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Geographic and Socioeconomic Variation in Healthcare: Evidence from Migration

PÉTER ELEK – ANITA GYŐRFI – NÓRA KUNGL – DÁNIEL PRINZ

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ABSTRACT
We study variation in healthcare utilization across geographies and socioeconomic groups in Hungary. Exploiting migration across geographic regions and relying on high-quality administrative data on healthcare use and income we show that the role of place-specific supply factors is heterogeneous across types of care and across socioeconomic groups. Overall, place-specific factors account for 68% of the variation in outpatient spending and 35% of the variation in drug spending, but almost none of the variation in inpatient spending. Place effects explain four-fifth of outpatient spending variation for non-employed working-age individuals, but less than two-fifth for individuals with above-median wage incomes. There is a positive association between place effects and outpatient capacity, especially for low-income individuals. These results suggest that access to healthcare varies especially for low-income people even in a context with universal coverage.

JEL codes: I11, I14, C23
Keywords: healthcare utilization, healthcare supply, regional variation, socioeconomic status

Péter Elek
Centre for Economic and Regional Studies
and Corvinus University of Budapest
elek.peter@krtk.hu

Anita Győrfi
Vienna Graduate School of Economics
anita.gyoerfi@univie.ac.at

Nóra Kungl
Vienna Graduate School of Economics
nora.kungl@univie.ac.at

Dániel Prinz
World Bank
dprinz@worldbank.org

Földrajzi és szocioökonómiai tényezők szerepe az egészségügyben: becslések országon belüli költözések alapján

ELEK PÉTER – GYŐRFI ANITA – KUNGL NÓRA – PRINZ DÁNIEL

ÖSSZEFOGLALÓ

Az egészségügyi ellátások igénybevételének földrajzi és szocioökonómiai tényezők szerinti eltéréseit vizsgáljuk Magyarországon. Az országon belüli költözésekre támaszkodva, egyéni szintű egészségügyi és munkapiaci adminisztratív adatokat használva megmutatjuk, hogy a helyspecifikus kínálati tényezők szerepe heterogén ellátástípus és társadalmi-gazdasági státusz szerint. Helyspecifikus tényezőkből adódik a járóbeteg-kiadások varianciájának 68%-a, a gyógyszerkiadások varianciájának 35%-a, a fekvőbeteg-kiadások varianciájából viszont lényegében semmi. A helyspecifikus tényezők a nem foglalkoztatott munkaképes korúak esetén a járóbeteg-kiadás varianciájának négyötödét, a mediánnál nagyobb bérjövedelemmel rendelkezők esetében viszont kevesebb mint kétötödét magyarázzák. Pozitív kapcsolat van a helyspecifikus tényezők és a járóbeteg-ellátási kapacitás között, különösen az alacsony jövedelműek esetében. Ezek az eredmények azt sugallják, hogy az egészségügyi ellátáshoz való tényleges hozzáférés még egy formálisan univerzális lefedettségű egészségügyi rendszerben is ingadozó, elsősorban az alacsony jövedelműek körében.

JEL: I11, I14, C23

Kulcsszavak: egészségügyi ellátások igénybevétele, egészségügyi ellátások kínálata, területi eltérések, társadalmi-gazdasági helyzet

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Péter Elek
Anita Győrfi
Nóra Kungl
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Abstract

We study variation in healthcare utilization across geographies and socioeconomic groups in Hungary. Exploiting migration across geographic regions and relying on high-quality administrative data on healthcare use and income we show that the role of place-specific supply factors is heterogeneous across types of care and across socioeconomic groups. Overall, place-specific factors account for 68% of the variation in outpatient spending and 35% of the variation in drug spending, but almost none of the variation in inpatient spending. Place effects explain four-fifth of outpatient spending variation for non-employed working-age individuals, but less than two-fifth for individuals with above-median wage incomes. There is a positive association between place effects and outpatient capacity, especially for low-income individuals. These results suggest that access to healthcare varies especially for low-income people even in a context with universal coverage.

*Elek: Centre for Economic and Regional Studies and Corvinus University of Budapest (elek.peter@krtk.hu). Győrfi: Vienna Graduate School of Economics (anita.gyoerfi@univie.ac.at). Kungl: Vienna Graduate School of Economics (nora.kungl@univie.ac.at). Prinz: World Bank (dprinz@worldbank.org). This research was supported by the National Research, Development and Innovation Office (grant number: OTKA FK 134573) and by the Lendület programme of the Hungarian Academy of Sciences (grant number LP2018-2/2018). Balázs Mayer provided excellent research assistance. The individual-level data used in this paper is under the ownership of the Central Administration of National Pension Insurance, the National Health Insurance Fund Administration, the Educational Authority, the National Tax and Customs Administration, the National Labor Office, and the Pension Payment Directorate of Hungary. The data was processed by the Institute of Economics, Centre for Economic and Regional Studies. We thank the Databank of the Centre for Economic and Regional Studies for providing access and help with the administrative database. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not represent the views of the World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

1 Introduction

Equitable access to health and healthcare is an important policy goal for national governments and international organizations. Nevertheless, inequalities in health are large and persistent even in the most developed countries, including countries with universal health insurance (OECD, 2019). The exact causes of these inequalities are varied and include inequities in access, behavioral differences, as well as differences in the utilization of health systems even if access is nominally universal.

While *socioeconomic* inequalities are an important concern, significant *geographic* variation in healthcare use has also been documented in a variety of countries and health insurance programs (e.g. Finkelstein, Gentzkow and Williams, 2016; Bíró and Prinz, 2020; Godøy and Huitfeldt, 2020). Such variation may be concerning for policy makers because it may serve as evidence of health inequality, access inequality, or of inefficient program design. Therefore understanding the sources of this variation and separating the role of supply-side factors (e.g. access to physicians and hospitals, physician preferences) and demand-side factors (e.g. patient preferences, differences in the health of residents) is important.

In this paper, we examine the interaction between geographic and socioeconomic inequality in healthcare spending in the context of Hungary, an emerging economy and former socialist country in Eastern Europe with universal health insurance. In particular, we study how the causal impact of place on healthcare use, identified by patient migration, varies by socioeconomic status (SES). To do so, we leverage high-quality administrative panel data on demographics, healthcare use, incomes, social insurance and welfare benefit take up, and other domains over the 2009-2017 period.

We start by documenting significant geographic variation in healthcare spending. Total healthcare spending in the highest-spending district is 1.5 times higher than in the lowest-spending district, and significant variation exists for all of its components: this ratio is 2.4 for outpatient spending, 1.7 for inpatient spending, and 2.0 for drug spending.

This wide variation across different areas in healthcare spending may be caused by a number of different factors. Health and the need for treatment may vary, preferences of the residents of different areas could be heterogeneous, access to care may differ, or physicians may have differing practice styles across regions. Therefore after documenting significant cross-sectional variation across districts, we turn to decomposing this variation into place ("supply-side") and patient ("demand side") components. To do so, we follow a "movers" approach that allows us to estimate two-way fixed effects models in which place and patient effects can be separately identified. This approach has been used in labor economics to separate firm and worker effects to understand earnings inequality, and also in prior studies in health economics to study the role of place in geographic variation (e.g. Abowd, Kramarz and Margolis, 1999; Card, Heining and Kline, 2013; Finkelstein, Gentzkow and Williams, 2016). The idea behind this approach is that patients who move between different places allow us to identify effect of these places on healthcare spending, independent from compositional differences and demand-side factors.

We find that there is considerable heterogeneity in the role of place across types of spending. Place effects explain 68% of the variation in outpatient spending and 35% of the variation in drug spending, but almost none of the observed variation in inpatient spending.

There is also important heterogeneity by socioeconomic status in the role of place in outpatient spending. In our working age sample, the estimated place share is 79% for non-workers and 63% for those in the bottom quartile of the wage distribution, which is significantly higher than the place share of 35-38% for workers above the median wage . We find similar patterns among the elderly: place-specific factors explain 89% of the variation for low-SES pensioners but only 67% for high-SES pensioners.

To understand the mechanisms underlying our results, we examine the correlates of the estimated place effects. We find that outpatient place effects are positively associated with local outpatient care capacity, and the gradient of this relationship is steeper at lower levels of capacity, pointing to capacity constraints. The estimated relationship between capacity and place effects is consistent with quasi-experimental evidence on the impact of outpatient capacity increases (Elek, Váradi and Varga, 2015). Importantly, we find that outpatient capacity influences the utilization of lower-income individuals more strongly than that of higher-income ones.

We most directly contribute to the literature that has used "movers" to understand the role of supply-side and demand-side factors in geographic variation in healthcare (Finkelstein, Gentzkow and Williams, 2016; Moura, Salm, Douven and Remmerswaal, 2019; Godøy and Huitfeldt, 2020; Salm and Wübker, 2020; Zeltzer, Einav, Chasid and Balicer, 2021; Johansson and Svensson, 2022; Badinski et al., 2023). We make three contributions to this literature. First, our work highlights that the role of supply-side factors is heterogeneous across both types of care and across socioeconomic groups.[1] In particular, we show that place matters the most to low-income individuals. Second, we show that place is likely more important for them because they are disproportionately affected by capacity constraints. Third, while the existing literature has focused on advanced economies, to the best of our knowledge we are the first to focus on a former socialist country in Eastern Europe.

[1]Previous work studied heterogeneities in terms of age (Finkelstein, Gentzkow and Williams, 2016), gender (Moura, Salm, Douven and Remmerswaal, 2019; Salm and Wübker, 2020), and education (Godøy and Huitfeldt, 2020), while we focus on socioeconomic status defined by income level.

More broadly, our work is related to the literature on inequalities in healthcare use. While most studies focus on demand-side reasons for inequality, including financial constraints (Allin and Hurley, 2009), less flexibility at work (Acton, 1975), and informational differences about the benefits of medical care (Glied and Lleras-Muney, 2008; Cutler and Lleras-Muney, 2010), a more recent strand of the literature studies the potential supply-side sources of inequalities in healthcare utilization (Brekke, Holmås, Monstad and Straume, 2018; Chen and Lakdawalla, 2019; Martin, Siciliani and Smith, 2020; Currie, Kurdyak and Zhang, 2022; Kristiansen and Sheng, 2022; Turner et al., 2022). We make two contributions to this literature. First, we study the interaction of geographic and socioeconomic inequalities. Second, we provide evidence on the importance of capacity constraints as a potential mechanism underlying inequalities.

The remainder of the paper proceeds as follows. Section 2 provides background on the institutional framework of Hungarian healthcare. Section 3 describes our data and sample construction. Section 4 introduces our empirical framework. Section 5 presents our results. Finally, Section 6 concludes.

2 Background

Hungary, a European Union member state with a population of about 9.8 million inhabitants, has a single-payer healthcare system, where services are administered by the National Health Insurance Fund Administration (NHIFA). Primary, specialist outpatient, and inpatient care are all free of charge at the point of use. (However, informal payments were common in the public system and private healthcare has become more important in the study period, especially in outpatient care.) Outpatient care is reimbursed by the NHIFA based on procedure codes associated with visits. Inpatient reimbursements are based on diagnosis-related groups (DRGs). Primary care is financed on a capitation basis. Prescription drugs are subsidized, where subsidy rates range from 25% to 100% and are slightly less than 50% on average.

The country is divided into 197 districts, corresponding to the local administrative unit (LAU) level 1 classification of Eurostat. The average population of districts is approximately 50,000. They are generally composed of a seat town with nearby smaller towns and villages. The capital city of Budapest, with a population of 1.75 million, consists of 23 districts. Specialist outpatient services are available in the vast majority of district seats, and hospitals operate in roughly half of them. The twenty counties (including Budapest) represent the next administrative level, where county seats provide higher-level inpatient services. On the primary care level, there are around 6,600 general practices in the country.[2]

[2]For more details on the healthcare system see Gaál et al. (2011).

3 Data and Sample

3.1 Data Sources and Variables

We use an individual-level administrative panel data set that covers monthly healthcare, labor market and demographic information for years 2009–2017 on a random 50% sample of the 2003 population of Hungary. The healthcare data contains variables that capture the frequency of use, including the number of outpatient visits, inpatient days, and prescriptions. It also contains information on expenditures measured by total reimbursement amounts (and out-of-pocket payments for prescriptions) by type of care. Importantly for our analysis, reimbursement rates do not vary by district or provider for outpatient care, inpatient care, or prescriptions. We do not specifically examine primary care, financed on a capitation basis, due to lack of detailed data.

We break outpatient care use down into six categories by specialty of care, specifically examining internal care, surgery and trauma, gynecology, reumatology, cardiology, and laboratory diagnostics. Similarly, we divide pharmaceutical use by category based on the Anatomical Therapeutic Chemical (ATC) classification, and focus in our analyses on antidiabetics, antihypertensives, psycholeptics, psychoanaleptics, antiinfectives, and drugs for obstructive airway disease.

The labor market segment of the dataset contains monthly employment status, occupation classification using the International Standard Classification of Occupations (ISCO), labor market earnings, and information on unemployment, disability, and pension benefits. Finally, the demographic variables include gender, age, and most importantly the district of residence.

We also use district-level indicators on healthcare supply, geography, and broad socioeconomic status from various other databases, including the Pulvita system of the National Directorate General for Hospitals (OKFŐ), data on general practices from the NHIFA, as well as municipal statistics included in the Settlement Statistics Database System (T-STAR) and additional data from the Central Statistical Office. We measure outpatient care supply with per capita outpatient capacity (weekly number of specialist outpatient hours) and inpatient care supply with the per capita number of hospital beds in the district. Distance from the district seat to the county seat captures access to higher-level healthcare and other services as well as employment opportunities. We also use the per capita taxable income of the district to control for broad socioeconomic status.

3.2 Movers

We categorize a person as a mover if her district of residence changed exactly once in the period between 2010-2016. There are two types of addresses in Hungary: a permanent address is defined for every citizen at every time, while a small fraction of the population also has a temporary address. We can observe both permanent and temporary addresses in the data. We define movers based on the change of their permanent residence. To improve precision, we also check whether a mover acquired a new temporary residence that coincides with the destination district up to six months before the change of her permanent residence. For movers who moved to their new permanent address after such a change in the temporary address, we shift the time of the move accordingly. This modification applies to around 15% of movers.

Because we want to study moves that plausibly affect the context of healthcare use, such as hospitals and providers accessed, we exclude moves that are within the commuting zones of larger cities. In particular, to exclude mobility within the agglomeration of Budapest and of county seats, we do not examine within-county moves and moves between Budapest and the surrounding Pest County.

To further improve the precision of our identification of moves, we exclude cases for which an individual changes her residence but does not appear to be getting her prescriptions in the area to which she moved. We do so based on a variable which provides information on the county where an individual filled most of her prescriptions in a given quarter (missing if no prescription was filled). In particular, we exclude cases where the modal county of prescriptions coincides with the destination county in fewer than 50 percent of post-move quarters (defined based on change of residence).

Finally, we restrict the sample to those who were aged between 30 and 80 at the time of the move. The reason for this restriction is that the study-related temporary moves of younger people are less reliably observed in the data, while people aged above 80 years are more likely to live in nursing homes.[3]

Throughout the paper we use data annualized by the time of the move (and not by calendar year). Relative year zero is defined as the first four quarters when the person entirely lives in the destination district according to her place of residence. To verify that individuals whom we categorize as movers actually move, Appendix Figure A1 shows separately the annual share of individuals for whom the county where they claimed most of their prescriptions is their origin county and the same share for destination counties. The figure suggests that although there is some discrepancy between the two location indicators, the shares change

[3]According to Monostori and Gresits (2019), less than 3% of the 75-79 age group lived in a nursing home in 2016, while this share increased to 5% and 9%, respectively, for the 80-84 and 85-89 age groups.

by about 60 percent from relative year -1 to 0.

Table 1 indicates that movers are younger, use less healthcare and are more likely to be employed than non-movers (all differences are statistically significant at the 1%-level). Appendix Figure A2 displays the evolution of the rate of employment, old-age pensioners, disability pensioners, and unemployment benefit recipients among movers. There is a slight drop in employment (and a corresponding slight, less than 2 percentage points, increase in unemployment) around the time of the move but no such change is seen for old-age and disability pensions.

4 Empirical Framework

4.1 Fixed Effects Model

To separately identify the individual- and place-specific components of healthcare use, our empirical strategy exploits migration across geographic areas. Following Abowd, Kramarz and Margolis (1999) and Finkelstein, Gentzkow and Williams (2016), we consider a simple statistical model of healthcare use:

$$y_{ijt} = \alpha_i + \gamma_j + \tau_t + x_{it}\beta + \varepsilon_{it}, \tag{1}$$

where i indexes individuals, j indexes geographic areas, t indexes years, y_{ijt} is a measure of spending, the α_i are individual fixed effects, the γ_j are place fixed effects, the τ_t are year effects, and x_{it} is a vector of individual-level time-dependent observable characteristics. We always include the interaction of gender and five-year age groups in x_{it}. In some specifications, we also control for the (potentially endogenous) labor force status of the individual. The individual and place effects in this model can be separately identified if some individuals move across geographic areas.

Based on distributional considerations, the literature generally uses log(spending) or, to account for zeros, log(1+spending) as outcome variables in a (log-)linear setting. Our dependent variables are mainly count data (number of visits or days) or non-negative continuous data with a substantial amount of zeros (health expenditure), so it is more natural to specify the conditional expectation in a Poisson model:

$$E\left(y_{ijt}\right) = \exp\left(\alpha_i + \gamma_j + \tau_t + x_{it}\beta\right) \tag{2}$$

where, for simplicity, the conditions are omitted.

4.2 Difference-in Differences and Event Study Representation

The above specification can be transformed for movers as follows:

$$E\left(y_{it}\right) = \exp\left(\alpha_i + \gamma_{o(i)} + \tau_t + \mathbb{I}_{\{t \geq t_i^0\}} \times \left(\gamma_{d(i)} - \gamma_{o(i)}\right) + x_{it}\beta\right) =$$

$$\exp\left(\underbrace{\alpha_i + \gamma_{o(i)}}_{\alpha_i'} + \tau_t + \mathbb{I}_{\{t \geq t_i^0\}} \underbrace{\left(\frac{\gamma_{d(i)} - \gamma_{o(i)}}{\log \bar{y}_{d(i)} - \log \bar{y}_{o(i)}}\right)}_{\theta} \underbrace{\left(\log \bar{y}_{d(i)} - \log \bar{y}_{o(i)}\right)}_{\Delta_i} + x_{it}\beta\right) =$$

$$\exp\left(\alpha_i' + \tau_t + \mathbb{I}_{\{t \geq t_i^0\}} \times \theta \times \Delta_i + x_{it}\beta\right) \quad (3)$$

where $o(i)$ is the origin and $d(i)$ is the destination district, $\alpha_i' = \alpha_i + \gamma_{o(i)}$ is an individual fixed effect, t_i^0 denotes the time of the move, and the indicator function $\mathbb{I}$ takes value one after the move. The variable $\Delta_i = \log \bar{Y}_{d(i)} - \log \bar{Y}_{o(i)}$ is the difference between the log of the average healthcare utilization in the destination and the origin districts. The parameter of interest, θ shows the average change in healthcare utilization after moves as a share of the difference between the average utilization in the destination and the origin districts. For non-movers, $\mathbb{I}$ is zero for all time periods and the equation becomes $\exp\left(\alpha_i' + \tau_t + x_{it}\beta\right)$.

Parameter θ can be interpreted as the place share that measures the fraction of geographic differences explained by differences in place characteristics. If only place effects matter, individuals will adjust their healthcare use entirely to the destination area's average utilization, and $\theta = 1$. On the other extreme, if only patient characteristics matter, the move will not result in a change in utilization, hence $\theta = 0$.

Equation (3) is an individual-level fixed-effects model. As long as the conditional expectation is well-specified, the model can be consistently estimated with the Poisson fixed effects (FE) estimator, free from the incidental parameter problem (see e.g. Wooldridge, 2010). In fact, such a Poisson specification has advantages over the more usual log-linear OLS specification for modeling non-negative continuous data with possibly many zeros (see e.g. Correia, Guimarães and Zylkin, 2020, and the references therein).

Note also that we still model the data on a multiplicative scale (as in a log-linear model). As Finkelstein, Gentzkow and Williams (2016) point out, such an assumption is economically very attractive because the utilization of patients with high individual fixed effects will vary more across regions than that of patients with low individual fixed effects. The intuition behind the larger dispersion is that for individuals with worse health, care availability and care quality matter more, while healthier patients' utilization will be low independent of geographic differences.[4]

Also, equation (3) corresponds to difference-in-differences with a continuous treatment, and nonlinearities in the θ parameter can be examined by presenting different coefficients for various treatment intensities, e.g. for positive and negative moves (Callaway, Goodman-Bacon and Sant'Anna, 2021).

The fixed effects model (3) can be rewritten in an event study framework, where θ_k is estimated separately for each time period (k is the year relative to the move):

$$E\left(Y_{it}\right) = \exp\left(\alpha_i' + \tau_t + \sum_{k=-5}^{k=4} \theta_k \times \mathbb{I}_{\{k=t-t_i^0\}} \times \Delta_i + x_{it}\beta\right). \quad (4)$$

The regressions are estimated on the sample when the year relative to the move is between -5 and +4, where θ_{-1} is the reference year parameter and thus set to zero. This allows us to provide graphical evidence on the identifying assumptions discussed below.

The estimate of θ in equation (3) reflects the true place share only if the potential health outcomes are independent of individuals' choice of destination. Card, Heining and Kline (2013) and Godøy and Huitfeldt (2020) discuss endogenous mobility in three categories:

1. Sorting on match effects: individuals may sort to districts based on district-specific utilization premiums.

2. Drift: individuals with gradually declining health may move to higher/lower-utilization districts.

3. Transitory error: individuals experiencing a simultaneous health shock may systematically choose higher/lower utilization districts.

Although these types of endogeneity cannot be directly assessed from the data, certain patterns may point to their presence or absence.

First, if sorting on the match component is dominant, we would expect to see more individuals moving to districts with higher utilization than the other way around. Hence we examine the distribution of the difference of the post- and pre-move average district-level utilization. Appendix Figure A3 shows the distribution of the destination-origin differences in the log average utilization measures. Since the distribution is symmetric and close to normally distributed, the match effect is unlikely to be important because approximately the same number of individuals are moving to high-utilization districts as low-utilization ones.

[4]See Badinski et al. (2023) for an application of the Poisson model in the mover-based setting.

Second, if drift is present, we would expect different pre-move trends in patients' utilization depending on whether their destination district has higher or lower average utilization than the origin district. The evolution of healthcare utilization of "positive" and "negative" movers shown in Appendix Figure A4) and also the more formal event study results of Figure 2 suggest roughly parallel pre-move trends, hence drift is unlikely to threaten our results.[5] These plots also show that individuals adjust their outpatient care use and pharmaceutical consumption—but not inpatient care use—immediately after moving to a new district which shows that short-term habit formation is unlikely to be important, though we cannot rule out habit formation beyond our time frame.

Third, endogeneity from the transitory error is the most difficult to assess. However, if "positive" and "negative" movers change their healthcare utilization in a roughly parallel way around their move (suggested by Appendix Figure A4) then it is unlikely that patients with sudden health shocks systematically move towards higher utilization districts.

4.3 District-Level Correlates of Healthcare Use

After estimating the place-specific component of healthcare utilization, denoted by γ_j in equation (2), we turn to analyzing what underlying factors may explain this component. Potential explanatory variables include healthcare supply variables such as the availability of outpatient and inpatient units, and the quality of equipment as well as the specialization and the beliefs (about effective treatments) of the physicians working in these facilities. Also, non-healthcare-specific factors such as long-term local economic, social and geographic conditions may play a role. Importantly, while the approach introduced above allows us to use movers to identify the place-specific component of healthcare separately from individual-specific factors, our analysis of the correlates of this place-specific component uncovers associations, rather than causal effects.

The approach generally followed by the literature (e.g. Finkelstein, Gentzkow and Williams, 2016) investigates these relationships via a two-step approach by correlating the estimated place effects with the place-level observables. Here, in a similar (and in special cases identical) one-step approach, we directly use the movers to estimate panel models of healthcare utilization with individual fixed effects and place-level explanatory variables:

$$E\left(y_{it}\right) = \exp(\alpha_i' + \tau_t + \sum_{k=-5}^{k=4} \mathbb{I}_{\{k=t-t_i^0\}} \times \delta_k + z_{j(i,t),t} \times \eta + x_{it}\beta) \tag{5}$$

[5] A slight pre-trend may be caused by the measurement error in observing the exact date of the move as suggested by Appendix Figure A1.

where z_{jt} denotes the observed (and possibly time-varying) place characteristics of district j (number of outpatient hours and hospital beds, distance from county seat, dummy for county seat, and per capita taxable income), and we control for individual, calendar time and event time fixed effects and gender - age group interactions. As Agha, Frandsen and Rebitzer (2019) point out, individual fixed effects filter out time-invariant patient characteristics similarly to as in equation (3).[6]

5 Results

5.1 Summary Statistics

Figure 1 and Appendix Table A1 show the district-level variation of per capita outpatient, inpatient and drug spending and utilization. Each of the three types of healthcare utilization shows significant variation across areas, although the geographic patterns are different. As column (5) of Appendix Table A1 shows, total healthcare spending in the highest-spending district is 1.5 times higher than in the lowest-spending district, and significant variation exists for all of its components: this ratio is 2.4 for outpatient spending, 1.7 for inpatient spending, and 2.0 for drug spending. As reimbursement rates are set at a national level, spending variation is driven by the quantity and composition of utilization, rather than geographic variation in reimbursement rates. Utilization varies significantly as well, with the highest-utilization district recording 2.0 times more outpatient visits, 2.6 times more inpatient days, and 1.7 times more prescriptions than the lowest. Total spending is higher by 20%, outpatient spending by 59%, inpatient spending by 25%, and drug spending by 26% in the top quartile of districts than in the bottom quartile (column 6) on average.

5.2 Main Results

Our main results are presented in Figure 2, Table 2, and Table 3. Figure 2 shows our event study estimates of place effects from estimating equation (4). In line with our identifying assumptions, it shows little evidence of pre-trends in any of the measures of utilization before the move. Then after the move, measures of utilization adjust towards the level of utilization in the destination district.

Panels (a) and (b) of Figure 2 suggest that outpatient utilization (visits and spending) adjust by more than 60% of the gap between the average utilization in the origin and destination districts, suggesting that the place component of outpatient utilization is explains more

[6] See also Zeltzer, Einav, Chasid and Balicer (2021) for a similar solution.

than three-fifths of the variation. Based on estimating equation (3), column (1) of Table 2 shows that pooling over the entire post-move period, the place component of spending is 68% on average. Columns (1) and (2) of Table 3 show that place effects account for 63-68% of the difference in outpatient utilization between above- and below-median districts and also between the top and bottom quartiles of districts. The remaining 32-37% of the difference is accounted for by demand-side factors.

Turning to inpatient utilization, panels (c) and (d) of Figure 2 suggest that place effects are negligible. There are several reasons why place-specific factors may matter for outpatient but not for inpatient use. Inpatient care is associated with more serious illness. This means that it is likely to be less discretionary or dependent on physician practice styles and more dependent on individual health status. It is also less likely to be subject to capacity or access constraints than outpatient care.

Finally, panels (e) and (f) of Figure 2 show our event study estimates of prescription drugs. Panel (e) and column (3) of Table 2 suggest that place effects explain approximately 19% of the frequency of utilization, while panel (f) and column (3) of Table 2 show a larger, 35% place share for spending. Table 3 shows similar estimates for spending from our additive decomposition. The difference in the share of variation explained for quantity and spending is consistent with places influencing the types and consequently the cost of drugs prescribed on top of the quantity prescribed.

Going beyond the broad categories of outpatient, inpatient, and pharmaceutical utilization, we also examine our results for subcategories of outpatient and prescription drug spending in Appendix Table A2, Appendix Figures A5, and A6. The top panel of Appendix Table A2 and Appendix Figure A5 suggest that place effects are relatively similar across specialties. The lowest point estimate (60%) is obtained for cardiology, while place effects are the largest for lab diagnostics (74%). This is consistent with lab diagnostics being somewhat more discretionary and subject to wider variation in practice patterns.

The bottom panel of Appendix Table A2 and Appendix Figure A6 reveal much more significant differences in place effects across drug classes. It appears that place effects are substantial for antiinfectives, which include antibiotics, but are small for other classes. This is consistent with the use of antibiotics often being discretionary and highly dependent on place-specific supply-side factors as documented in other countries as well. At the same time, the use of drugs like antidiabetics and antihypertensives is less likely to respond to place-specific factors in the short-term.

We now turn to examining the robustness of our main results to several alternative specifications. We re-estimate our main results from equation (3) when (1) we include non-movers in the estimation sample, (2) we include controls for labor market status and income,

(3) we control for differences in the age- and gender-composition of the districts in calculating Δ_i, and (4) we consider larger geographical units, and calculate Δ_i as the difference between the log usage of the destination and origin county instead of districts. The first row of Appendix Table A3 repeats our baseline results from Table 2. The second, third, fourth and fifth rows show results from the alternative specifications. These are very similar to the baseline results.

The results so far offer two key takeaways. First, place-specific factors matter for healthcare use. Using moves across districts we account for individual-specific or demand-side factors, and highlight the importance of place-specific or supply-side factors. In other words, the different composition of individuals living in different areas cannot explain all of the substantial geographic variation in healthcare utilization. Second, the extent to which place matters varies across types of care. Place matters the most for outpatient care, explaining two-thirds of the geographic variation. This is consistent with the idea that outpatient care is the most likely to be discretionary and subject to practice style variation, as well as capacity constraints and access differences. Place also matters for prescription drugs, explaining about a fifth of the variation in the number of prescriptions and about a third of the variation in spending. Prescription drug spending is likely to be influenced by supply-side factors, such as the practice style of the physicians writing prescriptions in an area, but is not subject to capacity and access constraints in the way outpatient care can be. Finally, place-specific factors do not seem to explain the variation in inpatient utilization. This may be because inpatient stays are mostly non-discretionary but instead result from serious illness. Local, district-specific capacity constraints are likely to also matter less.

5.3 Heterogeneity

The role of place may be different for different groups of individuals. Accordingly, we examine various dimensions of heterogeneity in our main results. We focus on three important dimensions: gender, age, and income. Figure 3 and Appendix Table A4 provide an overview of our estimates of place shares for outpatient spending by subgroup and Appendix Figure A7 shows event study plots broken down by each of the subgroups. Panel (2) of Appendix Table A4 displays an alternative specification of our heterogeneity results for outpatient spending and Appendix Table A5 reports heterogeneity results for inpatient and prescription drug spending.

Heterogeneity by gender and age is relatively muted. Although the point estimate of the average place share for women (71%) is slightly higher than for men (63%), the differences are not statistically significant. Similarly, the point estimate for the younger age group of

40 to 54 (74%) is slightly higher than for the older age group of 65 to 79 (65%), they are not statistically different from each other.

Heterogeneity is more pronounced across income groups, though our estimates are fairly noisy. In the working-age population, the average place share is 79% for individuals who do not work and 63%, 54%, 35%, and 38%, respectively, in the four quartiles of the wage income distribution of those who work. For older individuals, the place share is 89% for those with below-median and 67% for those with above-median pensions.

We also estimate place shares separately for moves to lower- and higher-utilization areas. According to Figure 4 and Appendix Table A6, "negative" moves have a stronger impact on outpatient utilization: when an individual moves to a lower-utilization district, her outpatient spending drops by 89% of the origin-destination gap on average but when she moves to a higher-utilization district, her utilization increases by 57% of the gap on average.

Overall, our heterogeneity results suggest that place matters more for lower-income individuals and that mover's utilization is more sensitive to moving to lower-utilization areas. These findings are consistent with capacity constraints being an important determinant of outpatient use and capacity constraints affecting lower-income individuals more.

5.4 District-Level Correlates of Healthcare Use

Our results so far show that place-specific factors impact healthcare utilization and that these impacts are heterogeneous across groups of individuals. In the final part of the paper we examine what characteristics of places are correlated with the estimated causal effects of place on utilization as identified by movers across areas. Unlike our main results, this analysis is only correlational but nevertheless can shed light on potentially important mechanisms.

Based on equation (5), Table 4 shows how district-level variables are associated with the healthcare use of movers controlling for individual fixed effects, calendar time, event time and gender – age group interactions.[7] Outpatient utilization is positively associated with outpatient capacity, and inpatient days (but not inpatient spending) with inpatient capacity (measured as the number of hospital beds). Substitution between the two types of care may be important since outpatient utilization is negatively associated with the number of hospital beds and inpatient care use is negatively associated with the number of outpatient hours.

Distance from the county seat is negatively associated with healthcare use, while the county seat dummy also has a negative coefficient in some specifications because more specialized capacities in the county seat partly serve the population of neighboring rural-type districts as well. Finally, apart from drug spending, the average taxable income of the dis-

[7]Summary statistics of the district-level variables are displayed in Appendix Table A7.

trict as a general socioeconomic indicator does not affect the healthcare use of movers after controlling for the above supply and geographic variables.

Appendix Table A8 shows the same associations when instead of estimating equation (5) we simply regress the estimated place effects from equation (2) on the potential explanatory variables. The magnitudes of the associations between place-specific characteristics and place effects are similar to the results of the one-step procedure presented above.

In Table 5 we examine heterogeneity across age and gender groups in the association between capacity measures and healthcare use, also allowing for non-linearities in the relationship. Column (1) suggests that the partial association between outpatient capacity and outpatient use is stronger at lower levels of capacity, which is consistent with capacity constraints being more binding. Column (2) suggests that outpatient capacity is more strongly associated with care use for women, but there is no significant heterogeneity by age. In line with our previous results on capacity constraints being more important for lower-income individuals, column (3) shows that in the 40-54 years old population, the association between outpatient capacity and utilization is stronger for lower-wage, working age individuals. (Column 4 shows that heterogeneity by pension income is not significant in the 65-79 years old group.)

While estimating the effect of outpatient capacity on healthcare utilization, in the above regressions we controlled for individual fixed effects and other healthcare supply, geographic and socioeconomic variables. However, it is theoretically still possible that unobserved variables that change upon moving confound the results. Hence, it is instructive to compare the magnitude of the estimated effects of outpatient capacity with a quasi-experiment, in which new outpatient service locations were established in 2010-2012 in twenty Hungarian districts that had lacked such capacities before (Elek, Váradi and Varga, 2015). This development increased the average number of weekly outpatient hours from zero to 1.2 per 100 inhabitants in these districts, while holding fixed all other observable and unobservable characteristics.

Elek, Váradi and Varga (2015) estimated in a difference-in-differences framework that the number of outpatient visits increased on the log scale by 0.217 as a result of the development. A mechanical application of our mover-based results would imply an increase of $0.133 \times 1.2 - 0.0064 \times 1.2^2 = 0.150$ in the quadratic specification (column (1) of Table 5). Hence, after taking into account the nonlinear effect of outpatient capacity, the two identification strategies (one based on the changing capacities that movers face upon moving, the other based on a quasi-experiment of increasing capacities in some given districts) yield surprisingly similar results. This suggests that unobserved variables play a relatively minor role in our mover-based correlational analysis of place effects, and points to the validity of such estimation strategies in explaining the variation in healthcare use.

We note that the development of new outpatient units (the quasi-experiment) increased women's outpatient care utilization more strongly than men's, which is in line with our mover-based results showing women's greater responsiveness to outpatient hours. Also, Elek, Molnár and Váradi (2019) estimated a decrease in inpatient care use as a result of the quasi-experiment and hence a substitution between outpatient and inpatient care, which is reflected in the mover-based setting (see the negative estimated effect of outpatient capacity on the number of inpatient days in Table 4 and Appendix Table A8).

6 Conclusion

Substantial geographic variation in healthcare utilization has been documented in a variety of countries and healthcare settings. This paper documents the interaction of this geographic variation with socioeconomic status in the context of Hungary, a healthcare system with universal coverage. Our results show that place matters for healthcare use but it matters differentially for different types of care and different people.

Using movers to decompose utilization into place- and individual-specific components we have demonstrated that place effects explain two-thirds of geographic variation in outpatient spending, but only one-third of prescription drug spending and almost none of inpatient spending. Heterogeneity across income groups is equally pronounced: for working-age individuals who do not work, place effects explain four-fifth of geographic variation in outpatient care use, while they explain less than two-fifths for individuals with above-median incomes. This suggests that supply-side factors matter more for lower-income individuals.

Our results suggest that capacity constraints may be an important explanation for geographic variation and the documented patterns of heterogeneity. Place effects are larger for more discretionary outpatient care use. They are also larger for lower-income individuals who are presumably more likely to be affected when there is a shortage of physicians or other capacity. Directly assessing the relationship between outpatient capacity and utilization also reveals a positive relationship between these two variables, with magnitudes in line with previous quasi-experimental evidence.

Increasing the capacity of the healthcare system might enable better access to care for low-SES individuals and enable providers to spend more time and resources on all patients. When resources are scarce, low-SES groups are hurt disproportionately even in a system of universal health care. Future work should investigate the causal mechanisms behind the role of healthcare capacity in socioeconomic disparities when access is nominally equal and universal.

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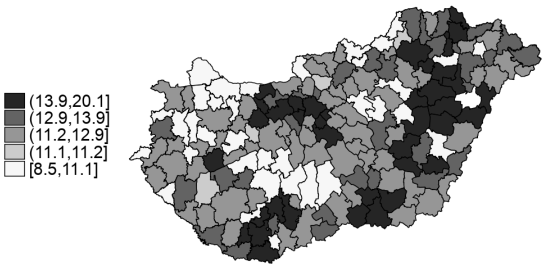
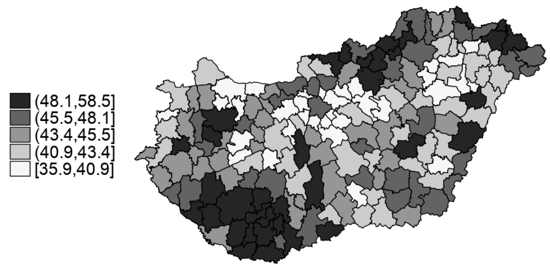
Figure 1: Geographic Variation in Healthcare Spending

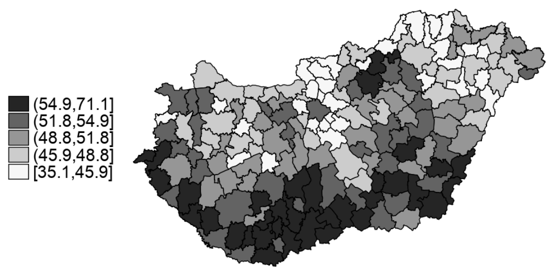
(a) Outpatient Spending



(b) Inpatient Spending



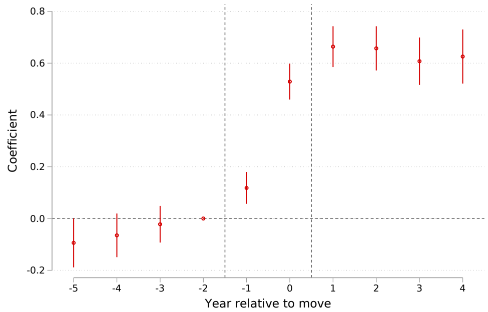
(c) Drug Spending



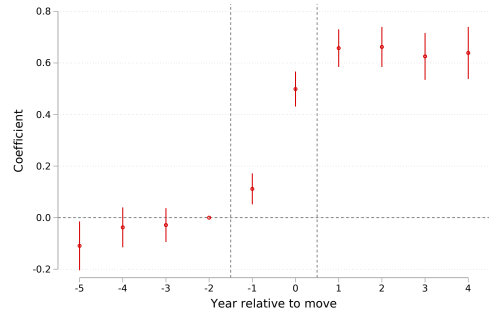
Note: Figure shows average outpatient, inpatient, and prescription drug spending by district in thousand HUF. The 197 districts are divided into quintiles by type of spending. The lower and upper limits of each quintile are displayed in the legend. The sample includes all movers and non-movers ($N = 3,662,646$ individuals).

Figure 2: Event Study

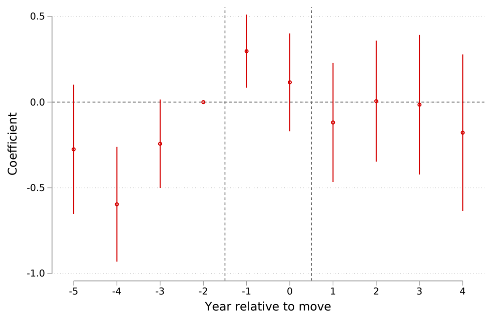
(a) Outpatient Visits



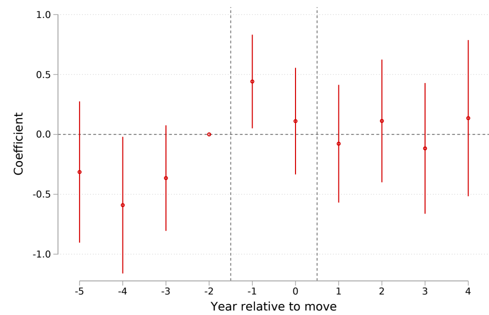
(b) Outpatient Spending



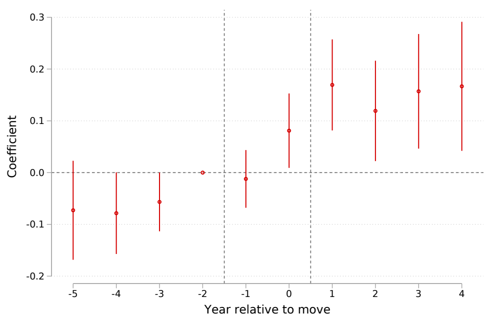
(c) Inpatient Days



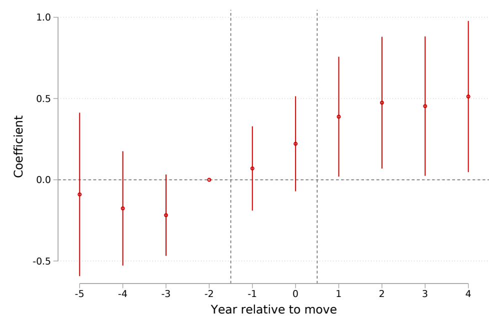
(d) Inpatient Spending



(e) Drug Prescriptions

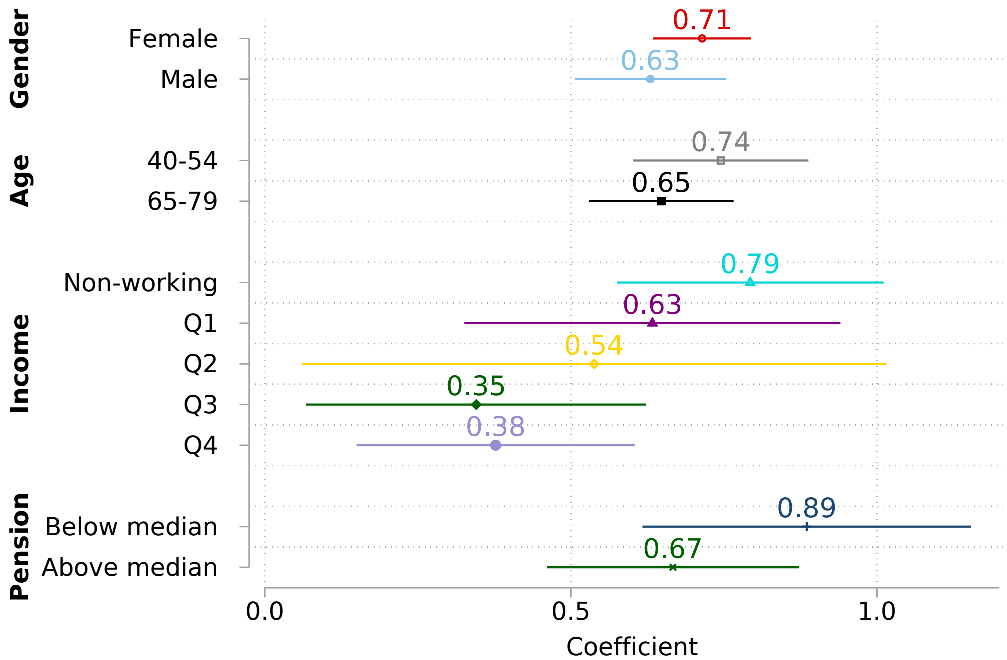


(f) Drug Spending



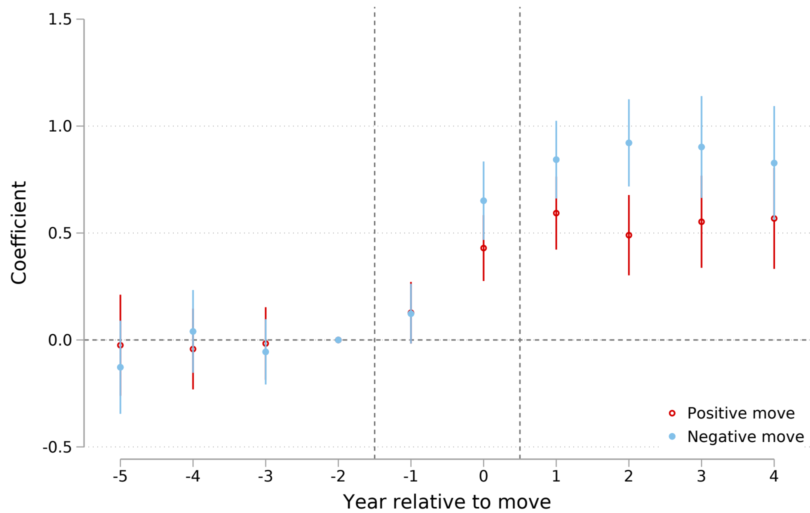
Note: Figure shows event study estimates of place effects for outpatient, inpatient, and prescription drug utilization. These are the coefficients θ_k from estimating equation (4). The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. The sample includes all movers ($N = 245,742$ individual-years).

Figure 3: Difference-in-Differences: Average Place Effects—Heterogeneity



Note: Figure shows pooled difference-in-differences estimates of place effects for outpatient spending for different subgroups. These are the coefficient θ from estimating equation (3), estimated separately for each subgroup. The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. Wage income categories (non-working, quartiles of positive wage income) are defined for the 40-64 age group. Pension income categories (below or above the median) are defined for the 65-79 age group. Income is measured two years before the move. The sample includes all movers ($N = 125,334$ individual-years for women; $N = 112,693$ individual-years for men; $N = 74,387$ individual-years for the 40-64 age group; and $N = 30,896$ individual-years for the 65-79 age group).

Figure 4: Event Study: Outpatient Spending by Move Type



Note: Figure shows event study estimates of place effects for outpatient spending by type of move. These are the coefficients θ_k from estimating equation (4). The red hollow circles show estimates of place effects for moves from lower- to higher-utilization districts ("positive" moves) and the blue full circles show estimates of place effects for movers from higher- to lower-utilization districts ("negative" moves). The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. The sample includes all movers ($N = 124,485$ individual-years for "positive" moves and $N = 121,257$ for "negative" moves).

Table 1: Summary Statistics

	(1) Non-movers	(2) Movers
Male	0.47	0.49
Age	47.5	41.9
Outpatient visits	7.2	6.2
Outpatient spending (HUF)	12,206	10,435
Inpatient days	2.1	1.9
Inpatient spending (HUF)	37,920	27,877
Drug prescriptions	17.9	11.9
Drug spending (HUF)	53,247	35,032
Total spending (HUF)	103,371	73,344
Working	0.47	0.50
White collar job	0.21	0.28
Blue collar job	0.26	0.22
Unemployment benefit	0.02	0.02
Pensioner	0.20	0.11
Number of individuals	3,598,056	64,590

Note: Table shows summary statistics of non-movers and movers. Annual healthcare use measures are calculated in 2009, the first year of our data.

Table 2: Difference-in-Differences: Average Place Effects

	(1) Outpatient care	(2) Inpatient care	(3) Pharmaceuticals
Frequency	0.676***	-0.011	0.189***
	(0.0403)	(0.171)	(0.0499)
Spending	0.679***	0.107	0.351*
	(0.0343)	(0.227)	(0.204)
Observations	245,742	107,055	237,618

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for outpatient, inpatient, and prescription drug utilization. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions. For each utilization type, the first row shows a measure of frequency and the second row shows spending. Frequency measures are outpatient visits, inpatient days, and number of prescriptions. Number of observations are individual-years.

Table 3: Additive Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
	Outpatient Spending		Inpatient Spending		Drug Spending	
	Top vs. bottom		Top vs. bottom		Top vs. bottom	
	50%	25%	50%	25%	50%	25%
Mover sample						
Difference in log average utilization	0.29	0.47	0.31	0.51	0.35	0.57
Place component	0.20	0.29	0.15	0.29	0.11	0.19
Patient component	0.09	0.17	0.16	0.21	0.24	0.38
Place share	0.68	0.63	0.49	0.58	0.32	0.34
Patient share	0.32	0.37	0.51	0.42	0.69	0.66
Full sample						
Difference in log average utilization	0.29	0.46	0.29	0.48	0.33	0.53
Place component	0.18	0.29	0.12	0.27	0.08	0.15
Patient component	0.11	0.17	0.17	0.21	0.25	0.38
Place share	0.63	0.63	0.42	0.56	0.25	0.28
Patient share	0.37	0.37	0.57	0.44	0.75	0.72

Note: Table shows additive decomposition estimates of place effects for outpatient, inpatient, and prescription drug utilization. These are based on the coefficients γ_j from estimating equation (2). Controls include calendar year fixed effects and gender – age group interactions. For each utilization type, the first column shows the difference between above- and below-median districts and the second column shows the difference between the bottom and top quartiles of districts.

Table 4: District-Level Correlates of Healthcare Utilization

	(1) Outpatient visits	(2) Outpatient spending	(3) Inpatient days	(4) Inpatient spending	(5) Drug prescriptions	(6) Drug spending
Outpatient hours,	0.079***	0.102***	-0.059**	-0.005	0.019***	0.031
per 100 capita	(0.006)	(0.007)	(0.029)	(0.020)	(0.005)	(0.019)
Hospital beds,	-0.047***	-0.097***	0.129*	0.072	-0.002	0.015
per 100 capita	(0.016)	(0.018)	(0.073)	(0.052)	(0.013)	(0.039)
County seat	-0.172***	-0.226***	0.121	-0.048	-0.042**	-0.064
	(0.025)	(0.028)	(0.115)	(0.080)	(0.019)	(0.057)
Distance from	-0.018***	-0.019***	0.017	-0.016	-0.008**	-0.018*
county seat, 10 km	(0.004)	(0.005)	(0.018)	(0.013)	(0.003)	(0.010)
Log income	-0.005	-0.027	0.169	-0.143	0.050	-0.277**
per capita	(0.040)	(0.048)	(0.167)	(0.141)	(0.033)	(0.113)
Observations	203,910	203,910	100,465	100,437	198,029	198,029

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows the estimated relationship between healthcare utilization and district-level measures of capacity, access, and income. These are the coefficient η from estimating equation (5). Controls include calendar year fixed effects and gender – age group interactions. Number of observations are individual-years.

Table 5: Nonlinear and Heterogeneous Effect of Outpatient Capacity on Outpatient Visits of Movers

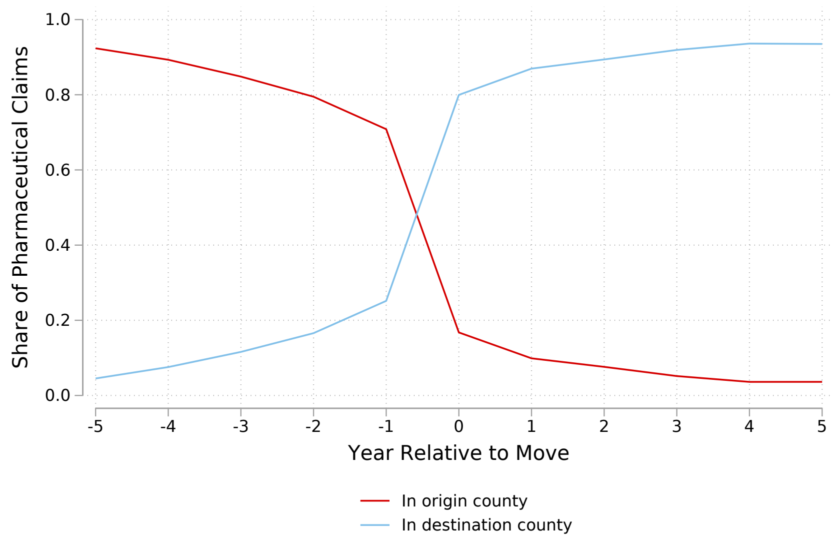
	(1) 30-79 years	(2) 30-79 years	(3) 40-54 years	(4) 65-79 years
Outpatient hours, per 100 capita	0.133***	0.068***	0.091***	0.067***
	(0.019)	(0.009)	(0.020)	(0.024)
Outpatient hours, per 100 capita^2	-0.0064***			
	(0.0022)			
Interaction with female		0.023***	-0.007	0.030*
		(0.009)	(0.016)	(0.018)
Interaction with (age-40 years)		-0.00027		
		(0.00028)		
Interaction with wage or pension income			-0.0108**	-0.0027
(million HUF)			(0.0049)	(0.0074)
Number of observations	203,910	203,910	49,504	22,688

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows the estimated relationship between healthcare utilization and district-level measures of capacity, stratified by gender, age, and income. These are the coefficient η from estimating versions of equation (5) with quadratic terms or interactions. Controls include calendar year fixed effects and gender – age group interactions. Number of observations are individual-years.

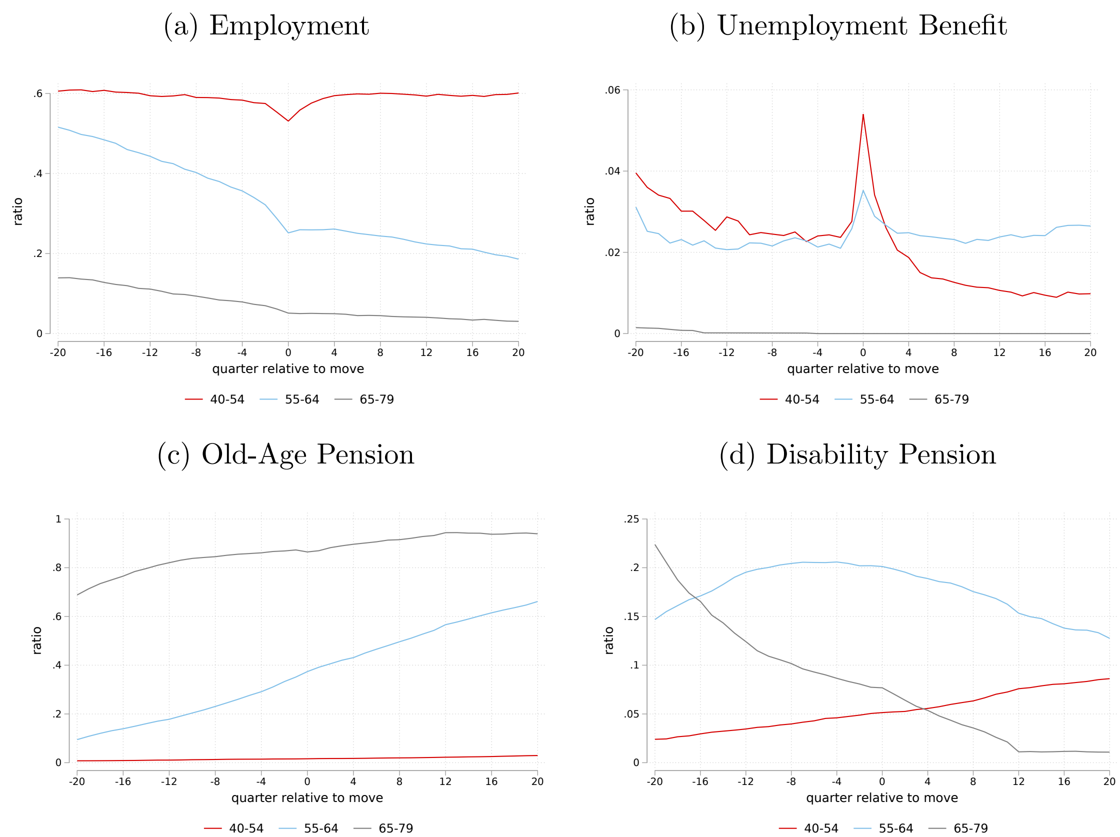
Appendix

Appendix Figure A1: Evolution of Share of Pharmaceutical Claims in Origin and Destination County



Note: Figure shows the evolution of the share of movers for whom the county where they claimed most of their prescriptions is their origin county and their destination county. Quarterly data are annualized by year relative to the move. Relative year zero is defined as the first four quarters when the individual lived in the destination district according to the place of residence. The sample includes all movers ($N = 64,590$ individuals).

Appendix Figure A2: Evolution of Labor Market Outcomes



(a) Employment

(b) Unemployment Benefit

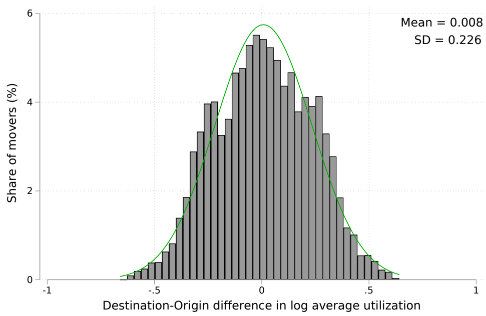
(c) Old-Age Pension

(d) Disability Pension

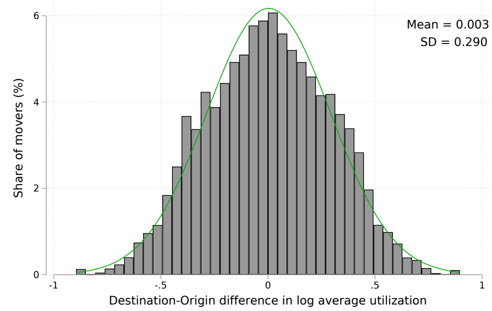
Note: Figure shows the evolution of labor market outcomes, including the probabilities of being employed, receiving unemployment benefits, receiving an old-age pension, and receiving a disability pension among movers by age group. The sample includes all movers ($N = 64,590$ individuals).

Appendix Figure A3: Distribution of Destination-Origin Difference in Log Utilization

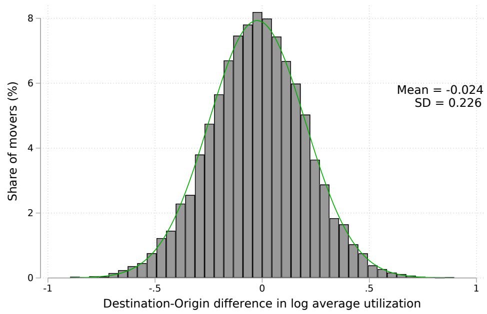
(a) Outpatient Visits



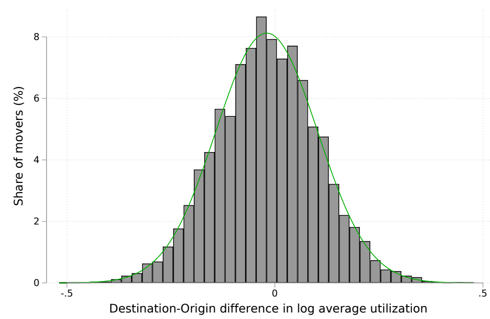
(b) Outpatient Spending



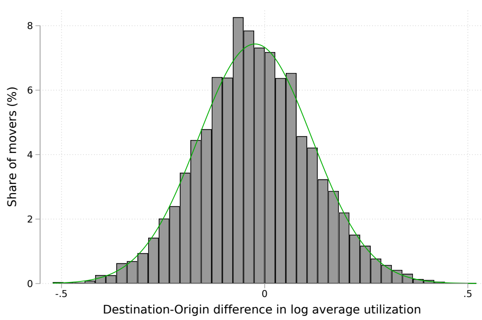
(c) Inpatient Days



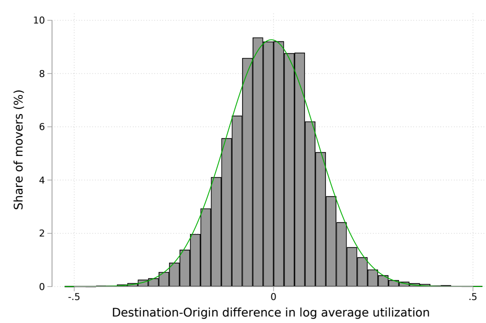
(d) Inpatient Spending



(e) Drug Prescriptions



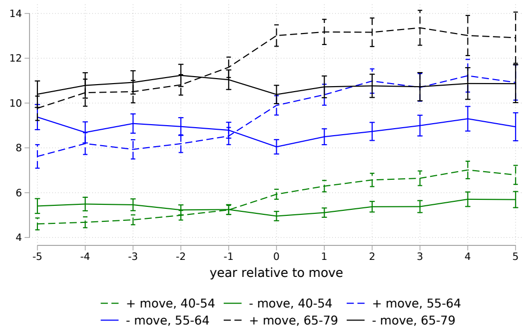
(f) Drug Spending



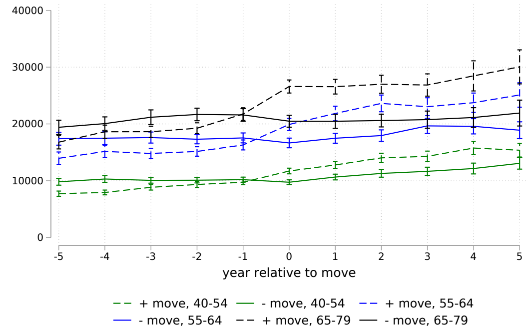
Note: Figure shows the distributions of the logarithmic difference between the average outpatient, inpatient, and prescription drug utilization of a mover's origin district and destination district. The sample includes all movers ($N = 64,590$ individuals).

Appendix Figure A4: Evolution of Healthcare Utilization of Movers

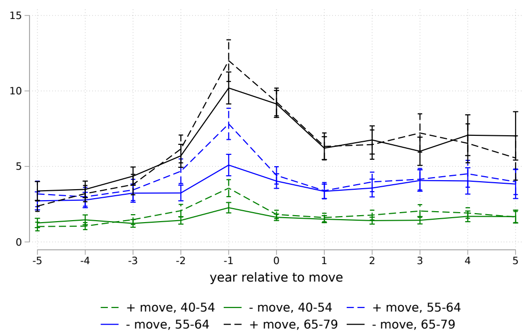
(a) Outpatient Visits



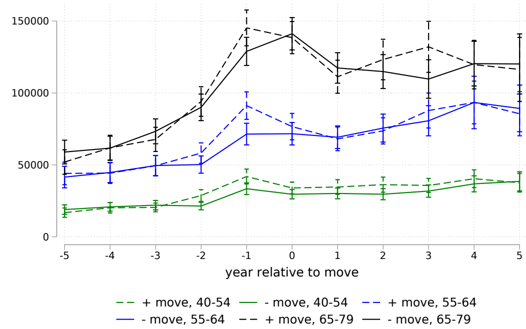
(b) Outpatient Spending



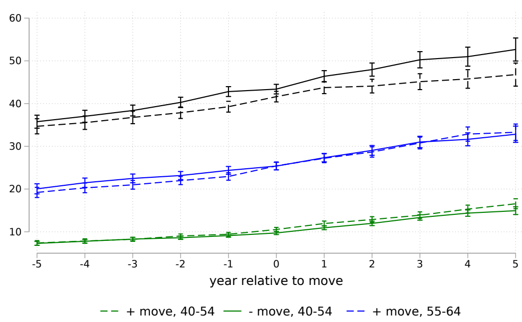
(c) Inpatient Days



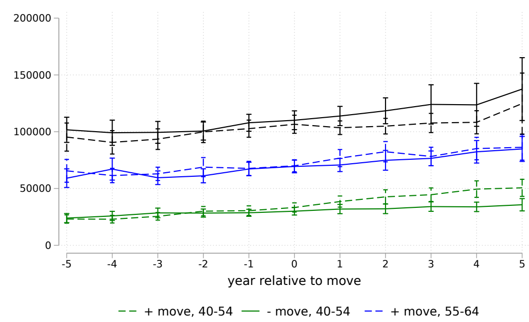
(d) Inpatient Spending



(e) Drug Prescriptions



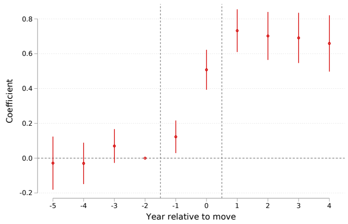
(f) Drug Spending



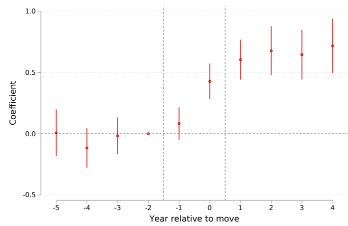
Note: Figures show healthcare utilization of movers of three age groups split by the direction of the move (positive or negative difference between the average utilization of the destination and origin district). 95% confidence intervals for the means are shown.

Appendix Figure A5: Event Study: Outpatient Specialties

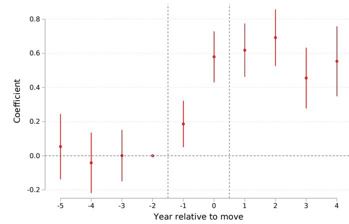
(a) Internal Care



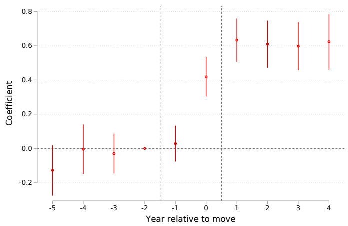
(b) Surgery and Trauma



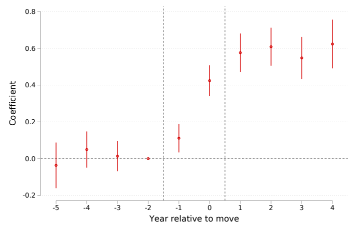
(c) Gynaecology



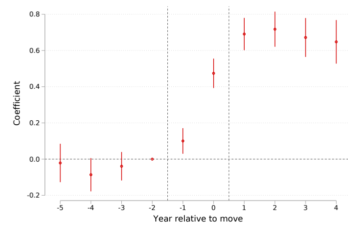
(d) Reumatology



(e) Cardiology



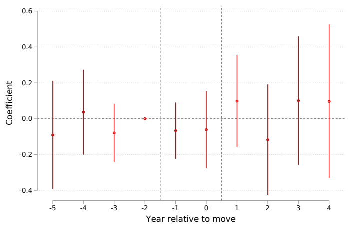
(f) Lab Diagnostics



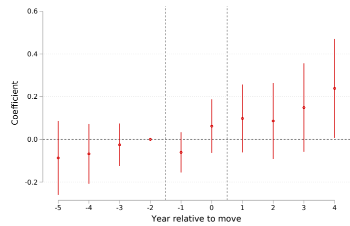
Note: Figure shows event study estimates of place effects for outpatient spending by specialties. These are the coefficients θ_k from estimating equation (4). The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. The sample includes all movers ($N = 245,742$ individual-years).

Appendix Figure A6: Event Study: Therapeutic Classes of Drugs

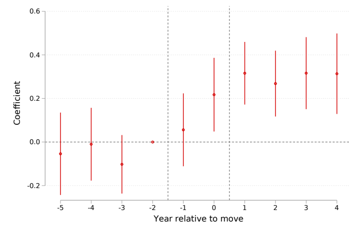
(a) Antidiabetics



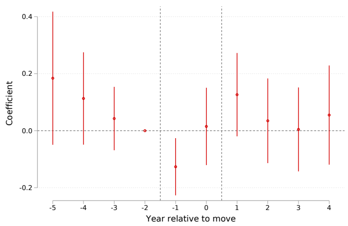
(b) Antihypertensives



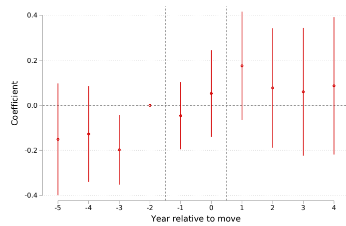
(c) Antiinfectives



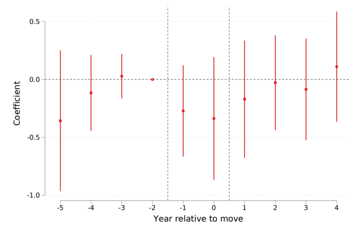
(d) Psycholeptics



(e) Psychoanaleptics



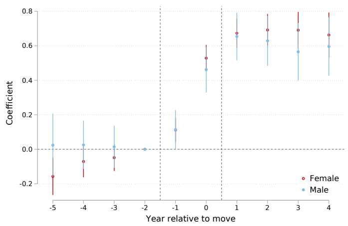
(f) Obstructive Airway



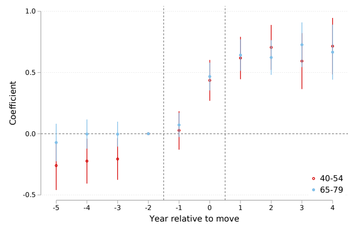
Note: Figure shows event study estimates of place effects for prescription drug spending by therapeutic class. These are the coefficients θ_k from estimating equation (4). The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. The sample includes all movers ($N = 245,742$ individual-years).

Appendix Figure A7: Event Study: Heterogeneity

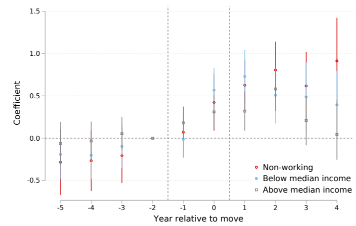
(a) By Gender



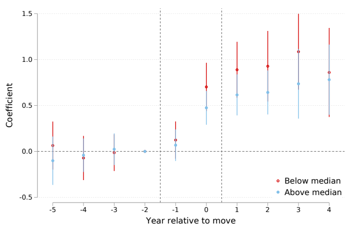
(b) By Age Group



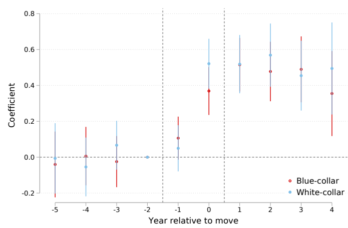
(c) By SES (40-54)



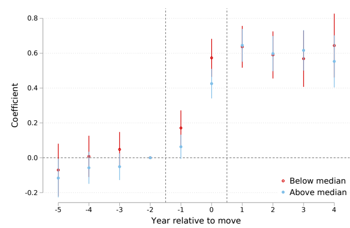
(d) By SES (65-79)



(e) By Job Type



(f) By Health Status



Note: Figure shows event study estimates of place effects for outpatient spending by subgroup. These are the coefficients θ_k from estimating equation (4). The bars show 95% confidence intervals. Controls include calendar year fixed effects and gender – age group interactions. Wage income categories (non-working, quartiles of positive wage income) are defined for the 40-64 age group. Pension income categories (below or above the median) are defined for the 65-79 age group. Income is measured two years before the move. Job type is defined by International Standard Classification of Occupations (ISCO) code. Health status is measured by drug spending (below or above the median calculated by calendar year, age group and gender). The sample includes all movers ($N = 245,742$ individual-years).

Appendix Table A1: Summary Statistics and Regional Variation of Healthcare Use

	(1) Mean	(2) S.D.	(3) Lowest spending district	(4) Highest spending district	(5) Difference max-min (%)	(6) Difference top-bottom quartile (%)
Total spending	120.2	353.6	99.1	151.3	53	20
Outpatient spending	15.0	30.2	9.3	22.7	145	59
Inpatient spending	47.9	220.4	38.3	64.2	68	25
Drug spending	57.3	230.7	41.6	81.2	95	26
Outpatient visits	7.8	12.5	5.3	10.3	95	47
Inpatient days	2.3	12.2	1.6	4.1	163	55
Prescriptions	20.9	30.8	16.3	27.4	68	30
Total spending, by group						
Female	126.8	343.4	103.6	157.1	52	22
Male	112.7	364.7	92.7	149.0	61	22
Age groups						
40-54	80.7	307.0	59.6	119.8	101	33
65-80	228.3	445.4	175.4	279.3	59	18
40-54 years						
Non-working	119.0	399.9	67.7	190.6	182	58
Below median wage	73.7	288.5	55.7	104.1	87	27
Above median wage	55.1	217.2	39.9	74.9	88	30
65-80 years						
Below median pension	215.0	421.5	173.7	258.6	49	19
Above median pension	233.5	466.2	174.2	285.1	64	19
Job types						
Blue-collar	68.4	253.1	53.1	111.5	110	30
White-collar	70.6	276.8	52.3	97.5	87	24

Note: Table shows individual-level summary statistics (mean and standard deviation) and measures of regional variation for healthcare spending (thousand HUF / year) and use (as frequency variables). Column (3) and (4) show usage in the highest and lowest spending districts and Column (5) shows the percentage difference between the two. Column (6) shows the percentage difference between average usage in the top quartile of districts and the bottom quartile. The bottom part of the table shows differences in total spending by groups.

Appendix Table A2: Difference-in-Differences: Average Place Effects—Outpatient Specialties and Therapeutic Categories

	(1)	(2)	(3)	(4)	(5)	(6)
	Outpatient specialties					
	Internal care	Surgery, trauma	Gynecology	Reumatology	Cardiology	Lab diagnostics
Spending	0.708***	0.660***	0.683***	0.595***	0.599***	0.738***
	(0.0623)	(0.0819)	(0.0743)	(0.0608)	(0.0521)	(0.0440)

	Drug categories					
	Anti-diabetics	Antihyper-tensives	Anti-infectives	Psycho-leptics	Psycho-analeptics	Obstructive airway
Spending	0.0351	0.112	0.336***	0.0473	0.174	-0.0615
	(0.160)	(0.0935)	(0.0652)	(0.0777)	(0.127)	(0.167)

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for outpatient specialties and therapeutic classes. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions.

Appendix Table A3: Difference-in-Differences: Average Place Effects—Robustness

	(1) Outpatient visits	(2) Outpatient spending	(3) Inpatient days	(4) Inpatient spending	(5) Drug prescriptions	(6) Drug spending
Baseline	0.676***	0.679***	-0.011	0.107	0.189***	0.351*
	(0.0403)	(0.0343)	(0.171)	(0.227)	(0.0499)	(0.204)
Full sample	0.701***	0.710***	0.0769	0.103	0.188***	0.304**
	(0.0357)	(0.0311)	(0.158)	(0.210)	(0.0455)	(0.127)
With controls	0.671***	0.676***	-0.0329	0.0712	0.196***	0.351*
	(0.0402)	(0.0344)	(0.170)	(0.227)	(0.0500)	(0.204)
Adjusted	0.686***	0.683***	-0.0192	-0.0277	0.196***	0.395*
	(0.0409)	(0.0346)	(0.176)	(0.231)	(0.0538)	(0.230)
County-level	0.698***	0.690***	-0.191	0.0730	0.0960	0.618**
	(0.0474)	(0.0421)	(0.269)	(0.348)	(0.0626)	(0.268)

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for outpatient, inpatient, and prescription drug utilization. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions in all rows. The first row replicates our baseline specification from Table 2 estimated on movers. The second row re-estimates the same specification on the full sample. The third row re-estimates the same specification but also includes controls for employment and income. The fourth row re-estimates the same specification using Δ_i calculated as the destination-origin difference of the log average usages, controlling for gender and age. The fifth row re-estimates the same specification using Δ_i calculated as the difference between the log usage in the destination and origin counties instead of districts. For each utilization type, the first column shows a measure of frequency and the second column shows spending. Frequency measures are outpatient visits, inpatient days, and number of prescriptions.

Appendix Table A4: Difference-in-Differences: Average Place Effects—Heterogeneity for Outpatient Spending

	(1)	(2)	(3)	(4)	(5)	(6)
		Baseline			Δ_i not group-specific	
	Place share	(S.E.)	Difference	Place share	(S.E.)	Difference
Gender						
Female	0.714***	(0.0409)		0.718***	(0.0409)	
Male	0.630***	(0.0631)	-0.0843	0.608***	(0.0631)	-0.109
Age group						
40-54	0.745***	(0.0730)		0.671***	(0.0730)	
65-79	0.648***	(0.0603)	-0.0987	0.826***	(0.0603)	0.153
SES, working age						
Non-working	0.793***	(0.111)		0.841***	(0.111)	
q1	0.633***	(0.157)	-0.156	0.628***	(0.157)	-0.212
q2	0.538**	(0.244)	-0.232	0.482**	(0.244)	-0.349
q3	0.345**	(0.142)	-0.462**	0.451***	(0.142)	-0.408**
q4	0.377***	(0.116)	-0.454***	0.448***	(0.116)	-0.437***
SES, pensioners						
Below median pension	0.885***	(0.137)		1.096***	(0.137)	
Above median pension	0.667***	(0.105)	-0.206	0.772***	(0.105)	-0.311
Job type						
Blue-collar	0.481***	(0.0673)		0.581***	(0.0673)	
White-collar	0.484***	(0.0718)	-0.00448	0.479***	(0.0718)	-0.108

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for outpatient spending by subgroup. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions. Wage income categories (non-working, quartiles of positive wage income) are defined for the 40-54 age group. Pension income categories (below or above the median) are defined for the 65-79 age group. Income is measured two years before the move. Job type is defined by International Standard Classification of Occupations (ISCO) code. Columns (4), (5), and (6) replicate the same results using the aggregate, rather than group-specific utilization difference between the origin and destination district.

Appendix Table A5: Difference-in-Differences: Average Place Effects—Heterogeneity for Inpatient and Drug Spending

	(1)	(2)	(3)	(4)	(5)	(6)
	Inpatient spending			Drug spending		
	Place share	(S.E.)	Difference	Place share	(S.E.)	Difference
Gender						
Female	0.235	(0.266)		0.558***	(0.208)	
Male	-0.0110	(0.360)	-0.241	0.0423	(0.298)	-0.517
Age group						
40-54 years	-0.554*	(0.297)		0.119	(0.225)	
65-79 years	0.796*	(0.446)	1.370**	0.222	(0.277)	0.0974
SES, working age						
Non working	-0.606**	(0.277)		-0.0785	(0.118)	
Below median wage	1.858**	(0.775)	2.420***	0.570	(0.530)	0.640
Above median wage	-0.107	(0.746)	0.401	0.346	(0.336)	0.528
SES, working age						
Non working	-0.606**	(0.277)		-0.0785	(0.118)	
q1	1.538***	(0.595)	2.084***	-0.132	(0.260)	0.0201
q2	3.116**	(1.373)	3.802***	0.511	(0.614)	0.394
q3	-0.537	(0.837)	0.204	-0.436	(0.652)	-0.360
q4	0.758	(0.833)	1.063	0.342	(0.311)	0.614*
SES, pensioners						
Below median pension	0.0749	(0.692)		-0.111	(0.574)	
Above median pension	0.610	(0.715)	0.529	0.365	(0.449)	0.453
Job type						
Blue collar	0.495	(0.477)		-0.491	(0.366)	
White collar	0.925	(0.578)	0.512	0.286	(0.380)	0.775
Health status						
Below median	-0.105	(0.282)		-0.314	(0.442)	
Above median	0.121	(0.266)	0.178	0.170	(0.234)	0.447

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for inpatient and prescription drug spending by subgroup. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions. Wage income categories (non-working, quartiles of positive wage income) are defined for the 40-64 age group. Pension income categories (below or above the median) are defined for the 65-79 age group. Income is measured two years before the move. Job type is defined by International Standard Classification of Occupations (ISCO) code.

Appendix Table A6: Difference-in-Differences: Average Place Effects—Positive and Negative Moves

	(1) Outpatient visits	(2) Outpatient spending	(3) Inpatient days	(4) Inpatient spending	(5) Drug prescriptions	(6) Drug spending
Baseline	0.676***	0.679***	-0.011	0.107	0.189***	0.351*
	(0.0403)	(0.0343)	(0.171)	(0.227)	(0.0499)	(0.204)
Positive move	0.362***	0.566***	0.466	-0.0709	0.221*	0.144
	(0.0944)	(0.0827)	(0.475)	(0.614)	(0.133)	(0.421)
Negative move	0.851***	0.888***	0.399	0.492	0.147	0.933*
	(0.102)	(0.0886)	(0.324)	(0.458)	(0.0995)	(0.492)

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows pooled difference-in-differences estimates of place effects for outpatient, inpatient, and prescription drug utilization. These are the coefficient θ from estimating equation (3). Controls include calendar year fixed effects and gender – age group interactions in all rows. The first row replicates our baseline specification from Table 2. The second row re-estimates the same specification on the sample of moves from lower-utilization to higher-utilization districts ("positive" moves). The third row re-estimates the same specification on the sample of moves from higher-utilization to lower-utilization districts ("negative" moves). For each utilization type, the first column shows a measure of frequency and the second column shows spending. Frequency measures are outpatient visits, inpatient days, and number of prescriptions.

Appendix Table A7: Summary Statistics for District-Level Variables

	(1) Mean	(2) S.D.	(3) Lowest	(4) Highest
Outpatient hours, per 100 capita	1.643	1.172	0.000	6.674
Hospital beds, per 100 capita	0.464	0.559	0.000	3.100
County seat	0.103	0.305	0.000	1.000
Distance from country seat, 10 km	3.155	1.968	0.000	9.901
Log income, per capita	13.88	0.186	13.52	14.38

Note: Table shows summary statistics of district-level variables between 2009-2017 (excluding the districts of Budapest).

Appendix Table A8: Regressions of Place Effects on District-Level Variables

	(1) Outpatient visits	(2) Outpatient spending	(3) Inpatient days	(4) Inpatient spending	(5) Drug prescr.	(6) Drug spending
Outpatient hours,	0.075***	0.092***	-0.089**	0.003	0.017**	0.053**
per 100 capita	(0.012)	(0.014)	(0.039)	(0.031)	(0.008)	(0.021)
Hospital beds,	-0.043	-0.097***	0.185**	0.052	-0.002	0.003
per 100 capita	(0.028)	(0.032)	(0.090)	(0.073)	(0.019)	(0.049)
County seat	-0.155***	-0.197***	0.201	0.024	-0.025	-0.133*
	(0.042)	(0.049)	(0.138)	(0.112)	(0.029)	(0.075)
Distance from	-0.013*	-0.017*	0.020	-0.010	-0.003	-0.015
county seat, 10 km	(0.007)	(0.008)	(0.024)	(0.020)	(0.005)	(0.013)
Log income	0.010	-0.009	-0.029	-0.058	-0.012	-0.233**
per capita	(0.063)	(0.073)	(0.206)	(0.167)	(0.043)	(0.112)

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Table shows the weighted least squares regression results (weighted by the population of the districts) of the estimated place effects on district-level variables. Districts of Budapest are excluded because of the irrelevance of the district-level supply variables there.
Place effect were estimated using Equation (2). Transitory years -1 and 0 were excluded.
Number of districts: N =174.