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Discussion Paper no. 2025-11

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JEL Classification: H51, I11, I13, I14, I18, J18

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Regional variation in mental healthcare utilization and suicide: Evidence from movers in Australia[1]

Karinna Saxby[†] Thomas Buchmueller[ʄ] Sonja C. de New[♀ ‡ Ψ] Dennis Petrie[♀]

Abstract

Poor mental health is a major global health issue, with many countries documenting high levels of unmet need and regional disparities in mental healthcare utilization. To determine how best to address these disparities, it is important to understand what drives regional variation. Using Census-linked microdata from Australia, we exploit cross-region migration to identify the extent to which patient and place factors drive regional variation in utilization of mental healthcare services and mental health prescriptions (antidepressants, anxiolytics, antipsychotics). We find that place factors account for approximately 72% and 19% of the regional variation in utilization of mental healthcare services and mental health prescriptions, respectively, with the rest reflecting patient-related demand. We also find suggestive evidence that larger place effects predict fewer mental health related ED presentations, self-harm hospitalizations, and suicides. Altogether, our findings suggest there is inadequate and inequitable supply in regions with low utilization, rather than inefficiently high utilization in high utilization regions.

Keywords: healthcare supply, healthcare demand, healthcare spending, mental health, regional variation, suicide

JEL codes: H51, I11, I13, I14, I18, J18

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[1] We would like to thank the participants of the participants of the 43rd Annual Australian Health Economics Society conference, the 2022 Economics of Health Workshop, the 2023 IRDES Workshop on Applied Health Economics, Zoe Aitken, Naimi Johansson, Johannes Kunz, Gang Chen, Umair Khalil, Tony Scott, Andrew Ireland, Jan Kabatek, Jonathan Zhang, Madi Stone, and Peter Butterworth for their feedback which helped to significantly improve the paper. We would also like to thank Ben Harrington, Talei Parker, Sandra Flynn, Rashmin Chitale, Humaira Khan, Zac Steyn and the rest of the ABS microdata team for their tireless vetting and assistance. The study was approved by the University of Melbourne's Human Ethics Advisory Group and Human Ethics Sub-Committee and was supported by the Australian Government Research Training Program Scholarship.

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1. Introduction

Poor mental health is a leading cause of disease burden worldwide, with an estimated one million people dying each year from suicide (Whiteford et al., 2013, Vigo et al., 2016, Wasserman, 2016). Despite the existence of effective treatment, such as cognitive behavioural therapy and pharmacotherapy (e.g., antidepressants, anxiolytics), many countries have documented high levels of unmet need and persistent regional variation in mental healthcare utilization (Moscone and Knapp, 2005, Cipriani et al., 2018, Maconick et al., 2021). The appropriate policy response to this variation depends on what causes it. Broadly speaking, this variation could be considered warranted if differences are due to patient need or preferences, but problematic if it is due to factors such as the availability of appropriate services or patients' ability to pay. In particular, supply-driven variation could signal inefficiencies – if high utilization areas are characterized by excessive treatment yielding negligible marginal benefits – or inequity – if patients in low utilization areas are unable to access beneficial care. Considering a history of "chronic underfunding" and workforce shortages for mental healthcare across many countries, the latter may be more plausible (Krausz et al., 2019, WHO, 2021).

Empirical evidence on the population-level causes and consequences of variation in mental healthcare utilization is critical for the design of effective mental health policy. In this study, we investigate regional variation in mental healthcare utilization and mental health outcomes in Australia, a setting where the supply of mental health providers is limited and unevenly distributed (Phillips, 2013, Johar et al., 2017, Productivity Commission, 2020, Pulok et al., 2020). Specifically, our analysis focuses on government spending under Australia's universal health insurance scheme, Medicare, which generally reimburses a fixed amount for eligible mental health services and prescriptions. There are large differences in mental healthcare utilizations across regions. For example, per capita spending on mental healthcare services in urban Central and Eastern Sydney is around nine times greater than rural Western Queensland. Aggregate data suggest that spending differences are correlated with health outcomes: suicide rates are much higher in rural Western Queensland (10.3 suicides per 100,000 population each year) compared to urban Sydney (3.5 suicides per 100,000 population each year).

Previous studies on the causes of regional variation in mental health and mental healthcare utilization have largely relied upon observable patient and regional level characteristics (Lê Cook et al., 2013, Awaworyi Churchill et al., 2019, Shiner et al., 2022). However, it is challenging with such an approach to distinguish demand- or supply- related factors. Patient demand for mental health treatment is largely unobservable and hindered by limited availability of population-level estimates on mental illness (Moscone et al., 2007). Risk factors that are often used as proxies for mental illness, such as area-level deprivation measures, may be influenced by supply and other place-based factors. At the same time, the greater availability of mental health providers in some regions may be a response to higher patient demand. Accounting for unobservable patient preferences is particularly important in the context of mental healthcare where mental health stigma and the perception of treatment efficacy can dramatically influence help seeking behaviour (Sickel et al., 2014).

To address these endogeneity concerns, we apply a 'movers' strategy that exploits patient migration across regions to identify the effects of patient and place-based factors (Finkelstein et al., 2016, Moura et al., 2019, Godøy and Huitfeldt, 2020, Salm and Wübker, 2020, Johansson and Svensson, 2022). The basic idea of this approach is that if regional differences in healthcare utilization are explained primarily by demand-side factors, individuals' utilization will remain unchanged after they move, regardless of whether they relocate to a region with lower or higher average utilization. On the other hand, if regional differences are mainly driven by place-base factors, the utilization of patients who move will tend to adjust towards the average utilization of their destination region.

Our analysis is based on longitudinal administrative healthcare claims data linked to the Australian Census. We separately analyse the regional variation in the utilization of mental healthcare services and mental health prescriptions. These data provide comprehensive information on utilization and, importantly, allow us to observe when individuals move from one region to another.

To aid with interpretation of the main results, we test whether the estimated place effects are correlated with several region-level measures of supply: the number of psychiatrists and psychologists per capita, out-of-pocket costs, and mean wait times for mental health treatment. Finally, we explore whether larger place-based utilization predicts reductions in acute mental healthcare use or fewer suicides.

Our main results indicate quite different patterns for mental healthcare services and prescriptions. Place effects account for roughly 72% of the regional variation in utilization of mental healthcare services. In contrast, we find that place effects account for only 19% of the variation in the utilization of mental health prescriptions. These results are consistent with the fact that in Australia, most mental health medications are prescribed by GPs, whereas most mental health services are provided by specialty providers. There is also much less regional variation in the supply of GPs as compared to specialty mental health providers (Department of Health and Aged Care, 2023) and prescribing generally requires less health professional time. Thus, in Australia supply constraints are likely to be less relevant for prescription drugs than for mental health services. Furthermore, because GPs have limited financial incentives to over-prescribe, there is less reason to expect that supplier induced demand would produce regional variation in prescribing. We find that greater availability of mental healthcare providers and lower out-of-pocket costs are positively correlated with the estimated place effects, particularly for mental health services. We also find a positive relationship between waiting times and the place effects for mental health prescriptions. These patterns suggests that regional variation in mental healthcare utilization is largely driven by variation in supply and that where it is difficult to see mental health providers, patients are more likely to be treated with prescription drugs.

The welfare implications of these results depend on the extent to which greater supply translates to better health outcomes. We find suggestive evidence that higher place-based utilization is associated with improved mental health outcomes. A one standard deviation increase in place-based utilization for mental health services predicts a 10% reduction in mental health emergency department (ED) presentations, a 20% reduction in self-harm hospitalisations, and a 10% reduction in suicides. These associations suggests that the variation in utilization reflects inadequate supply across regions rather than inefficient high supply in high-utilization areas.

This paper contributes to a growing literature that seeks to determine the relative importance of demand and supply-side factors in explaining regional variation in health care utilization. The results from existing studies indicate that the importance of supply-side factors varies substantially across types of care and institutional context. For example, whereas Finkelstein et al. (2016) find that place factors explain 60% of the variation in all health care utilization among Medicare beneficiaries in the US, Salm and Wübker (2020) find that place effects account for only 9% of the variation in ambulatory care utilization in Germany. The only other concurrent study focusing on mental healthcare in this literature, which used US Medicare data, found that place factors explained 46% and 15% of the variation for mental healthcare services and prescription medicines, respectively (Ding, 2023). Our study also connects to the literatures on the determinants and consequences of scarce mental healthcare supply. In particular, our results align with previous evidence that selection of providers into regions can lead to large inequities in healthcare access (Gravelle and Sutton, 2001, Rosenthal et al., 2005, Isabel and Paula, 2010, Grobler et al., 2015, Swami and Scott, 2021) and that easing supply constraints can improve health outcomes (Ludwig et al., 2009, Okeke, 2023).

Our findings have important implications for mental health policy. Recent legislative inquiries in Australia have emphasized the need for "improved targeting" and more equitable access of mental healthcare (Productivity Commission, 2020, Pirkis et al., 2022). Australia has implemented various policies aimed at reducing regional variability in GP access, including financial incentives and compulsory service (Swami and Scott, 2021, Department of Health and Aged Care, 2022). These policies may have contributed to the improved accessibility of mental health prescriptions. However, there have been relatively few measures to increase the supply of specialty mental health providers in underserved areas. The identified relationships between place-based expenditure and mental health outcomes further suggests that, at a population level, universally increasing effective supply might be more beneficial than focusing on allocative inefficiencies across regions.

The paper is organised as follows. Section 2 describes the institutional setting and data. Section 3 presents the empirical strategies for estimating the relative importance of patient- and place-related factors and discusses our identifying assumptions. The main results, robustness checks, heterogeneity analyses, and potential mechanisms are presented and discussed in Section 4. Section 5 explores the association with place-based expenditure and mental health outcomes. Section 6 concludes.

2. Institutions and data

Institutional setting

All Australian citizens and permanent residents are eligible for free or subsidized healthcare under Australia's universal health insurance scheme, Medicare, which provides comprehensive coverage for inpatient and outpatient care and prescription medications.

Subsidised out-of-hospital mental healthcare services are provided by GPs, psychiatrists, psychologists, and other allied health professionals (AIHW, 2022b).[2] These services are reimbursed on a fee-for-service basis and the recommended fee for services ('schedule fee')

[2] Some mental health providers operate outside the Medicare system and do not accept government payments. These providers typically offer services on a private-pay basis, meaning clients are responsible for the full cost of treatment without Medicare rebates. We do not observe such treatment in our administrative data.

and the associated government benefit is listed under the Medicare Benefits Schedule (MBS). Generally, 100% of the Medicare Benefits Schedule (MBS) fee is reimbursed for GP services and 85% of the fee is reimbursed for specialist services. However, as all providers can set their own fees, individuals incur out-of-pocket costs for services if providers charge a fee above the government-stipulated MBS benefit. Providers are given incentives to charges fees equal to the benefit (known as 'bulk-billing') for welfare recipients, aged pensioners, and low-income earners ('concessional' patients) (Department of Health, 2020). There is substantial variation in the fees charged across regions and provider types. Over 2011 to 2019, the average out-of-pocket cost was AUD55.7 per psychiatrist visit and AUD33.2 per psychologist visit. During this period, the government covered approximately 83% of the total expenditure on Medicare-subsidised mental health services.[3] Annual out-of-pocket costs are capped, to varying degrees, by public Safety Net programs.[4] If individuals reach the MBS Safety Net, the government will increase the subsidised benefit to 100% of the schedule fee.

GPs are responsible for developing 'Mental Health Treatment Plans' and serve as the gatekeeper for referrals to secondary mental healthcare providers.[5] During our observation window, these treatment plans enabled patients to have six government-subsidized sessions with a mental health professional in the first instance, with the option for an additional four sessions as needed (Department of Health and Aged Care, 2020, AIHW, 2022a). However, the limited supply of specialty mental health care providers has been a long-standing concern (Productivity Commission, 2020, ACIL Allen, 2021). Australia's mental health workforce remains well below government targets (ACIL Allen, 2021). As of 2020, the number of practicing psychologists was only 35% of the target (ACIL Allen, 2021). The psychiatry workforce was slightly closer to the target level but still fell short, approaching approximately

[3] Based on own calculations from data used in this study. All costs presented in 2019 AUD with prices adjusted for inflation using the health Consumer Price Index (ABS, 2024). In 2019, the conversion rates were 1.44 AUD to 1.00 USD and 1.84 AUD to 1.00 GBP (OECD, 2024).

[4] In 2019, these caps were AUD470.00 for out-of-hospital medical services and, for prescription medicines, AUD390.00 for concessional patients and AUD1550.70 for general patients (Australian Government, 2019, Department of Health, 2019). Approximately 5.5% of the population reached the MBS safety net in 2010 (Services Australia, 2025).

[5] Some GPs also provide focused psychological treatments, such as cognitive behavioural therapy, though this is rare: in 2019-20, GP-delivered psychological strategies represented only 1% of all GP claims.

66% (ACIL Allen, 2021). Using Medicare claims data, we estimate that patients wait an average of 58 days from a GP's referral before receiving a psychotherapy session.[6]

Supply constraints are less of an obvious concern for mental health prescriptions as compared to mental health services. Approximately 90% of all prescriptions written in Australia are subsidised under Medicare through the Pharmaceutical Benefits Scheme (PBS) (Hall et al., 2020), with the majority (>80%) being prescribed by GPs (AIHW, 2022b). Pharmaceutical prices and cost-sharing rules are determined nationally. In 2022, the prescription medicine co-payment was AUD42.50 for ordinary patients and AUD6.80 for concessional patients (Australian Government, 2022).[7] However, if the government-subsidized price of a prescription medicine is lower than the patient's co-payment, the patient pays the lower subsidized price. While patients may opt for brand-name medicines over generics, the government's subsidy is fixed based on the price of the reference (usually generic) product and the patient's co-payment is capped at the standard co-payment level (or the lower subsidized price). If individuals reach the PBS Safety Net, co-payments reduce to $0 for concessional patients and to the concessional rate for general patients. There is no additional coinsurance beyond the standard co-payment for PBS-listed medicines.

Data, sample, and descriptive statistics

The data are sourced from the Person-Level Integrated Data Asset (PLIDA, previously known as MADIP), which links data from the 2011 Census population to longitudinal administrative data on Medicare, social security, tax records, and death records (ABS, 2022). Full details on the construction of the sample follow previous PLIDA analyses (Saxby et al., 2023) and are presented in Appendix Figure A1. Classification of mental health services is based on Medicare codes (AIHW, 2022b) and mental health prescriptions are identified based on the Anatomical Therapeutic Chemical (ATC) classes for antidepressants ('N06A'), anxiolytics ('N05B'), and antipsychotics ('N05A').

PLIDA identifies individuals' residential location from several data sources. Updates to their location are then based upon when individuals most recently reported their residence to any of the following administrative agencies: Department of Social Services (e.g., when engaging with social services for welfare payments), Australian Taxation Office (e.g., annual tax returns),

[6] Based on calculations from data used in this study.

[7] Prescription medicine co-payments are adjusted on 1 January each year in line with inflation.

and Department of Health and Aged Care (e.g., for receiving medical care or prescription medicines). In addition, all individuals self-reported their location in the 2011 Census (conducted 9 August 2011). The consolidation of location data from various administrative sources is a particular advantage relative to other studies that rely on patients receiving treatment to identify location (Salm and Wübker, 2020).

In Australia, a fundamental geographic unit for organizing health care resources and coordinating care is the Primary Health Network (PHN) (Australian Government, 2021). These regions signify regional healthcare markets centred around hospital networks and are analogous to hospital referral regions used in similar studies investigating regional variation in healthcare utilization (Finkelstein et al., 2016, Godøy and Huitfeldt, 2020). There are 31 PHNs across Australia, with population sizes ranging from 62,000 to 1,900,000 (AIHW, 2022c). We conduct our analysis at the PHN level rather than using a smaller geographic unit to ensure that patients receive a large fraction of their care within the region where they live. Approximately four-fifths of total mental healthcare expenditures falls within a patient's PHN, which is similar to the share reported in other studies using a 'movers' design (Finkelstein et al., 2016, Godøy and Huitfeldt, 2020). This is important for our empirical strategy because it minimises the possibility that individuals who move from one region to another continue to receive care from the same providers after they move.

As aforementioned, in this study, we focus on what drives the variation across regions in commonwealth government spending on mental healthcare.[8] Figure 1 presents the regional variation in annual government expenditure for mental health services and prescriptions (based on a 25% sample of non-movers). Across all PHNs, the average annual government expenditure per person is AUD38.9 for mental health services and AUD19.3 for mental health prescriptions. The regional averages vary considerably, from 79% below to 63% above the national average for mental health services and from 54% below to 30% above the average for mental health prescriptions. The coefficients of variation are 0.35 and 0.21 for mental health services and prescriptions, respectively. These are higher than the coefficients of variation for hospital expenditure in Norway (0.13) (Godøy and Huitfeldt, 2020), prescription drug

[8] Government expenditure is also a helpful way to combine a diverse set of mental healthcare services because the government benefits are mostly fixed and set based on the expected time and level of staff required to deliver a mental health service. We do not include out-of-pocket payments. In particular, as providers in Australia can decide their fee and this can differ across a provider's patients, greater out-of-pocket costs will not necessarily reflect a higher quantity or quality of mental healthcare.

expenditure in Sweden (0.16) (Johansson and Svensson, 2022), and overall expenditure among Medicare beneficiaries in the US (0.12) (Finkelstein et al., 2016). Generally, expenditure on mental health services is larger in more densely populated regions while the opposite is true for mental health prescriptions.

Our analysis period covers nine years, from 2011 to 2019. Our core sample includes Australian adults aged 18 and above at the time of the 2011 Census. Following previous studies (Moura et al., 2019, Godøy and Huitfeldt, 2020), we exclude individuals who moved more than once throughout the nine-year observation window and retain only a 25% random sample of non-movers for computational efficiency. Full details on sample construction are provided in Appendix Figure A.1.

The descriptive statistics for the resulting sample of non-movers (n=2,571,691) and movers (n=1,764,793) is presented in Table 1. Compared to non-movers, movers are on average younger (mean age 43 vs 49 years) and have slightly higher levels of educational attainment (25% vs 20% with a university degree). Movers are more likely to be in full time employment and have higher levels of income and are less likely to report a core activity limitation. Across the nine-year sample period, movers were slightly less likely than non-movers to have mental health prescriptions (27% vs 29%) and had lower average spending on prescriptions (AUD39 vs. AUD43). In contrast, movers were more likely to use mental health services than non-movers (38% vs 29%) and had higher mean expenditures (AUD64 vs. AUD59). Although this data does not capture underlying 'need' for mental healthcare, these levels of access reinforces Australia as a setting of underutilization (Black et al., 2024, Black et al., 2025). Over the nine-year observation window, movers are less likely to have died from any cause compared to stayers (5 vs 8%) but have similar rates of suicide mortality.

3. Empirical strategy

The main outcomes we analyse are the utilization of mental health services and mental health prescriptions. For both care types, we follow the literature (Finkelstein et al., 2016, Moura et al., 2019, Godøy and Huitfeldt, 2020, Salm and Wübker, 2020, Johansson and Svensson, 2022) and measure utilization as *ln(annual expenditures + 0.01).* Using expenditures as an outcome enables us to capture differences in the frequency and 'level' of care patients receive. Further, specifying the dependent variables in this way accounts for the skewness of healthcare expenditures and the propensity for individuals to have zero mental health expenditures in a given year. However, as it has recently been shown that the results can be sensitive to the chosen adjustment parameters (Chen and Roth, 2022, Mullahy and Norton, 2024), we also estimate alternative specifications as robustness checks.

We infer the relative importance of place-related factors from two types of regression models. One model estimates region fixed effects, which represent the portion of mean level utilization that can be attributed to place-based (i.e., supply) factors. An advantage of this specification is that the correlation between the region fixed effects and various measures of supply provides insight on potential mechanisms. Further, the correlation between region fixed effects and health outcomes provides evidence on the benefits of additional expenditures. Using data only on individuals who move from one PHN to another, we also estimate event-study models that track changes in mental health care utilization before and after the move. This specification provides evidence on key assumptions that we rely on for identification.

Fixed effects model

The fixed effects model is specified as follows:

$$y_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\gamma}_{\boldsymbol{r}(\boldsymbol{it})} + \boldsymbol{A}_{\boldsymbol{n}(\boldsymbol{it})} + \boldsymbol{\tau}_t + \boldsymbol{q}_{\boldsymbol{it}} + \xi_{it} \qquad (1)$$

Where y is the outcome of interest *(ln(expenditures + 0.01)* for mental health services or mental health prescriptions) for individual i in year t. Time-invariant individual characteristics are captured by patient fixed effects, denoted by $\boldsymbol{\alpha}_i$. We account for the effect of ageing with a vector of indicator variable for five-year age categories ($\boldsymbol{A}_{\boldsymbol{n}(\boldsymbol{it})}$). The model includes two sets of time-related fixed effects: year fixed effects ($\boldsymbol{\tau}_t$) and, for movers, fixed effects for the year relative to the move ($\boldsymbol{q}_{\boldsymbol{it}}$). The latter allow for the possibility that relocation in itself could affect mental health or simply that the process of moving changes the timing and frequency of health care visits. The main coefficients of interest are the region fixed effects ($\boldsymbol{\gamma}_{\boldsymbol{r}}$). These coefficients are only identifiable through movers and can be interpreted as the average within-individual change in utilization that occurs after individuals move to a given PHN (from the reference PHN).[9] Standard errors are clustered at the individual level.

Event-study model

[9] For each outcome, we define the reference region to be the one with mean expenditures closest to the national average. Western Victoria (PHN 206) is used for mental health services and Northern Queensland (PHN 307) is used for mental health prescriptions.

The event-study specification is derived from Eqn. 1 using the sample of movers only and is given by:

$$y_{it} = \boldsymbol{\alpha}'_i + \sum_{q=-7}^{7} \beta_m(\delta_i \times \boldsymbol{q}'_{\boldsymbol{it}}) + \boldsymbol{q}'_{\boldsymbol{it}} + \boldsymbol{A}_{\boldsymbol{n(it)}} + \boldsymbol{\tau}'_t + \xi'_{it} \tag{2}$$

Where, all the variables except δ_i are defined as in Eqn. (1).[10] The variable δ_i is a scaling factor that captures the difference in average utilization in individual i's destination region ($\bar{y}_{d(i)}$) and origin regions ($\bar{y}_{o(i)}$):

$$\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)} \tag{3}$$

With our natural log specification, δ_i is approximately the percentage difference in utilization between the two regions.[11] Larger absolute values of δ_i indicate larger differences across the destination and origin regions while a negative sign indicates the move was from a higher to lower utilization region and *vice versa*. With 31 PHN regions, δ_i can take on 930 possible values.

The main coefficients of interest, $\boldsymbol{\beta_m}$, represent the effect of the event-time multiplied by the scaling factor δ_i. We normalise the estimates of the $\boldsymbol{\beta_m}$ coefficients to the two years prior to the move, i.e., $\beta_{-2} = 0$.[12] For the periods after a move, these coefficients can be interpreted as the share of the difference in average utilization between destination and origin regions that can be attributed to place-based effects (the region fixed effects, γ, from Eqn. 1):

$$\beta_m = \frac{\gamma_{d(i)} - \gamma_{o(i)}}{\bar{y}_{d(i)} - \bar{y}_{o(i)}} \tag{4}$$

A β_m coefficient close to zero implies that utilization differences across regions are driven mainly by the patients who live there rather than by place-based factors. If this is the case, an individual's utilization should not change if they move from a low utilization to a high

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[10] Here we use the same notation across both the fixed effects and event-study models even though the estimated parameters, including those associated with patient, quarter-year, age-bin, and quarter relative to move variables, are likely to differ across the models.

[11] Each region's utilization is based on the 25% sample of non-movers' annual mental healthcare utilization pooled over years 2011–2019.

[12] We select the two years prior move as a reference region as we anticipate there are lags between when people move and when their address is updated in administrative databases.

utilization region, or vice versa. In contrast, if place-based factors are important determinants of utilization, β_m will be large. At the extreme, if regional differences are driven entirely by place-based factors, β_m will equal 1 and the utilization of movers will change to resemble utilization patterns in their destination region. Because δ_i is positive when someone moves to a higher utilization area and negative when they move to a lower utilization area, if patients' utilization converges to the level in their new region, the graph of the $\boldsymbol{\beta_m}$ coefficients will show a positive jump after the move regardless of whether the move is to a higher or lower utilization region.

Identifying assumptions

Causal identification of the region fixed effects in (1) requires several key assumptions. The first has to do with the exogeneity of moves. Unobserved differences between movers and stayers in time-invariant characteristics are not a problem because they will be captured by the individual fixed effects. However, unobservable *changes* in factors that affect utilization may be a source of bias if they are correlated with utilization in movers' origin or destination regions. This would be an issue, for instance, if individuals with deteriorating mental health systematically moved to regions with a greater supply of mental health providers. Such a pattern would cause the importance of place factors to be overstated. Our estimates could also be biased if mental health shocks coincided with the timing of a move, though here the direction of the bias would depend on whether the person is moving to a higher or lower utilization area. Thus, identification relies on the assumption that people do not decide where to move because of the destination's level of mental healthcare utilization.

Figure 2 reports the distribution of δ_i for mental health services and mental health prescriptions for the full sample of movers as well as people that had used any mental healthcare (either mental health services or mental health prescriptions) prior to moving. If individuals experiencing negative mental health shocks systematically moved to areas with better mental health resources (e.g., a greater supply of specialty providers) and all other movers did not sort systematically, the distribution of δ_i would be skewed to the right. This is not what we observe. For both mental health services and mental health prescriptions, the distribution is approximately normal: people are just as likely to move to a place with higher utilization as to a place with lower utilization. Importantly, among subsample of movers who had used mental healthcare prior to their move, we find similar distributions. This suggests that even among those accessing mental healthcare, there is no evidence of sorting to areas with greater mental health utilization. This symmetry is consistent with the identifying assumption that moves are exogenous to regional levels of mental healthcare utilization and echoes findings of prior studies using the 'movers' approach (Finkelstein et al., 2016, Moura et al., 2019, Godøy and Huitfeldt, 2020, Salm and Wübker, 2020, Johansson and Svensson, 2022).

Evidence from an external data source, the longitudinal Household Income and Labour Dynamics in Australia (HILDA) survey, provides additional support for the assumption that moving decisions are exogenous to destinations' healthcare utilization. The survey asks respondents who move their residence why they moved. Appendix Figure A2 summarizes the primary reasons given grouped in broad categories. Approximately 24% of all movers in HILDA said they moved for reasons having to do with housing, 17% said they moved for family reasons, and 14% moved because of work. Only 3% of people who moved said that they did so for reasons related to health.[13] Because HILDA also provides longitudinal information on where respondents live, we can assign the δ_i's calculated in the PLIDA data to each mover in the HILDA and then compare the distribution for people who say they moved for health reasons to people who moved for other reasons. These results are reported in Appendix Figure A3. Similar to the results in the PLIDA data (Figure 2), for both of our two utilization outcomes, the distribution is symmetric.[14] We also formally test this by regressing movers' difference in destination and origin utilization for mental health prescriptions and mental health services, with and without controlling for origin fixed effects, on an indicator variable equal to one for people who moved PHN regions for health reasons (Appendix Table A1). These results indicate that the difference in destination and origin utilization is not significantly associated with moving for health reasons.

If some people are moving for mental health reasons, we may expect to see changes in their utilization prior to the move. For example, someone experiencing worsening mental health may first begin utilizing care where they are living and then move to an area with greater mental health care resources. The event-study specification is useful for testing for this type of bias. If moves are exogenous to changes in mental health status, we should see similar patterns in

[13] Godøy and Huitfeldt (2020) report similar results from survey data. In their data, 3% of survey respondents who moved cite health concerns as the most important reason for moving.

[14] While it is useful to compare the distributions of 'deltas' among movers, it is important to note that the movers in the HILDA survey are a relatively small sample and may not be fully representative of the population of movers. For more details on HILDA, please see Watson (2012).

utilization in the periods prior to the move for people moving to higher or lower utilization regions.

The event study specification is also useful for testing for persistence in utilization patterns, or habit formation. This is particularly important for mental healthcare as mental illness is often a long-term condition, and individuals may have established habits regarding the utilisation of mental healthcare. For example, if living in a high-utilization area permanently changes individuals' demand for mental healthcare, the individual fixed effects may be affected by the supply of care in a mover's origin region, causing the true effect of place-related factors to be understated. If this is an issue, the event study model will show larger changes for people moving to a higher utilization region than for people moving to a lower utilization region. We can test for this asymmetry by estimating the event study model separately by the direction of the move.

4. Results

Event-study analysis

We first present the event-study results in order to better visualise movers' utilization patterns relative to migration and in doing so provide evidence on the identification assumptions just described. Figure 3 presents the point estimates from $\boldsymbol{\beta}_m$ for mental healthcare services and mental health prescriptions. For both outcomes, there is no apparent trend for most of the pre-move period followed by a shift up around the year of the move. The effect of moving occurs immediately after relocation for mental health prescriptions. For mental healthcare services, there is a gradual increase in the year before the move followed by a larger change after the move. A likely explanation for this pattern is that there is a lag between when people move and when their address is updated in the administrative data.[15]

[15] We confirm this is consistent with administrative lags in individuals updating their addresses by examining the location people receive care for health services and prescriptions relative to their move (Appendix Figure A.4). This analysis also shows us that individuals are slightly more likely to access prescriptions in their residence than services and the change around the year of move is steeper for prescriptions. These patterns align with the model of care for mental health treatment in Australia. Given specialist mental healthcare services (e.g. provided by psychologists, psychiatrists) are generally provided by a specific provider as a part of a mental health treatment plan, after moving it may take individuals some time to get a new referral to see a provider in their new location and they even may continue seeing an old provider in their origin region. Conversely, prescriptions for mental health conditions may include multiple repeats, enabling several months of treatment without requiring a new prescription but can be filled at any pharmacy, including in the destination region (Kjosavik et al., 2016).

Although there are clear changes in both types of utilization after the move, the magnitudes are quite different. For mental healthcare services the estimates of the $\boldsymbol{\beta_m}$ coefficients plateau at approximately 0.72, which implies that region-specific – i.e., place-based – factors explain nearly three-quarters of the variation in utilization across regions. The post-move increase in mental health prescriptions is much smaller: the estimated coefficients in the post-move period level off at approximately 0.20. This implies that variation across regions in the use of medications to treat mental health conditions are driven mostly by patient-level factors.

Our empirical strategy assumes the effect of move on utilization is symmetric – i.e., the magnitude of the change in utilization that occurs when a patient moves from a high utilization area to a low utilization area should be the same for a patient moving in the opposite direction. To test this assumption, we estimate separate models by the direction of the move (i.e., the sign of δ_i). These results are reported in Figure 4. For mental health services, the confidence intervals for each type of move are largely overlapping. In the case of prescriptions, there is less overlap, but the absolute magnitude of the 'jump' is similar. These results support the assumption of symmetry in our main specification. In addition, the fact that pre-move trends in utilization are similar irrespective of move direction suggests that latent demand for mental healthcare is not systematically correlated with destination and origin regions. This is consistent with the evidence from the HILDA survey, indicating that health factors are not an important determinant of migration decisions and further suggests that our results are unlikely to be biased by selective migration or habit formation.

Place-based fixed effects

Estimation of Eqn. 1 generates estimates of 31 place-based fixed effects ($\boldsymbol{\gamma_r}$) including a reference region. Figure 5 shows the plot of these estimates against each region's mean utilization. The relative importance of place-related factors in explaining regional variation in mental healthcare utilization can be approximated by the slope of the best fit line. The estimated slopes of that plot tell essentially the same story as the post-move β_m coefficients from the event-study model: place-related factors account for roughly 72% of the regional variation in the utilization of mental healthcare services and 19% of the variation in the utilization of mental health prescriptions. We find that the place fixed effects for prescription medicines are positively correlated with the place fixed effects for services (Appendix Figure A5), suggesting that there are common factors which pose as barriers to accessing mental health services and scripts (e.g., supply). We explore this further in the mechanisms section.

To facilitate interpreting these results in the Australian context for mental healthcare relative to general healthcare, we additionally looked at the relative importance of place for GP services, out-of-hospital services, and prescription medicines (Appendix Figure A6). We find that compared to mental health services, the relative place share accounts for 37% of the regional variation in utilization of GP services and 46% of the regional variation in utilization of out-of-hospital services. Conversely, the relative place share for prescription medicines (23%) is similar to the estimate for mental health prescriptions. This is consistent with our hypotheses that scarce and unequal supply of mental health providers is contributing to a larger place effect for mental health services, whereas the ability to obtain mental health prescriptions from GPs means that the supply of prescriptions is less constrained.

We can also compare our results to studies on other countries, though several factors, including differences in institutional settings and population characteristics complicate such comparisons. Moreover, it is important to note that, keeping place effects constant, greater variability in mean utilization across regions due to patient-related demand could predict a lower relative importance of place (i.e., the slope coefficient is given by the covariance between 'mean utilization' and 'place effects' divided by the variance of 'mean utilization'). With that caveat noted, our estimated place share for mental health services is slightly larger than what Finkelstein et al. (2016) finds for overall expenditure and what (Ding, 2023) finds for mental health expenditures in the U.S. Medicare program. There are even larger differences relative to what has been found in other countries with universal coverage: 27% for overall utilization the Netherlands (Moura et al., 2019) and 9% for outpatient care in Germany (Salm and Wübker, 2020). Our estimates for mental health prescriptions are slightly higher than what Ding finds in the U.S. Medicare program and results for all prescription medications in Sweden (5-8%) (Johansson and Svensson, 2022, Johansson et al., 2024), where, similar to Australia, patient co-payments for prescription medications are fixed across regions and doctors have limited financial incentives to prescribe medications.

Robustness checks and subgroup analysis

Table 2 presents results from alternative specifications of the fixed-effect models. The results reported are the slope coefficients from linear regressions of the region fixed effects and the region-level mean utilization. Coefficient estimates from our preferred specification (which correspond to the results reported in Figure 5) are reported in the first row ("Baseline model").

In rows 2 and 3, we report results based on smaller geographic units. Rather than the 31 PHNs in our main analysis, we divided the country into 88 and 340 spatial regions according to the Australian Bureau of Statistics' Statistical Area 4 (SA4) and Statistical Area 3 (SA3) definitions. SA4 regions capture labour market regions, similar to commuting zones in the U.S. SA3 regions closely align to local government jurisdictions, making them comparable to U.S. counties.[16] Employing smaller spatial units slightly reduces the relative place share for both mental health services (0.71 for SA4 regions and 0.66 for SA3 regions) and prescriptions (0.18 for SA4 regions and 0.16 for SA3 regions). The plot of the SA3 and SA4 place effects against the regions' mean utilization, and the corresponding event studies, are provided in Appendix Figure A7. These results suggest that the range of the estimated place effects are similar but the variation of mean utilization across regions increases when using smaller geographies. This is consistent with the organization of primary healthcare at the PHN level in Australia. Given PHNs are responsible for ensuring access to healthcare services, we may expect less variation in supply within a PHN than across PHNs. That is, if place-fixed effects are relatively 'constant' in capturing area-level supply, an increase in the number of regions will increase the variance in utilization across regions and predict a lower relative importance of place.

To account for the fact that movers tend to be younger and healthier and have higher levels of education, income, and employment, we re-weighted the data to make movers to look more like stayers with respect to these variables. This does not change the results materially (Row 4). We also investigate how results change if we restrict movers to those who use 75% or more of service claims in their destination region post move.[17] We find the relative place shares for this restricted sample are only slightly larger than our main results (Row 5).

As noted, analyses of health expenditure data may be sensitive to functional form assumptions. Therefore, following recommendations suggested by Mullahy and Norton (2024) and Chen and Roth (2022), we estimated several alternative specifications: a linear probability model where the dependent variable is a binary indicator for any use in a year (Row 6); OLS on untransformed expenditures (Row 7); and, a Poisson model (Row 8). The linear probability

[16] There are roughly four SA3 regions per PHN and two SA4 regions per PHN. Rural SA4s have populations ranging from 100,000 to 300,000 people, while metropolitan SA4s have populations ranging from 300,000 to 500,000 people. SA3 regions have populations ranging from 30,000 and 130,000 people (Australian Government, 2021). PHN population sizes range from 62,000 to 1,900,000.

[17] It is important to note that, by construction, this specification is restricted to movers who access healthcare. The distribution of the share of services claimed in movers' destination regions pre and post move is provided in Appendix Figure A.8.

and transformed linear regression results are essentially identical to our main estimates, while for mental healthcare services, the Poisson estimate is smaller (0.53).[18] Because the interpretation in the Poisson specification (i.e., relative change on the conditional expectation) puts less weight on the extensive margin than the other models, this pattern suggests that place-related factors matter more for access to any mental health services than for the intensity or frequency of use conditional on obtaining access. For example, in areas where the supply of mental health care providers is limited, patients may face difficulty obtaining an initial visit because providers are not taking new patients. But once they find a provider who agrees to treat them, the number of visits will depend not only on provider availability but also on the severity of their condition.

We additionally consider potential concerns arising from the recent literature on heterogeneity in treatment timing (De Chaisemartin and d'Haultfoeuille, 2020, Callaway and Sant'Anna, 2021, Sun and Abraham, 2021). Specifically, we might be concerned about negative 'treatment' weights if place impacted later movers (later 'treated' group) differently to earlier movers (earlier 'treated' group). This bias is likely to be small in our preferred fixed effects estimation approach as we have a very large pool of untreated units (i.e., non-movers) and no reason to suspect those moving early in the sample period would have systematically different treatment effects than those moving later in the sample period.[19] Nevertheless, we show our results are similar if we use a sample of earlier movers (Row 9) or later movers (Row 10). In Appendix Figure A10, we additionally include event-studies for each mover-year cohort which show that earlier and later movers have similar treatment effects.

Prior research finds that Australian men are less likely to visit a mental healthcare provider than women (Milner et al., 2020, Black et al., 2024). However, we do not find large differences between men and women in the importance of place-based factors (rows 11 and 12).

We also stratify the sample into two age groups: 18 to 64 (row 13) and 65+ (row 14). For mental health services, the relative importance of place-based factors for mental health services are similar, while for mental health prescriptions place matters more for younger adults than adults aged 65 and older. This may be because older populations tend to be long-term users of

[18] We additionally present the results from the Poisson event study in Appendix Figure A9.

[19] As we have a cohort sample, by definition, later movers will be older than earlier movers.

specific medications and more frequently visit the GP. People aged 65 and above are also more likely to have concession cards and thus face lower copayments for prescription medicines.

The results for the older group can be compared to Ding's (2023) analysis of mental health care utilisation in the US Medicare program. For mental health services, the relative place share for older adults in Australia is higher than what Ding finds in the US (0.69 vs. 0.46), whereas for mental health prescriptions, our results are smaller (0.07 vs. 0.15)

Mechanisms

A natural interpretation of these results is that the estimated place fixed effects reflect, at least in part, supply-side factors like the availability and practice styles of healthcare providers.[20] To test for such a relationship, we separately regress the place effects on several supply-related variables measured at the PHN level: the number of FTE psychiatrists, psychologists and GPs per capita,[21] the average out-of-pocket cost for mental health care visits, and mean wait times for mental health visits. We also consider the potential for area deprivation to impact place-based utilization using the regional level disadvantage index, which captures economic and social conditions in Australia (ABS, 2016b). Given the small number of PHN regions and the correlation among the different supply proxies, we estimate each association separately. For ease of interpretation, we estimate the relationship between the place fixed effects and standardize z-scores for each variable.

Figure 6 shows the results from these regressions. Although purely a correlational exercise, these estimates suggest the importance of supply constraints as a determinant of the place-based utilization of mental health services. There are positive and significant relationships between the number of FTE psychiatrists, psychologists, and GPs and our estimated place effects for the utilization of mental health services. In each of these cases, a one standard deviation increase in provider supply is associated with roughly a 0.5% increase in utilization. The supply of specialty providers is positively, albeit not significantly, related to the place effects for mental health prescriptions. GP supply is associated with a slightly larger positive

[20] There may be other area characteristics that affect mental health care utilization including climate (Mullins and White, 2019), crime rates (Kling et al., 2007, Curry et al., 2008, Dustmann and Fasani, 2016) and social attitudes (Bharadwaj et al., 2017, Saxby et al., 2020).

[21] These are the average PHN level FTEs between 2011 to 2019 and are obtained from the Australian Government Department of Health and Aged Care Health Workforce Data Tool (Department of Health and Aged Care, 2023).

place effect for mental health prescriptions, though this coefficient is also imprecisely estimated.

Interestingly, there is no significant relationship between waiting times and the place effects for mental health services and a positive relationship between waiting times and the place effects for mental health prescriptions. The latter result is consistent with a substitution effect: where it is difficult to see mental health providers, patients are more likely to be treated with prescription drugs. Higher out-of-pocket costs, particularly for psychologist services, are negatively associated the place effects for both prescriptions and services; suggesting that when supply is limited, prices are higher and may contribute to lower utilization.

Finally, there is a negative association between area-level disadvantage and place-based utilization for mental health services. Given that we would expect the burden of mental illness to be greater in more disadvantaged areas, this result likely reflects the tendency of mental health providers to locate in more affluent regions (Parliament of Australia, 2015, Fitzpatrick et al., 2018). Area-level disadvantage is positively associated with utilization of mental health prescriptions.

5. Health outcomes

A key policy question is whether the lower utilization of mental health services in areas where the supply of providers is limited has negative health consequences. To get at this question, we examine the relationship between the estimated place fixed effects and several important region-level mental health outcomes: the mental health related ED presentation rate, self-harm hospitalisations rate, and the suicide rate. Additionally, as a falsification test, we include non-suicide mortality rates as an outcome.[22] Following Godøy and Huitfeldt (2020), we estimate the following cross-sectional linear model at the PHN level:

$$m_r = \rho^r \boldsymbol{\hat{\gamma}_r} + \rho^c \boldsymbol{\bar{c}_r} + \epsilon_{rt} \quad (6)$$

[22] Suicide and non-suicide mortality rates are calculated from PLIDA. Information on the annual rate of mental health related ED presentations and self-harm hospitalisations per PHN is sourced from national hospital data provided by the Australian Institute of Health and Welfare (AIHW, 2022b, AIHW, 2022c).

where m_r is the log-transformed mental health outcome of interest[23] in region r, $\hat{\gamma}_r$ is the estimated place effect from Eqn. 1, and $\bar{c}_r$ is the region's average patient-related demand (given by the regional average of the sum of the individual and time-varying effects from Eqn. 1)

To facilitate interpretation, $\hat{\gamma}_r$ is normalised to have mean 0 and standard deviation of 1. The main coefficient of interest, ρ^r, describes the percentage change in the mental health outcome associated with a one standard deviation increase in the place effect. We estimate separate sets of models for mental health care services and mental health prescriptions. Estimates are weighted to the PHN population size.

The results from these regressions, reported in Table 3, suggest that areas with greater spending on mental health care services have better mental health outcomes. A one standard deviation increase in log spending on mental health services is associated with a roughly 10% reduction in mental health related ED presentations, a 20% reduction in self-harm hospitalisations, and a 10% reduction in the suicide rate. Higher spending on mental health prescriptions is associated with fewer mental health-related ED presentations, but there is not a statistically significant relationship between the region fixed effect for mental health prescriptions and self-harm hospitalisations or suicide.

We obtain a null result for our placebo outcome, non-suicide mortality, which suggests that the estimated relationship between area-level mental health utilizations and mental health outcomes is not coming from other area-level factors that lead to poor health outcomes in general. In Appendix Table A2 we add an area-level economic disadvantage index as a control. This causes the relationship between the area fixed effects and the adverse mental health outcomes to be stronger. This provides additional evidence that the place effects are not simply capturing the impact of living in a disadvantaged area (and aligns with our results in the mechanisms analysis).

6. Conclusion

In Australia, as in many countries, there is large regional variation in mental healthcare treatment and outcomes. We have estimated the relative importance of patient and place-specific factors in explaining this variation. We examine spending on mental health services

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[23] We select this functional form as it facilitates interpretation of our associations and is intuitive in that potentially we would expect higher supply in low 'need' regions would have a smaller impact than higher supply in high 'need' regions.

and mental health prescriptions separately and find qualitatively different results for the two. Our results suggest that place-specific factors explain roughly three-quarters of the regional variation in the utilization of mental health services. In contrast, we find that place-specific factors explain a smaller share—approximately one fifth—of the regional variation in spending on mental health prescriptions.

Additional analyses suggest that the regional variation in the utilization of mental health services reflects poor access to providers in low utilization areas as well as variation in provider practice styles. Estimated place effects are significantly correlated with area-level measures of provider supply and suggest there is some evidence of substitution between mental health treatments; where it is difficult to see mental health providers, there is higher place-based utilization of mental health prescriptions. However, our analysis of potential mechanisms is descriptive and exploratory; a better understanding around patients' ability to find substitutes for mental health care providers is an important topic for future research.

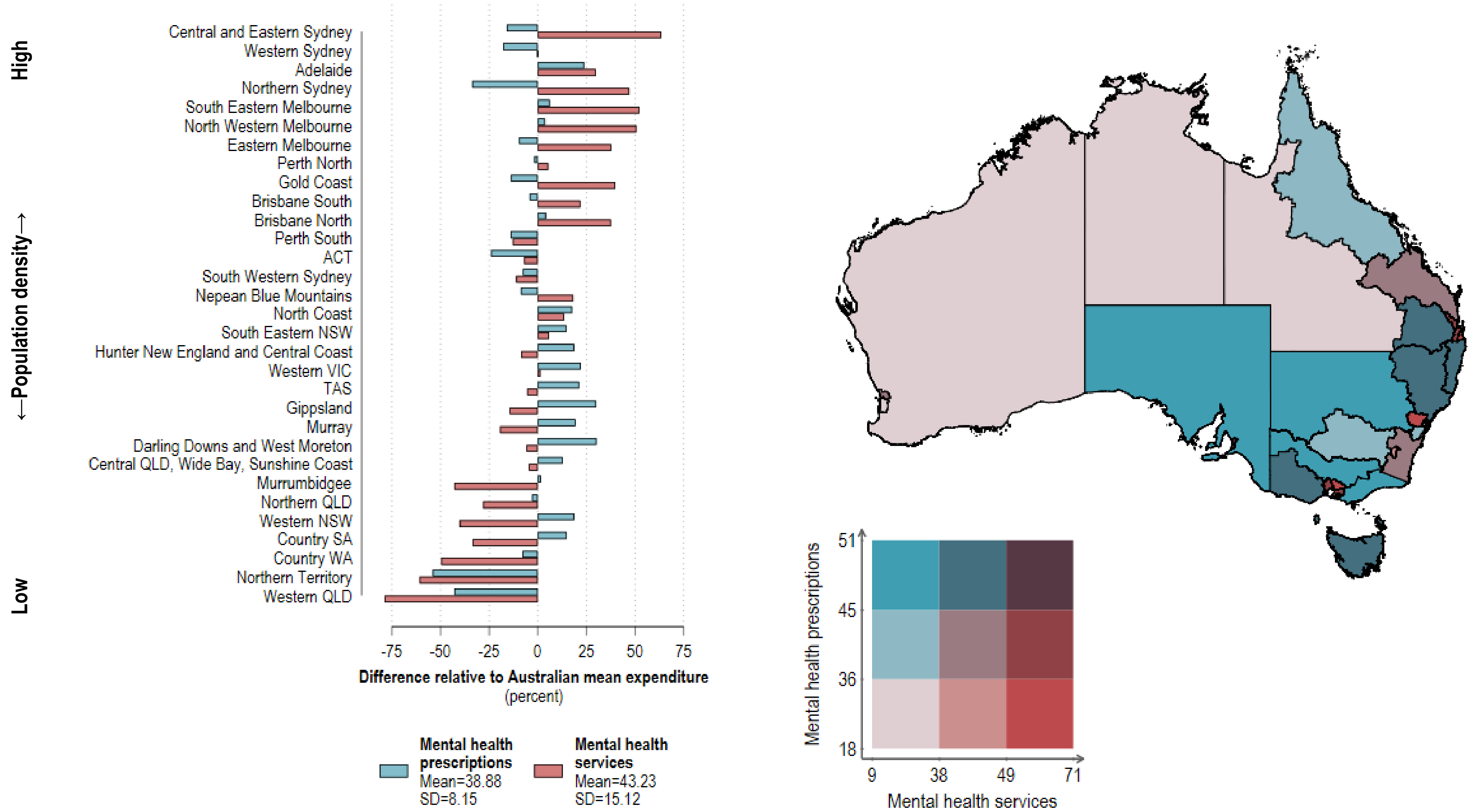
Our estimated place effects are also significantly correlated with better mental health outcomes. Areas where patients have better access to, and greater utilization of, mental healthcare services have lower rates of mental health related ED presentations, self-harm hospitalisations, and suicides. The finding that a greater supply of mental healthcare predicts better mental health outcomes is consistent with previous empirical research (Ludwig et al., 2009, Bower et al., 2011, Campbell et al., 2013, Lang, 2013, Ayyagari and Shane, 2015, Hawton et al., 2016, Gøtzsche and Gøtzsche, 2017, Kruse et al., 2022).

Our study has important implications for mental health policy. If we take our results at face value, increasing accessibility and utilization of both mental health prescriptions and services could improve population mental health and reduce acute mental healthcare costs (e.g., hospitalisations, ED visits). Easing supply-based constraints is likely to enhance access to mental healthcare services while patient-related factors may be more important for increasing uptake of mental health prescriptions.

In response to the COVID pandemic, the Australian government significantly invested into telehealth for mental health providers and increased the number of government-subsidized psychotherapy sessions individuals could receive within a 'Mental Health Treatment Plan' (Department of Health and Aged Care, 2020, Jayawardana and Gannon, 2021). While, in principle, telehealth could reduce regional variation in utilization of mental health services, the ability for this policy to increase access to services in underserved areas may yet be constrained by scarce supply. Indeed, initial research in this space suggests that the provision of additional psychotherapy sessions to existing consumers limited the capacity of providers to offer services to new users (Pirkis et al., 2022). Future research should investigate the effects of these policy changes and more broadly investigate how exogenous changes in supply impact utilization and mental health outcomes.

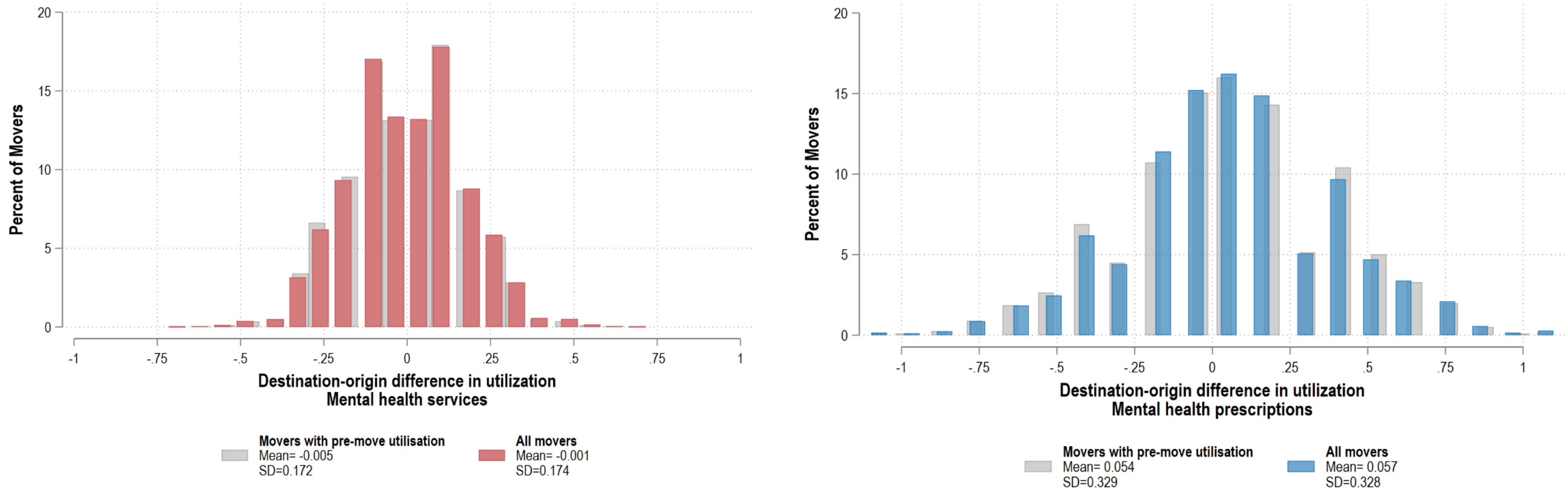
Figures and Tables

Figure 1: Geographical distribution of average annual government expenditure per person across PHNs regions in Australia.



Notes: Means pooled over years 2011–2019 using 25% sample of non-movers. Left panel shows percent difference relative to mean annual expenditure per capita. Expenditure presented in 2019 AUD. Right panel shows means aggregated into tertiles of expenditure across different PHN regions in Australia. Based on these tertiles, there are nine possible combinations of 'low,' 'moderate,' and 'high' expenditure for mental health services and prescriptions as well as the proportion of PHN regions in each category. QLD=Queensland, NSW=New South Wales, ACT=Australian Capital Territory, VIC=Victoria. Map created with assistance of BIMAP: Stata module (Naqvi, 2022).

Figure 2: Distribution of destination-origin utilization for mental health services (left) and mental health prescriptions (right)



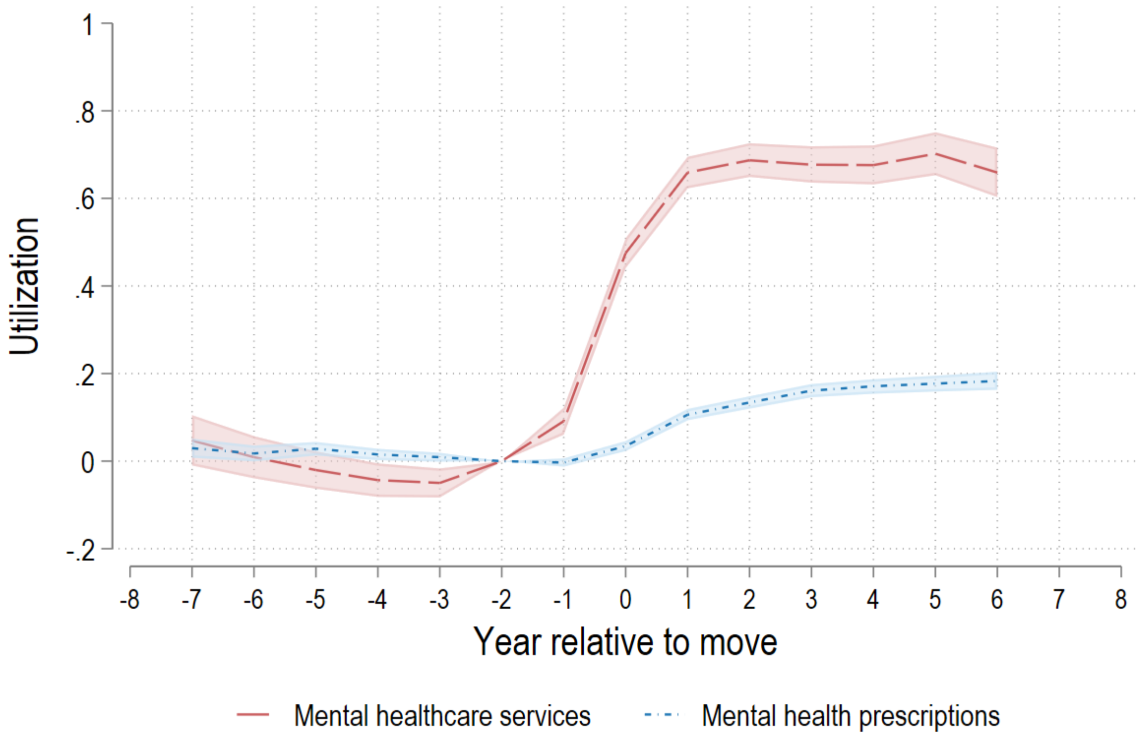
Notes: Distribution of destination-origin differences in utilization (i.e., 'deltas') of mental health services (left) and mental health scripts (right) based on sample of individuals that moved PHN regions exactly once and were age 18 years and above at the time of the 2011 Census (n=1,764,793). Bars in gray present distributions of deltas for subsample of movers that had used any mental healthcare (either services or prescriptions) prior to moving (n=563,938). Utilization defined as ln(annual expenditures + 0.01), presented in 2019 AUD.

Table 1: Descriptive statistics of estimation sample

	Stayer (n=2,571,691)	**Mover (n=1,764,793)**
	Mean/Prop.	Mean/Prop.
Female*	0.52	0.52
Age*	49.32	42.15
*Age group**		
Under 30	0.15	0.30
30-44	0.27	0.31
45-59	0.28	0.22
60-74	0.20	0.13
75 plus	0.09	0.05
*Highest level educational attainment**		
Less than high school	0.30	0.23
High school	0.16	0.19
Professional	0.11	0.12
Uni or above	0.20	0.25
Missing	0.23	0.20
*Employment status**		
Employed	0.61	0.68
Unemployed	0.03	0.04
Not in labour force	0.35	0.27
Missing	0.02	0.01
No. people in residence*	2.97	2.94
Needs assistance with core activities*	0.06	0.04
In top five deciles equivalised household income*	0.43	0.48
Mean annual benefit paid mental health prescriptions (2011-2019)	42.81	38.58
Mean annual benefit paid mental health services (2011-2019)	48.52	63.96
Zero benefit paid mental health prescriptions (2011-2019)	0.71	0.74
Zero benefit paid mental health services (2011-2019)	0.71	0.62
Year moved		
2012	-	0.16
2013	-	0.14
2014	-	0.12
2015	-	0.12
2016	-	0.12
2017	-	0.12
2018	-	0.11
2019	-	0.12
Move higher utilization region mental health services	-	0.50
Move higher utilization region mental health scripts	-	0.57
Death during 2011-2019	0.08	0.05
Death during 2011-2019 – suicide	0.001	0.001

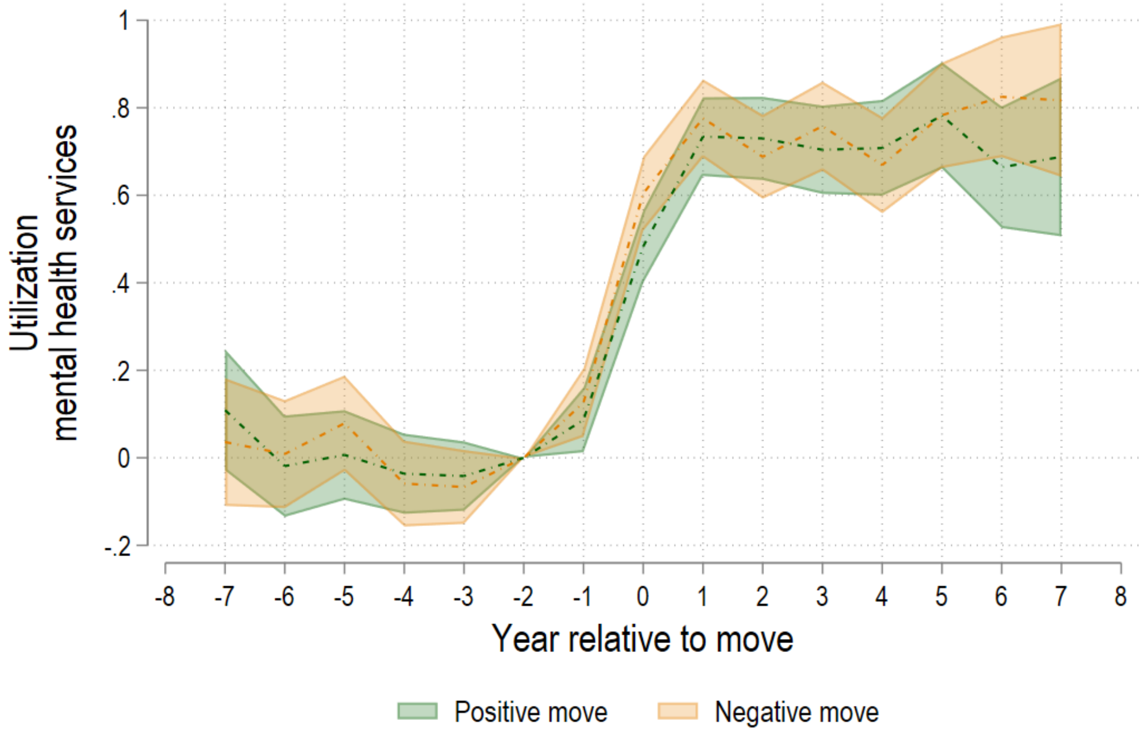
Notes: Table shows descriptive statistics for movers and a 25% random sample of non-movers age 18 years and above at the time of the 2011 Census. Notation * infers values are based on responses at time of 2011 Census. Mover sample comprises those who moved PHN regions exactly once between 2011 and 2019. Full details on sample construction are provided in Appendix Figure A.1.

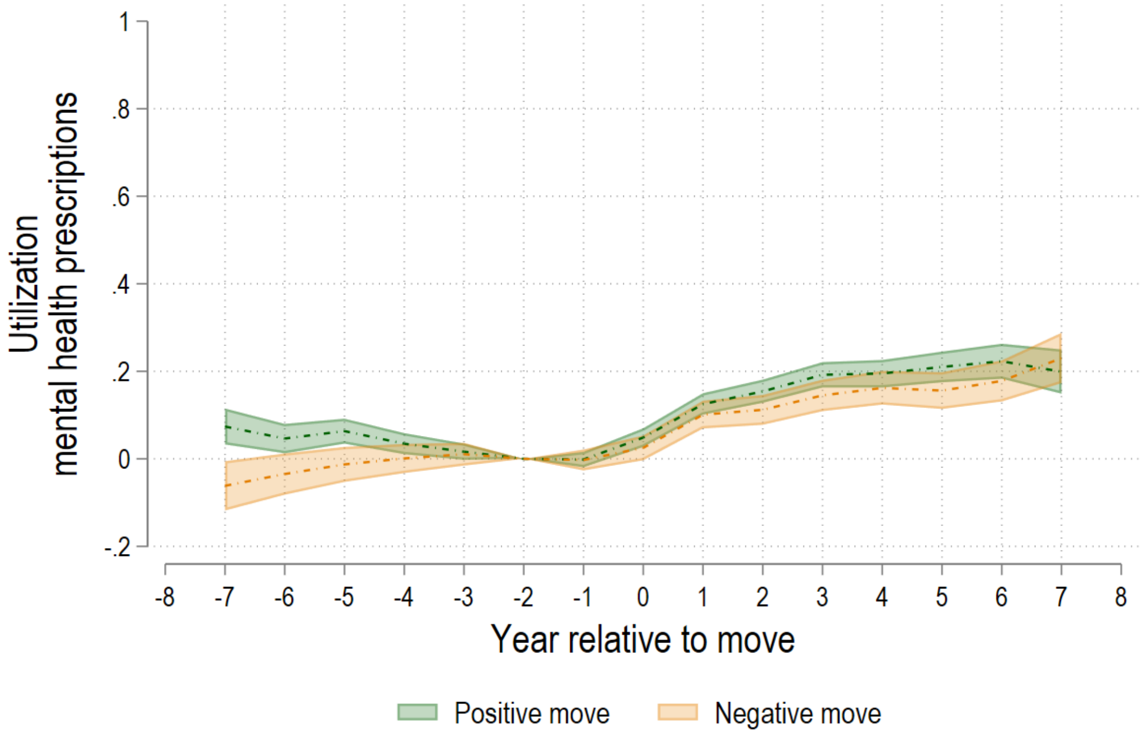
Figure 3: Event-studies for (a) mental health services and (b) mental health prescriptions.



Note: Point estimates $\boldsymbol{\beta_m}$ from Eqn. 2, referenced to two years before move. All models control for patient, age bin, place, year, and year relative to move fixed effects. $\boldsymbol{\beta_m}$ coefficients can be interpreted as the share of the difference in average utilization between destination and origin regions that can be attributed to place-based effects.

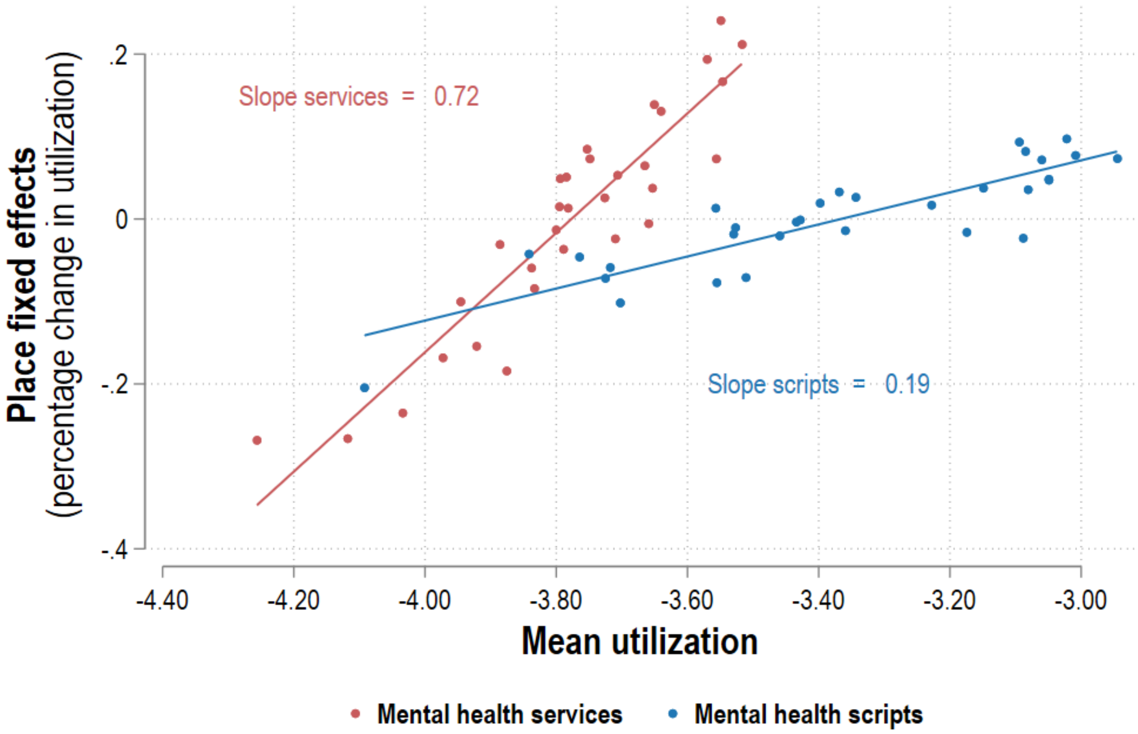
Figure 4: Event-studies for (a) mental health services and (b) mental health prescriptions by direction of move.





Note: Point estimates β_m from Eqn. 2, referenced to two years before move, when interacted with direction of move; i.e., whether moved to lower utilization region ('negative move,' δ_i<0) or higher utilization region ('positive move,' δ_i>0). All models control for patient, age bin, place, year, and year relative to move fixed effects.

Figure 5: Place fixed effects and average utilization across regions



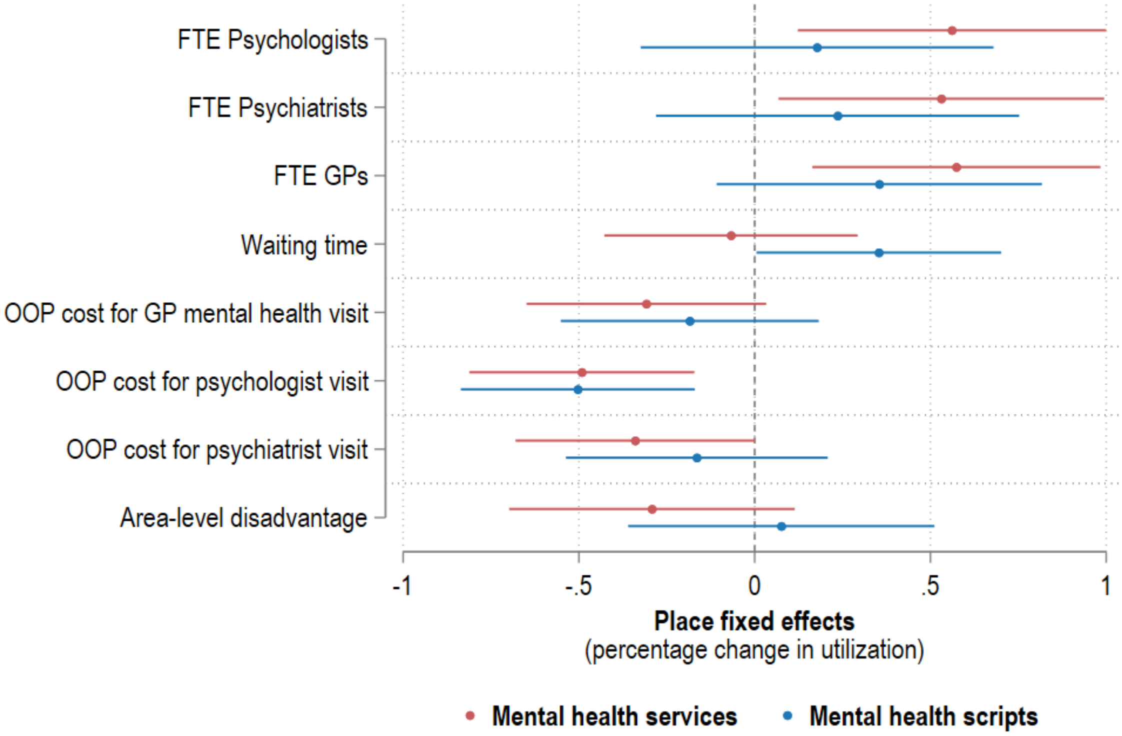
Notes: Figure shows estimated place fixed effects (γ_r from Eqn. 1) and average patient utilization by PHN regions across observation window, including the reference region; Western Victoria (PHN 206) is the reference region for mental health services and Northern Queensland (PHN 307) is the reference region for mental health prescriptions. Mean utilization pooled over years 2011–2019 using 25% sample of non-movers. Utilization defined as ln(government expenditure + 0.01) in 2019 AUD. Slope coefficient approximates relative share of variation in utilization across regions which is due to place-based factors.

Table 2: Relative importance of place under alternative specifications, for different care types, and subgroups

	Slope	
	Mental health services	**Mental health prescriptions**
(1) ***Baseline model (ln(expenditures+0.01)***	***0.72 (0.06)***	***0.19 (0.02)***
(2) SA4 region	0.71 (0.03)	0.18 (0.01)
(3) SA3 region	0.66 (0.02)	0.16 (0.01)
(4) Weighting movers	0.67 (0.06)	0.18 (0.02)
(5) Movers with 75% claim share in destination	0.76 (0.06)	0.25 (0.02)
(6) OLS – any utilization	0.72 (0.06)	0.20 (0.02)
(7) OLS – untransformed utilization	0.68 (0.07)	0.16 (0.06)
(8) Poisson	0.53 (0.04)	0.22 (0.05)
(9) Early movers (2012-2014)	0.67 (0.06)	0.21 (0.02)
(10) Later movers (2015-2018)	0.76 (0.06)	0.19 (0.02)
(11) Females	0.75 (0.06)	0.17 (0.02)
(12) Males	0.68 (0.06)	0.21 (0.02)
(13) 18-64 years	0.65 (0.03)	0.24 (0.03)
(14) 65 years and above	0.69 (0.07)	0.07 (0.05)

Notes: All models control for patient, age bin, place, year, and year relative to move fixed effects. Standard errors presented in brackets are estimated from linear regressions of the region fixed effects estimated ($\boldsymbol{\gamma_r}$ from Eqn. 1) against the region-level mean utilization (i.e., the standard error of the slope coefficient). Estimates are likely to suffer to some degree from attenuation bias given that the place effects themselves are estimated. Model (1) is the baseline model which estimates the extent to which place-based factors explain regional variation in utilization across PHN regions. Model (2) and Model (3) use smaller geographic boundaries to define movers. Model (4) applies Inverse Probability Weighting to make movers look more like non-movers with respect to age, income, education, employment status, and whether the individual reported a core activity limitation. These characteristics are derived from information reported at the time of the 2011 Census. Model (4) additionally applies 50 bootstrapped sample repetitions to adjust for uncertainty in propensity weights. Model (5) restricts the movers to those who use 75% or more of all claims in their destination region post move. Model (6) applies a linear probability model to using any expenditure towards mental health services/scripts as outcomes. Model (7) applies an untransformed OLS model for any utilization. Model (8) applies an untransformed OLS model for utilization. Model (9) estimates a Poisson model for utilization. Model (10) retains the 25% random sample of non-movers but restricts the movers sample to all movers who had moved between 2012 and 2014. Model (11) retains the 25% random sample of non-movers but restricts the movers sample to all movers who had moved between 2015 and 2018. Models (11) and (12) restrict the sample to females and males respectively. Model (14) restricts the sample to people 18-64 years old. Models (14) restricts the sample to people 65 years and above.

Figure 6: Correlates of estimated place effects



Notes: OOP=out-of-pocket. Figure shows associations between place fixed effects estimated separately for mental health services and prescriptions (γ_r from Eqn. 1) and different regional level characteristics, with associated 95%CIs. All regressions are ran separately controlling for population density as measured by population per m2. All covariates at the PHN level and standardised to mean zero and a standard deviation of one. Number Full Time Equivalent (FTE) psychologists and psychiatrists based on AIHW Mental Health Workforce data (AIHW, 2023). Waiting time estimated from PLIDA data as time from GP referral to first receiving mental healthcare service. OOP costs for GP mental health visit, psychologist visit, and psychiatrist visit from PLIDA data. Area-level disadvantage from the ABS Socio-Economic Indexes for Areas (ABS, 2016b).

Table 3: Acute mental healthcare utilization and mental health outcomes

	(1) **Mental health related ED presentations** β [95% CI]	(2) **Self-harm hospitalizations** β [95% CI]	(3) **Suicide rate** β [95% CI]	(4) **Mortality rate (non-suicide)** β [95% CI]
Place-based utilization -	**-0.101***	**-0.203****	**-0.097****	**-0.010**
Mental health services	[-0.196,-0.006]	[-0.329,-0.078]	[-0.169,-0.026]	[-0.055,0.035]
Place-based utilization -	**-0.214***	**0.143**	**-0.004**	**0.022**
Mental health prescriptions	[-0.382,-0.045]	[-0.085,0.371]	[-0.119,0.111]	[-0.059,0.103]
Mean of outcome (untransformed)	*1,257.7*	*124.2*	*5.5*	*430.5*

Notes: *p<0.05, ** p<0.01, *** p<0.001. Observations weighted by PHN population. Region fixed effects are those estimated from Eqn.1 (γ_r from Eqn. 1). Dependent variables (1) Annual number of mental health related ED presentations per 100,000 population per PHN between 2014 and 2020 provided from the Australian Institute of Health and Welfare (AIHW, 2022b). (2) Number of self-harm hospitalisations per 100,000 population per PHN-year in 2019-20, provided from the Australian Institute of Health and Welfare (AIHW, 2022c). (3) Number of suicides per 100,000 population per PHN-year calculated from 2011 Census cohort in PLIDA. (4) Number of non-suicide deaths per 100,000 population per PHN-year calculated from 2011 Census cohort in PLIDA. Estimated coefficients are likely to suffer from attenuation bias due to the place fixed effects being themselves estimates of the true place fixed effects.

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Appendix

Figure A. 1 – Sample construction

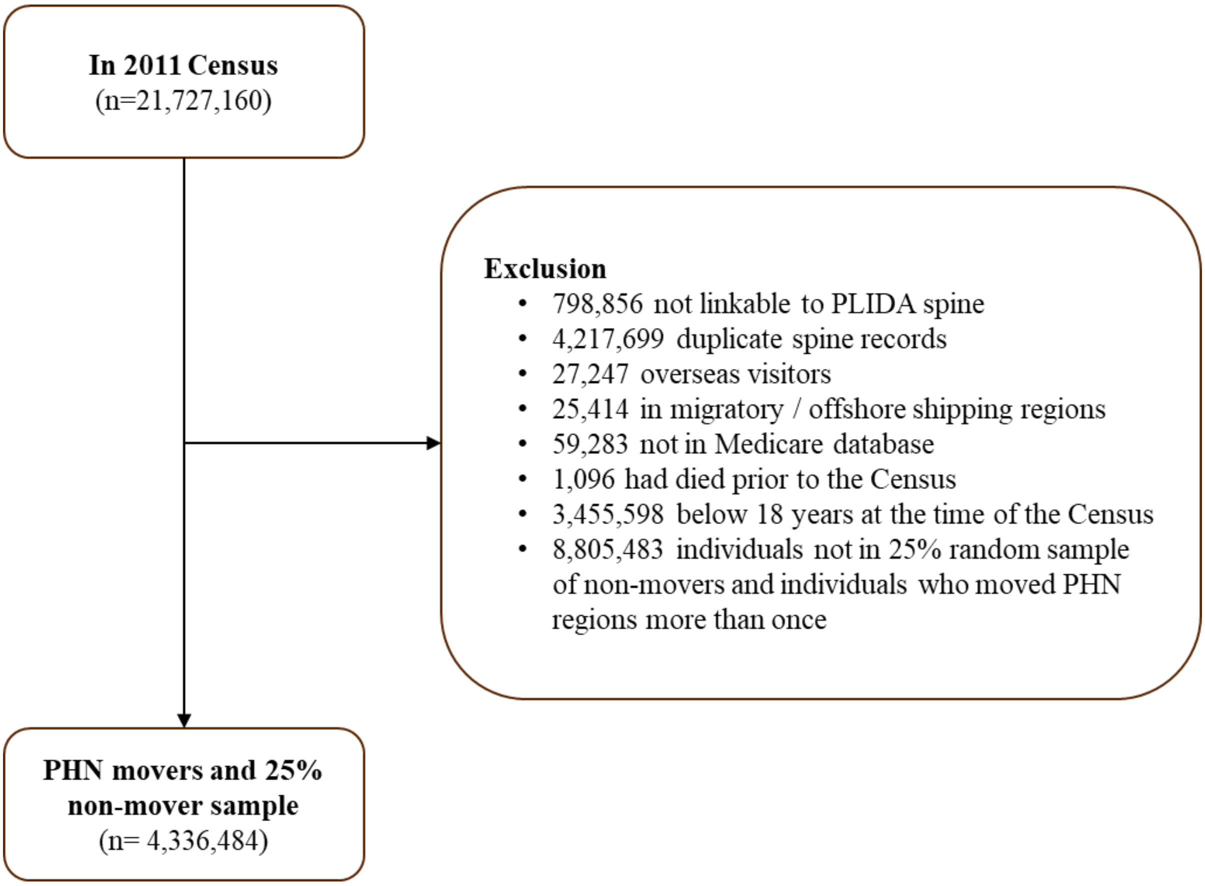
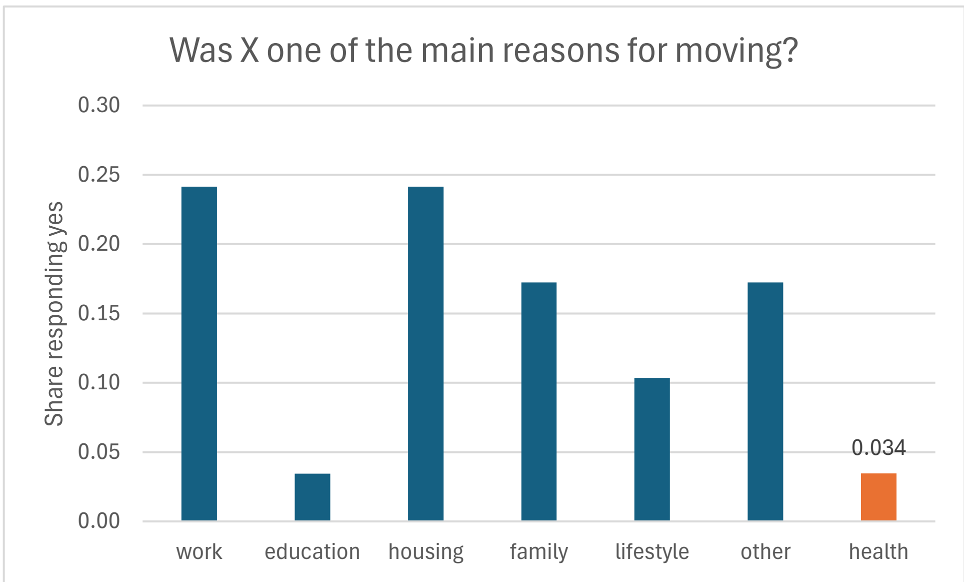


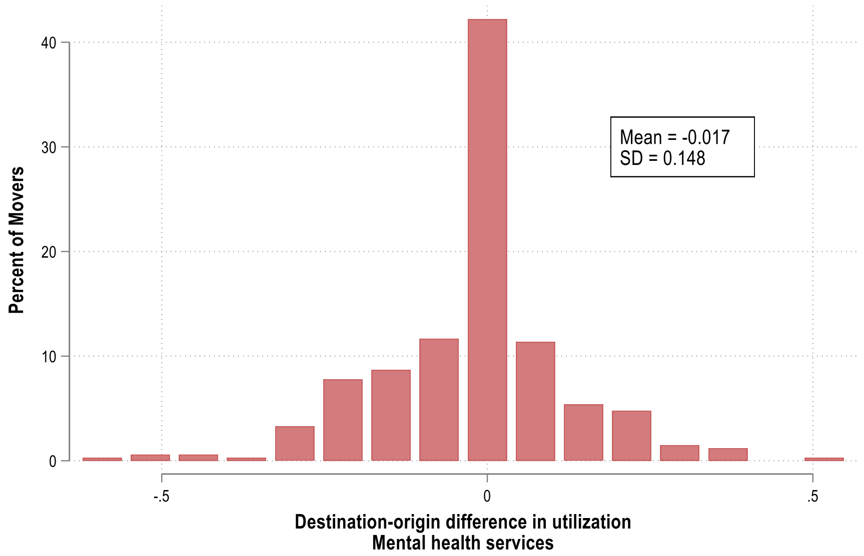
Figure A. 2 – Reasons for moving for those who had moved address in the HILDA survey

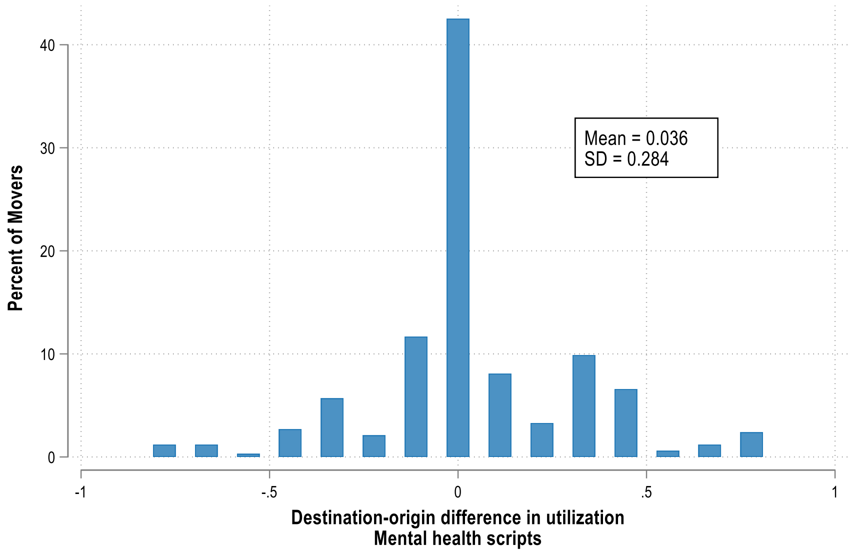


Notes: From 2021 HILDA Survey from all individuals that had moved PHN regions throughout 2001 and 2019 (n= 14,799). This includes multiple moves. As multiple responses can be selected, figure shows share responding yes out of total responses (n=10,967).

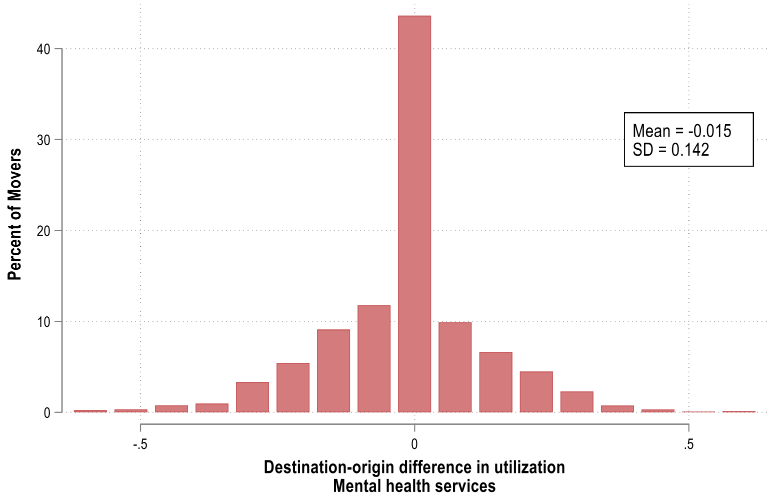
Figure A. 3 – Distribution of destination-origin differences in utilisation (δ_i) for movers who did and did not move for health reasons

Moved for health reasons





Moved for other reasons



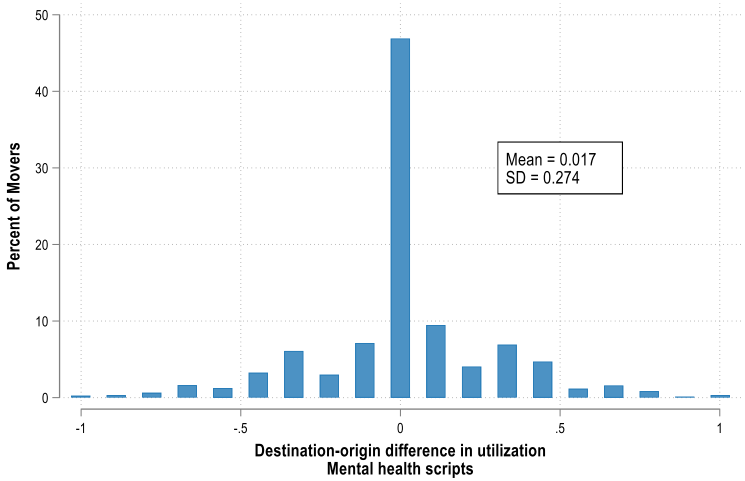
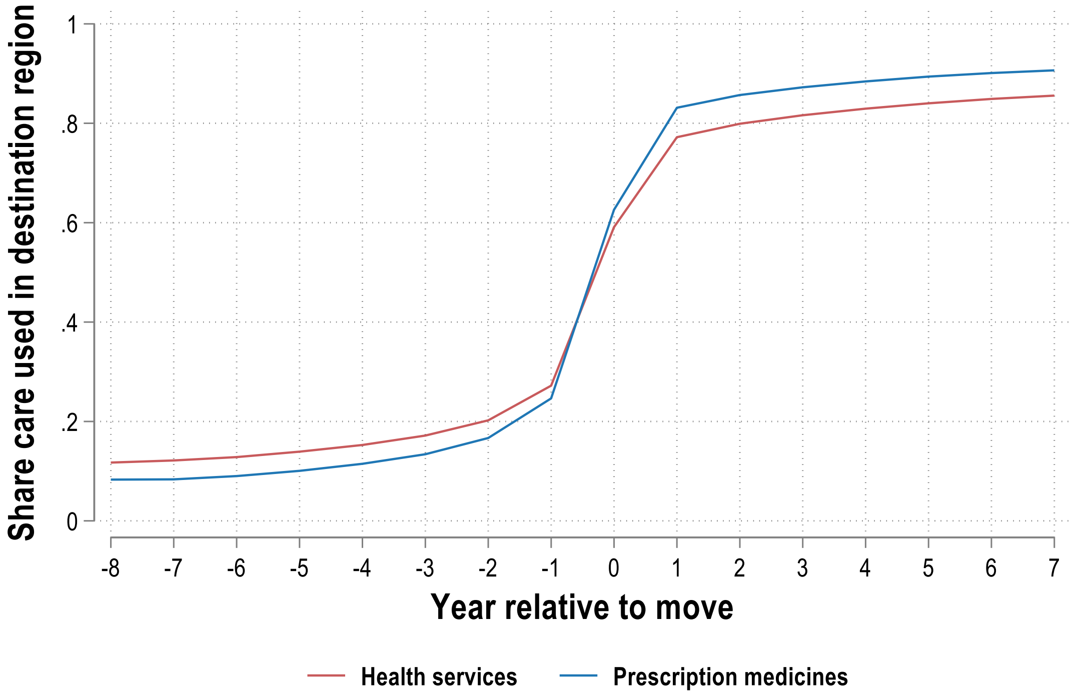


Table A. 1 – Moved for health reasons, destination less origin mental health service utilization for PHN movers

	(1) **Moved for health reasons**	(2) **Moved for health reasons**	(3) **Moved for health reasons**	(4) **Moved for health reasons**	(5) **Moved for health reasons**	(6) **Moved for health reasons**
Destination – origin utilization mental health prescriptions	-0.004 [-0.025,0.017]	0.019 [-0.008,0.047]	-	-	-0.004 [-0.025,0.017]	0.019 [-0.008,0.047]
Destination – origin utilization mental health services	-	-	0.004 [-0.034,0.043]	-0.027 [-0.084,0.029]	0.004 [-0.034,0.043]	-0.027 [-0.084,0.029]
Origin PHN fixed effects		✓		✓		✓

Note: 95% Confidence Intervals in brackets. Sample is all individuals that moved PHN regions once throughout 2011 and 2019. All models control for age, sex, and wave fixed effects. Model (1) controls for destination less origin utilization for mental health prescriptions, Model (2) controls for destination less origin utilization for mental health prescriptions as well as PHN origin fixed effects, Model (3) controls for destination less utilization for mental health services, Model (4) controls for destination less utilization for mental health services as well as PHN origin fixed effects, Model (5) controls for destination less origin utilization for mental health prescriptions and destination less utilization for mental health services, and Model (6) controls for destination less origin utilization for mental health prescriptions and destination less utilization for mental health services as well as PHN origin fixed effects.
*** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$**

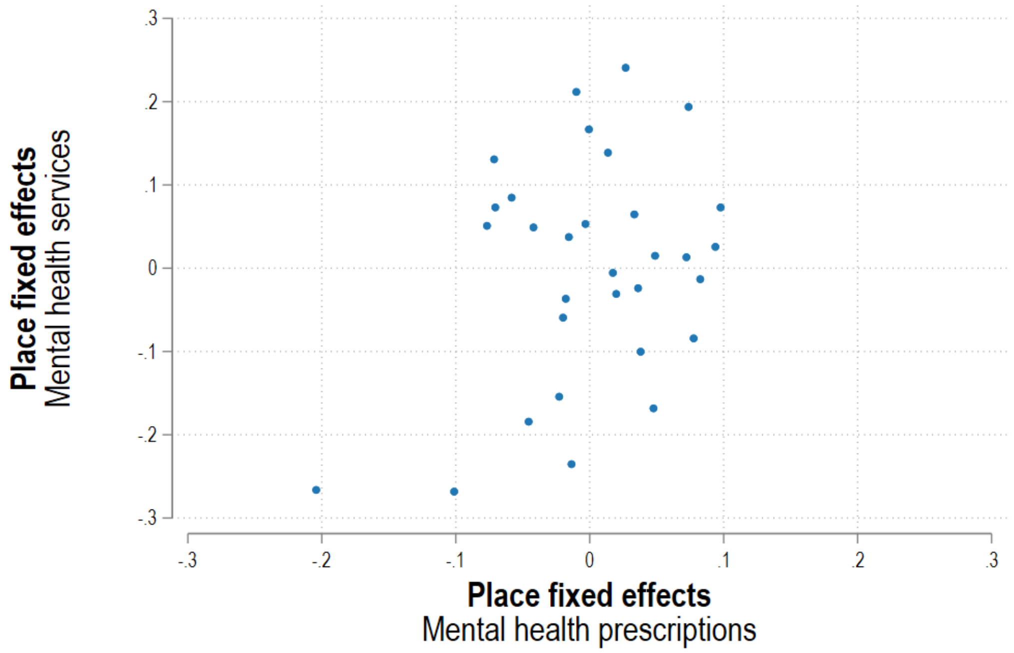
Figure A. 4 – Share of care received in destination region for PHN movers



Notes: For all PHN movers, figure shows share of care received in destination region out of all care received in destination and origin regions.

Distribution share of care received in destination region – pre move	Distribution share of care received in destination region – pre move

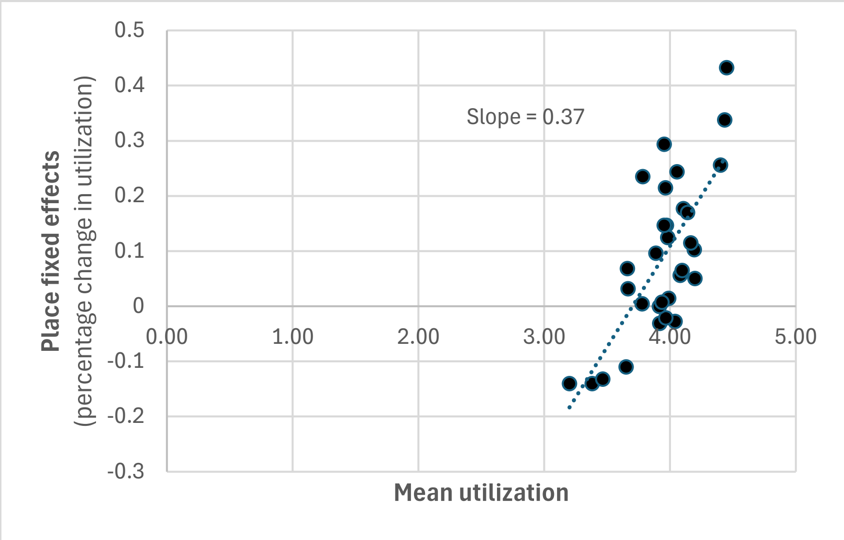
Figure A. 5 – Place fixed effects for mental health services vs place fixed effects for mental health prescriptions



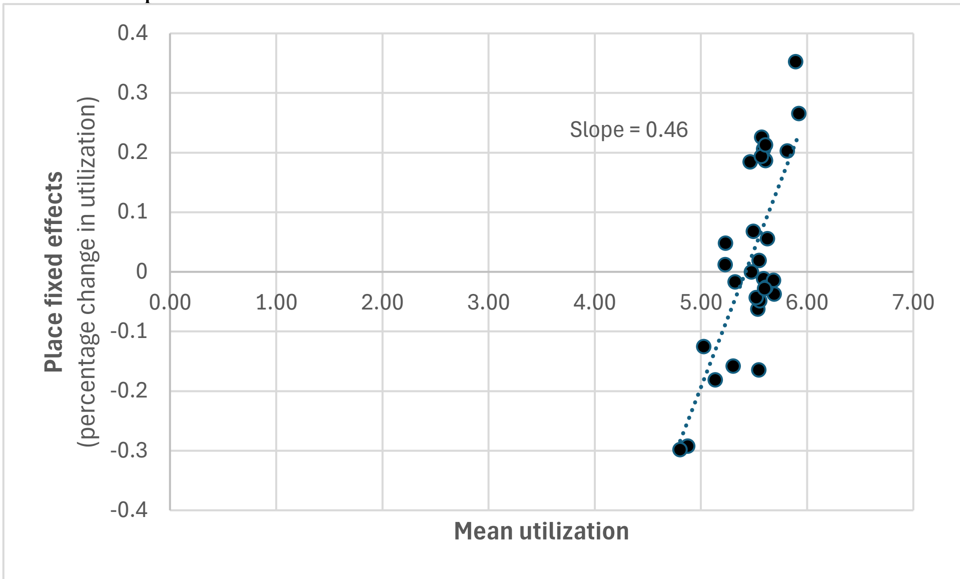
Notes: Figure shows estimated place fixed effects for mental health services against place fixed effects for mental health prescriptions. These are estimated for all PHN regions across observation window, including the reference region. The place fixed effects for mental health services and the place fixed effects for mental health prescriptions are positively correlated (Corr=0.32).

Figure A. 6 – Place fixed effects and average utilization across PHN regions for GP services, out-of-hospital medical services, and prescription medicines.

GP services



Out-of-hospital medical services



Prescription medicines

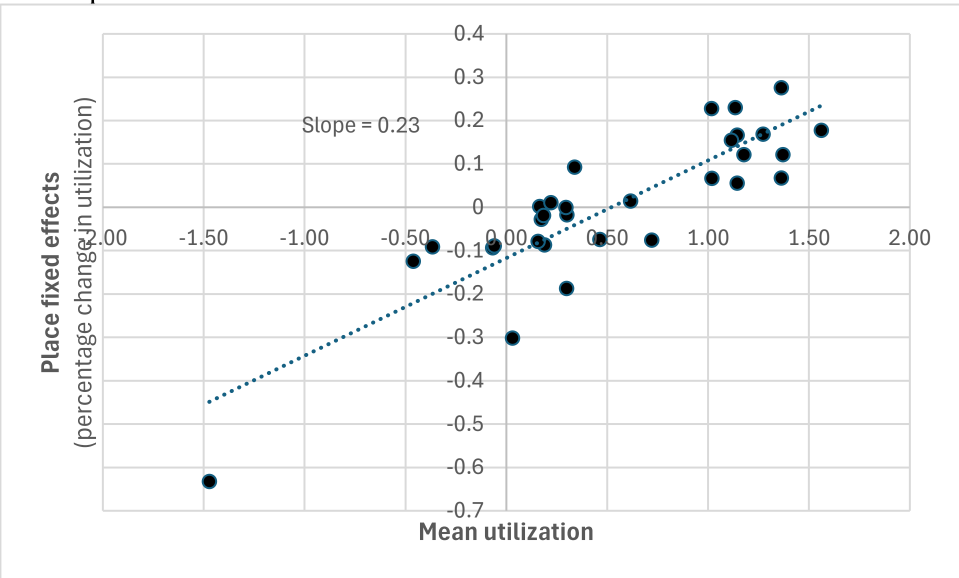
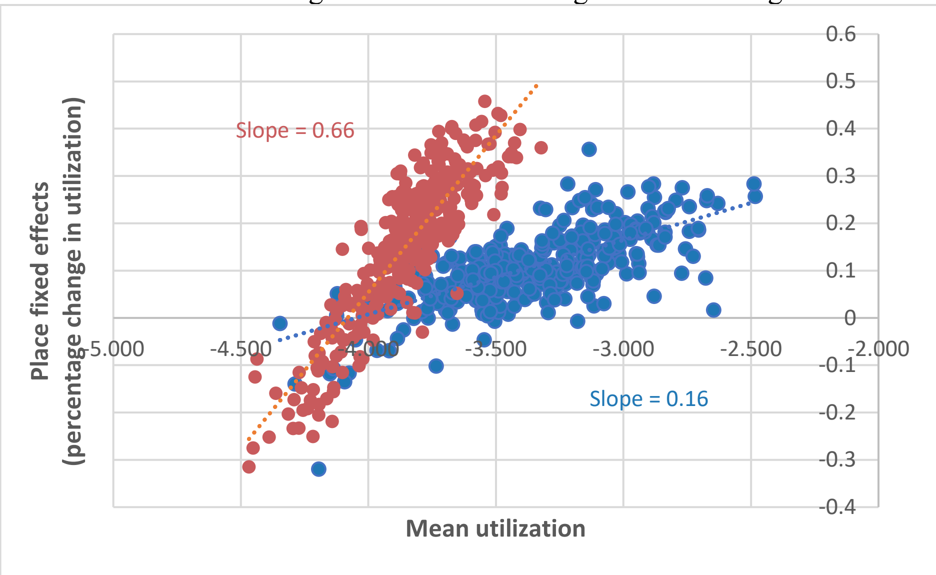
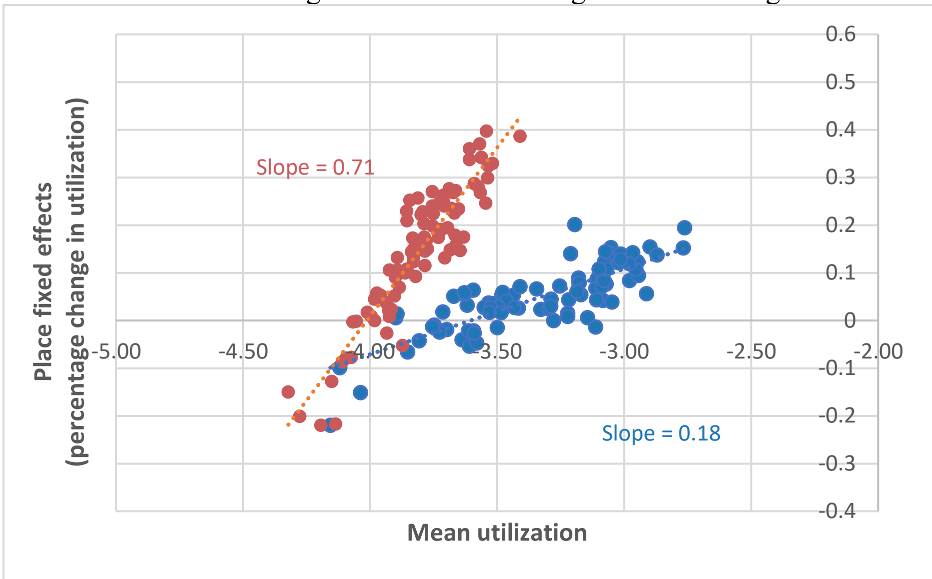


Figure A. 7 – Place fixed effects estimation and event studies when defining moves based on SA3 regions (left) and SA4 regions (right)

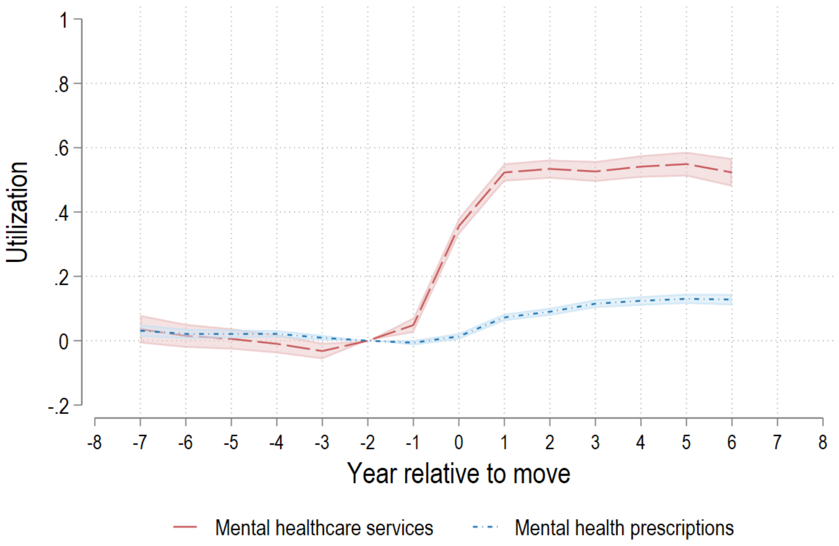
Place fixed effects and average utilization across regions for SA3 regions:



Place fixed effects and average utilization across regions for SA4 regions:



Event studies for SA3 regions:



Event studies for SA4 regions:

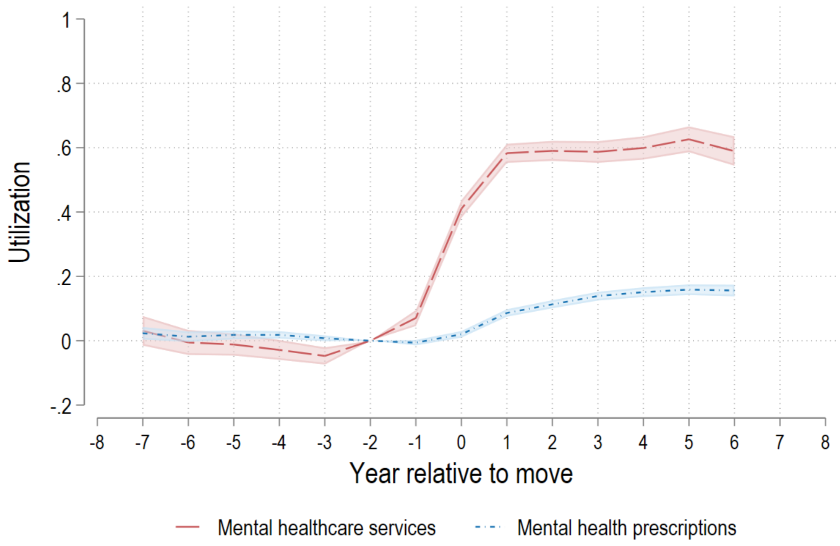
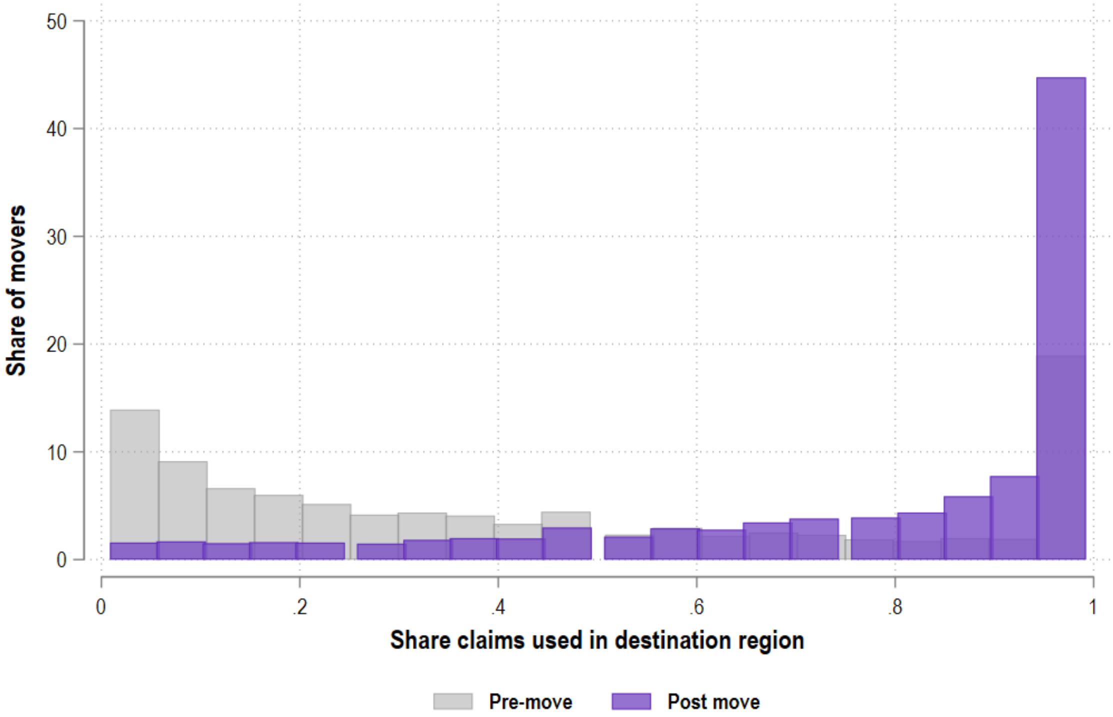


Figure A. 8 – Distribution of share of services claimed in destination region for movers pre and post move



Notes: Figure shows histograms for average share of claims used in the destination region for movers pre-move and post-move. By construction, each pre-move and post-move group is restricted to individuals who used services pre-move (n=838,528) or post-move (n=1,544,461).

Figure A. 9 – Event studies when estimating with Poisson

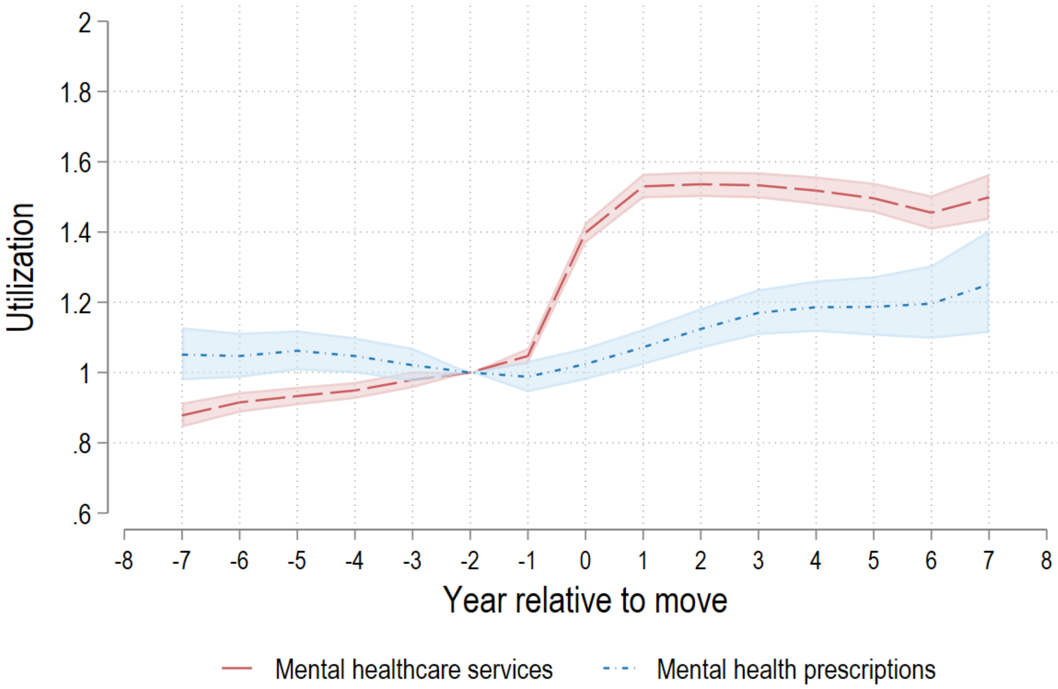
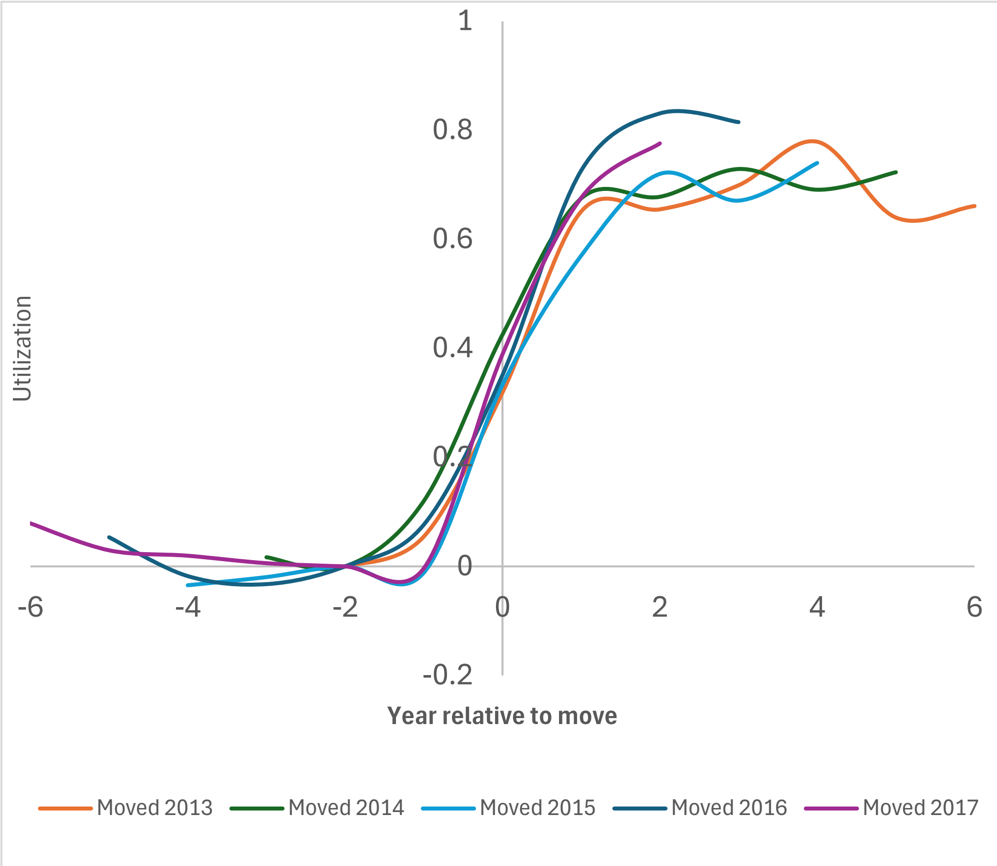


Figure A. 10 – Event-study analyses by year of move for mental health services (left) and mental health prescriptions (right)



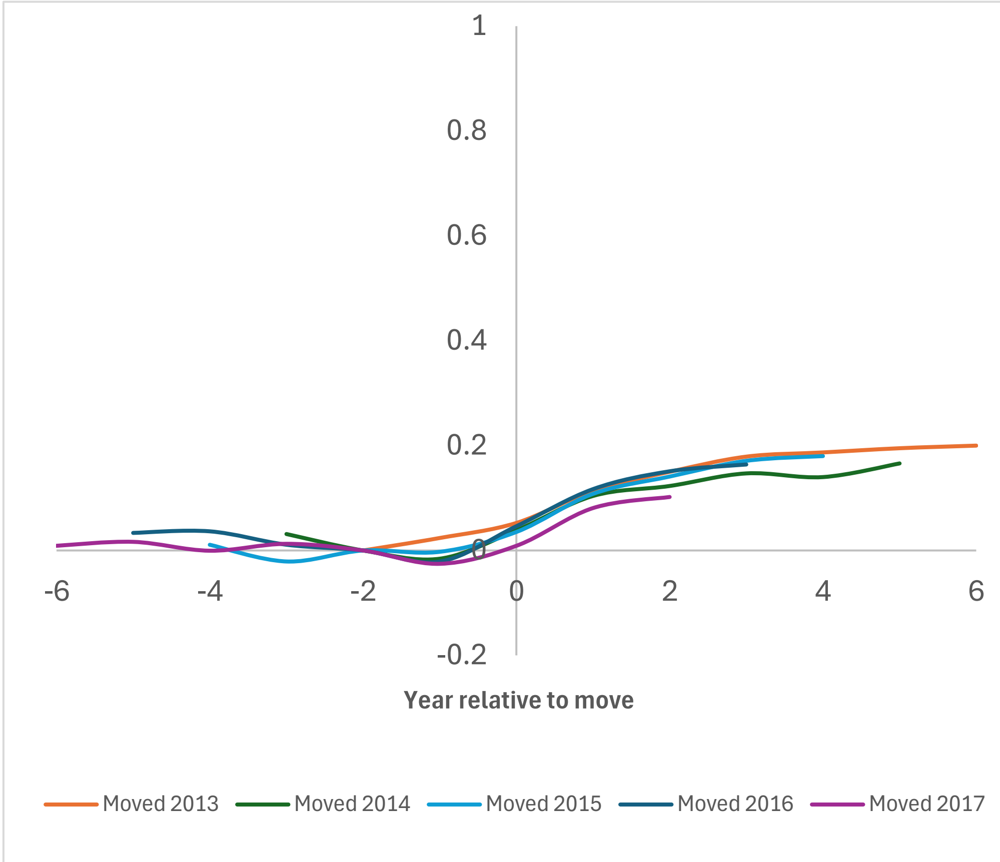


Table A. 2 –Mental health outcomes regression analyses when controlling for area-level disadvantage

	(1) **Mental health related ED presentations** β [95% CI]	(2) **Self-harm hospitalisations** β [95% CI]	(3) **Suicide rate** β [95% CI]	(4) **Mortality rate (non-suicide)** β [95% CI]
Place-based utilization:				
Mental health services	**-0.111*** [-0.202,-0.020]	**-0.211**** [-0.333,-0.089]	**-0.102**** [-0.170,-0.034]	**-0.003** [-0.046,0.041]
Mental health prescriptions	**-0.246**** [-0.384,-0.109]	**0.149** [-0.073,0.370]	**-0.012** [-0.138,0.114]	**-0.001** [-0.085,0.084]
Mean of outcome (untransformed)	*1257.7*	*124.2*	*5.5*	*430.5*

Notes: *p<0.05, ** p<0.01, *** p<0.001. All models control for area-level disadvantage as defined by the Australian Bureau of Statistics (ABS, 2016a). Observations weighted by PHN population. Region fixed effects from Eqn.1. Dependent variables (1) Annual number of mental health related ED presentations per 100,000 population per PHN between 2014 and 2019 provided from the Australian Institute of Health and Welfare (AIHW, 2022b). (2) Number of self-harm hospitalisations per 100,000 population per PHN-year in 2019-20, provided from the Australian Institute of Health and Welfare (AIHW, 2022c). (3) Number of suicides per 100,000 population per PHN-year calculated from PLIDA. (4) Number of non-suicide deaths per 100,000 population per PHN-year calculated from PLIDA.