average change in mental health care utilization rate		
Divorce	0.000127		
	(0.000734)		
Widow		0.000595	
		(0.000427)	
Retire			-0.000122
			(0.000282)
Observations	56,856	56,871	69,120
Mean of Dep. Var	-0.00326	-0.00327	-0.00328
Age group X Gender FEs	X	X	X
Year FEs	X	X	X
Origin State FEs	X	X	X

Notes: This table presents the correlation between moving direction and life events experienced in the last year. Observations are individuals above age 65 who moved across states in ACS data 2006-2018. Divorce and death of spouse are identified based on survey questions "whether you get divorced in the past 12 months" and "whether you get widowed in the past 12 years". Retirement is identified if the interviewee reported working in the past 12 months, but not in the labor force currently. Outcome variable is average changes in HRR mental health care utilization rate experienced by Medicare recipients moving in the same state-to-state direction. Gender by 5-year age group fixed effects, interview year fixed effects, and origin state fixed effects are controlled. Robust standard errors are clustered by state-to-state migration flow level. All regressions are weighted by ACS person weight.

Table A6: Place Effect of Mental Health Care Utilization, by Geographic Unit

	(1)	(2)	(3)	(4)
	State	County	HRR	HSA
Panel A: Post Moving				
$\delta_i * Post$	0.802	0.703	0.693	0.687
	(0.0306)	(0.0228)	(0.0264)	(0.0225)
Observations	2,416,994	2,416,994	2,378,085	2,405,923
Dep. Mean	0.127	0.127	0.126	0.127
Panel B: Year 0, 1-4, 5-8 Post Moving				
$\delta_i * Post_0$	0.419	0.446	0.435	0.450
	(0.0324)	(0.0238)	(0.0276)	(0.0236)
$\delta_i * Post_{1-4}$	0.771	0.678	0.670	0.665
	(0.0305)	(0.0227)	(0.0263)	(0.0224)
$\delta_i * Post_{5-8}$	0.922	0.773	0.772	0.747
	(0.0476)	(0.0353)	(0.0411)	(0.0347)
Observations	2,745,127	2,745,127	2,700,222	2,732,087
Dep. Mean	0.134	0.134	0.134	0.134
Diff. btw Year 5-8 and Year 1-4	0.151	0.0943	0.102	0.0827
P-value	0.000436	0.00287	0.00583	0.00811

Notes: This table replicates Table 3 column (1) presenting the effect of changes in the local mental health care utilization rate on an individual's care use, for different geographic units. The sample includes patient-year observations for movers across state borders between [-9,8] years relative to move. Panel A further excludes the year of move from the sample. Local mental health care utilization rates are calculated at state, county, HRR, and hospital service area (HSA) levels. All the regressions include individual FEs, calendar year FEs, relative year FEs, and five-year age group FEs. Standard errors are clustered at beneficiary level.

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

	(1)	(2)	(3)	(4)	(5)
	Min	P25	Median	P75	Max
# Psychiatrists/Psychologists per 1k MCR pop	0.34	0.96	1.31	1.87	5.52
Psychiatrists	0.17	0.49	0.68	1.04	2.97
Psychologists	0.04	0.37	0.64	0.94	3.00
# General practitioners per 1k MCR pop	2.37	4.30	5.21	6.33	17.96
# Nurse practitioners per 1k MCR pop	0.94	3.23	4.25	5.85	15.43
# Other specialists per 1k MCR pop	6.52	12.30	15.58	19.68	58.76
# Psychiatric beds per 1k MCR pop	0.00	1.79	2.87	4.64	24.89
# Other hospital beds per 1k MCR pop	0.00	10.71	16.62	22.17	84.85
# Psychiatric hospitals	0.00	0.15	1.00	2.23	10.92
# Psychiatric units in other hospitals	0.00	1.46	3.00	5.69	26.00
People are sympathetic to mental illness patients (1-Agree strongly to 5-Disagree strongly, N = 239)	1.57	2.33	2.47	2.57	3.30
Treatment can lead to normal life (1-Agree strongly to 5-Disagree strongly, N = 239)	1.13	1.39	1.47	1.54	2.63

Notes: This table presents the distribution of provider capacity and social perception towards mental illness at HRR level. Numbers of physicians are counted using Medicare Data on Provider Practice and Specialty (MD-PPAS) 2008-2018. The dataset is at physician-by-year level and includes individual provider who had a valid NPI and submitted a Medicare Part B non-institutional claim for evaluation and management services, procedures, imaging, or non-laboratory testing with a positive allowed charges amount in that year. Information on practice location is merged in using 20% claims data of each year. If a physician practiced in multiple HRRs in a given year, she will only be counted in the HRR where she submitted most of the claims. 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. Numbers of psychiatric hospitals, psychiatric units, and (psychiatric) hospital beds are from CMS Provider of Service Current Files (POS), 2006-2018. Numbers of (psychiatrist) beds are also denominated by 1,000 Medicare FFS recipients. Social perception towards mental illness is based on Behavioral Risk Factor Surveillance System (BRFSS) survey, 2007. Two questions on perceived sympathy and treatment efficacy were asked using a 5-point scale. Only interviewees above age 65 are included in calculating the HRR average. Since the mental health module is not surveyed in all states, only N = 239 HRRs are identified based on interviewee's zipcode.

Table A8: Place Effect on Intensive Margin: Moving Direction and Diagnosis History before moving

	(1)	(2)	(3)	(4)	(5)
	All movers	Pre-diagnosed movers		Not-yet-diagnosed movers	
Panel A: Log Mental Health Care Spending Conditional on Care Use					
$\delta_i * Post$		0.713		0.988	
		(0.0495)		(0.0367)	
$\delta_i * Post * Up$	0.697		0.698		0.938
	(0.114)		(0.114)		(0.0762)
$\delta_i * Post * Down$	0.948		0.946		1.029
	(0.111)		(0.111)		(0.0667)
Observations	248,612	195,533	195,533	81,946	81,946
Dep. Mean	6.328	6.307	6.307	6.247	6.247
Diff btw. Moving Up and Down	-0.250		-0.249		-0.0910
(P-value)	(0.115)		(0.118)		(0.358)
Panel B: Log Mental Health Care and Drug Spending Conditional on Care Use					
$\delta_i * Post$		0.578		0.870	
		(0.0753)		(0.0521)	
$\delta_i * Post * Up$	0.612		0.612		0.689
	(0.163)		(0.163)		(0.102)
$\delta_i * Post * Down$	0.800		0.793		0.855
	(0.163)		(0.163)		(0.0960)
Observations	134,264	103,678	103,678	48,206	48,206
Dep. Mean	6.799	6.815	6.815	6.534	6.543
Up - Down	-0.188		-0.181		-0.166
(P-value)	(0.415)		(0.433)		(0.007)
Individual FEs	X	X	X	X	
Year FEs	X	X	X	X	X
Relative Year FEs		X		X	
Relative Year * Up/Down FEs	X		X		X
Origin HRR FEs					X

Notes: This table presents regression results estimated from a difference-in-differences version of equation (3). The sample in column (1) includes patient-year observations for all movers during [-9,8] years relative to move excluding the year of moving. Columns (2)-(5) split the sample by whether the movers have any mental health claims before moving. The dependent variable in is log mental health care spending for patient i in year t conditional on her having mental health care use in that year. The dependent variable in panel B is log mental health care and drug spending conditional on having mental health care (sample restricted to people with Part D coverage). δ_i is the destination-origin difference in HRR mental health care utilization rate, which is interacted with an indicator for years after moving, and indicators for whether it is an upward moving ($\delta_i > 0$) or a downward moving ($\delta_i <= 0$). Regressions in columns (1)-(3) include beneficiary fixed effects, calendar year fixed effects, relative year fixed effects, and indicators for 5-year age groups. Regressions in columns (4)-(5) use sample of movers that did not have a mental health claim before moving, therefore the individual fixed effect is dropped and replaced by origin HRR fixed effects. Columns (1), (3), (5) also have fixed effects for relative year by upward/downward moving direction. Standard errors clustered at beneficiary level.

Table A9: Robustness Checks: Excluding Cognitive Disorders from Mental Health Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All movers				Pre-diagnosed movers		Not-yet-diagnosed movers	
	Any Mental Health Care Claim							
$\delta_i * Post$	0.654		0.598		1.337		0.455	
	(0.0256)		(0.0221)		(0.0785)		(0.0220)	
$\delta_i * Post_0$		0.416						
		(0.0274)						
$\delta_i * Post_{1-4}$		0.630						
		(0.0256)						
$\delta_i * Post_{5-8}$		0.705						
		(0.0400)						
$\delta_i * Post * Up$				0.848		1.630		0.672
				(0.0603)		(0.186)		(0.0549)
$\delta_i * Post * Down$				0.458		1.123		0.185
				(0.0471)		(0.138)		(0.0383)
Observations	3,213,579	3,653,723	3,213,579	3,213,579	694,010	694,010	2,519,569	2,519,569
Dep. Mean	0.0972	0.103	0.0972	0.0972	0.316	0.316	0.0370	0.0370
Diff. btw Year 5-8 and Year 1-4		0.0754						
(P-value)		(0.0362)						
Diff. btw Up and Down				0.390		0.507		0.487
(P-value)				(3.34e-07)		(0.0286)		(0)
Individual FEs	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Relative Year FEs	X	X	X		X		X	
Provider Capacity Controlled			X					
Relative Year * Up/Down FEs				X		X		X

Notes: This table replicates Table 3, Table 6, and Figure 4 regression results. Sample used in Columns (1)-(4) includes all movers during [-9,8] years relative to move, excluding the year of moving except in Column (2). Columns (5)-(8) split the sample by whether the movers have any mental health claims before moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim (focus only on anxiety, mood disorder, schizophrenia, and other mental health conditions, but do no include cognitive disorders) in year t. δ_i is the destination-origin difference in HRR mental health care utilization rate. Upward moving is defined as $\delta_i > 0$, and downward moving is defined as $\delta_i <= 0$. Provider capacity controls include the number of mental health professionals, psychiatric facilities and other providers (the same as described in Figure 4). Standard errors clustered at beneficiary level.

Table A10: Robustness Checks: Excluding Patients Ever Stayed in Nursing Facilities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All movers				Pre-diagnosed movers		Not-yet-diagnosed movers	
	Any Mental Health Care Claim							
$\delta_i * Post$	0.249		0.231		0.804		0.161	
	(0.0247)		(0.0228)		(0.0902)		(0.0200)	
$\delta_i * Post_0$		0.210						
		(0.0255)						
$\delta_i * Post_{1-4}$		0.250						
		(0.0246)						
$\delta_i * Post_{5-8}$		0.239						
		(0.0383)						
$\delta_i * Post * Up$				0.279		0.595		0.258
				(0.0611)		(0.217)		(0.0517)
$\delta_i * Post * Down$				0.217		0.852		0.0718
				(0.0454)		(0.165)		(0.0351)
Observations	1,948,112	2,227,847	1,948,112	1,948,112	358,219	358,219	1,589,893	1,589,893
Dep. Mean	0.0784	0.0823	0.0784	0.0784	0.301	0.301	0.0283	0.0283
Diff. btw Year 5-8 and Year 1-4		-0.0111						
(P-value)		(0.747)						
Diff. btw Up and Down				0.0625		-0.257		0.186
(P-value)				(0.411)		(0.346)		(0.00288)
Individual FEs	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Relative Year FEs	X	X	X		X		X	
Provider Capacity Controlled			X					
Relative Year * Up/Down FEs				X		X		X

Notes: This table replicates Table 3, Table 6, and Figure 4 regression results. Sample used in Columns (1)-(4) includes all movers who have never stayed in nursing facilities, during [-9,8] years relative to move, excluding the year of moving except in Column (2). Columns (5)-(8) split the sample by whether the movers have any mental health claims before moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim in year t. δ_i is the destination-origin difference in HRR mental health care utilization rate. Upward moving is defined as $\delta_i > 0$, and downward moving is defined as $\delta_i <= 0$. Provider capacity controls include the number of mental health professionals, psychiatric facilities and other providers (the same as described in Figure 4). Standard errors clustered at beneficiary level.

Table A11: Robustness Checks: Using All Diagnoses to Identify Mental Health Care Use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All movers				Pre-diagnosed movers		Not-yet-diagnosed movers	
	Any Mental Health Care Claim							
$\delta_i * Post$	0.438		0.401		0.584		0.230	
	(0.0252)		(0.0190)		(0.0438)		(0.0279)	
$\delta_i * Post_0$		0.124						
		(0.0249)						
$\delta_i * Post_{1-4}$		0.426						
		(0.0249)						
$\delta_i * Post_{5-8}$		0.496						
		(0.0391)						
$\delta_i * Post * Up$				0.321		0.452		0.110
				(0.0553)		(0.0968)		(0.0625)
$\delta_i * Post * Down$				0.533		0.725		0.252
				(0.0565)		(0.0967)		(0.0616)
Observations	3,213,579	3,653,723	3,213,579	3,213,579	1,401,388	1,401,388	1,812,191	1,812,191
Dep. Mean	0.262	0.274	0.262	0.262	0.465	0.465	0.105	0.105
Diff. btw Year 5-8 and Year 1-4		0.0707						
(P-value)		(0.0422)						
Diff. btw Moving Up and Down				-0.212		-0.273		-0.141
(P-value)				(0.00745)		(0.0460)		(0.107)
Individual FEs	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Relative Year FEs	X	X	X		X		X	
Provider Capacity Controlled			X					
Relative Year * Up/Down FEs				X		X		X

Notes: This table replicates Table 3, Table 6, and Figure 4 regression results. Sample used in Columns (1)-(4) includes all movers during [-9,8] years relative to move, excluding the year of moving except in Column (2). Columns (5)-(8) split the sample by whether the movers have any mental health claims before moving. The dependent variable is a dummy indicator for whether patient i had any mental health care claim (based on all diagnoses in the claims) in year t. δ_i is the destination-origin difference in HRR mental health care utilization rate. Upward moving is defined as $\delta_i > 0$, and downward moving is defined as $\delta_i <= 0$. Provider capacity controls include the number of mental health professionals, psychiatric facilities and other providers (the same as described in Figure 4). Standard errors clustered at beneficiary level.