Place or patient as the driver of regional variation in healthcare spending – Discrepancies by category of care

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1. Introduction

Healthcare spending varies substantially between geographic areas within the same healthcare system. Large regional variation in healthcare spending has been observed in a range of countries, including the US, Germany, Norway, Sweden, the Netherlands, Israel, etc. (Godoy and Huitfeldt, 2020; Johansson et al., 2018; Molitor, 2018; Moura et al., 2019; Salm and Wübker, 2020; Song et al., 2010; Zeltzer et al., 2021). Whether health policy should aim to reduce regional variation in healthcare spending largely depends on what drives the variation. If regional variation is primarily driven by place-specific factors such as the proximity to healthcare providers or professionals’ varying treatment decisions (“supply-side factors”), this could warrant policy intervention to improve efficiency and reduce inequalities (Skinner, 2011). Whereas regional variation caused by patient-specific factors such as health status and preferences (“demand-side factors”) can be seen as a natural consequence of varying healthcare needs between geographic areas. In the literature on causes of regional variation in healthcare spending, the conceptual idea has been to separate the effect of supply and demand (Finkelstein et al., 2016). However, since place-specific factors do not completely equate supply (and patient-specific do not completely equate demand), we henceforth use the terms place-specific and patient-specific factors.

In this paper, using data on regional migrants in Sweden, we analyze whether healthcare spending patterns change when moving between regions, with the aim to separate place- and patient-specific factors as drivers of regional spending variation. We rely on a random sample of 1 million Swedes followed from 2007 to 2016 that includes 53,620 movers with complete coverage on inpatient, specialized outpatient, and prescription drug use. If individual characteristics and preferences are most important for the regional differences, we expect movers’ healthcare use to remain constant when moving. If place-specific features are most important for healthcare spending, we expect regional movers to change their healthcare utilization behavior when moving between regions. We follow the previous literature relying on a similar empirical approach of patient migration, and estimate the relative effect of place using two way fixed effects (TWFE) models and event studies. In addition, we apply a state-of-the-art estimator developed by de Chaisemartin and
D’Haultfoeuille (2023). The estimator is robust to heterogeneous treatment effects to avoid “forbidden comparisons” and negative weights, which may otherwise cause bias in settings with multiple groups and time periods, variation in treatment timing and a continuous treatment (de Chaisemartin and D’Haultfoeuille, 2020; Goodman-Bacon, 2021).

The recent literature utilizing movers to separate place- and patient-specific factors as drivers of variation in healthcare spending started with Finkelstein et al. (2016) who showed that a place effect drives 50–60% of the variation in US Medicare spending. Similar results in a sample of individuals with employer-sponsored insurance in the US also showed that the place effect was driven by a combination of price and utilization volumes (Johnson and Biniek, 2021). From European and Israeli healthcare systems, results have indicated that place-specific factors explain between 10 and 50% of variation depending on the country and sample (Godøy and Huitfeldt, 2020; Johansson and Svensson, 2022; Moura et al., 2019; Salm and Wübben, 2020; Zeltzer et al., 2021). Considering that the empirical approach has been almost identical in the recent papers, the variation in results indicates that the institutional context and category of care studied likely influence the importance of place-specific factors. Two of the previous studies focus on Scandinavia, and Godøy and Huitfeldt (2020) uncovered a substantial place effect, explaining approximately 50% of variation in hospital spending in Norway, a healthcare system resembling the Swedish model. Johansson and Svensson (2022) identified a place effect ranging from 5% to 10% in prescription drug expenditure within the Swedish healthcare system.

In this paper, we make two specific contributions to the literature. First, we assess the importance of place- and patient-specific factors using a random sample of the general population from a single-payer universal healthcare system with complete coverage, and rich register data of all outpatient specialized care, inpatient care, and prescription drug use. The subcategorization for the category of care within the same system is important and has not been done in previous studies save for one exception (Moura et al., 2019). There are reasons to believe there may be heterogeneity between different categories of care, both with respect to the perspective of patients’ needs and to varying levels of gatekeeping and regulations related to providers. Elective care in outpatient specialist settings may leave more room for providers’ varying incentives to influence regional variation. Whereas inpatient specialist care is relatively more likely to be unforeseen, it may imply that inpatient care is less likely to be place-sensitive. Regarding prescription drugs, the market’s specific features in Sweden, such as fixed drug prices and pharmacy requirements to offer cost-effective generic alternatives, may discourage unnecessary spending on prescription drugs, making place-specific factors less pronounced.

Second, we show that the potential bias in traditional TWFE and event study regressions used in the previous literature is large. Recent econometrics contributions have pointed to pitfalls with TWFE models in study settings with multiple groups and time periods, variation in treatment timing and a continuous treatment (Callaway and Sant Anna, 2021; de Chaisemartin and D’Haultfoeuille, 2022; Goodman-Bacon, 2021; Sun and Abraham, 2021). The traditional TWFE regression is unbiased only under the assumptions of parallel trends and a constant treatment effect. In our study design, the assumption of a constant treatment effect is questionable both due to potential heterogeneity over calendar time and potential dynamics in the treatment effect (de Chaisemartin and D’Haultfoeuille, 2022). We amend the traditional TWFE regression with a new heterogeneity-robust estimator that strictly compares groups switching to treatment in a given time period with groups not-yet-treated during the same period and specifically takes into account dynamic effects (de Chaisemartin and D’Haultfoeuille, 2023).

Our results based on the traditional TWFE regressions show that place-specific factors explain as much as 75% of regional variation in outpatient care spending, 26% of inpatient care spending, and no more than 5% of prescription drug spending. But, we also find substantial discrepancies when we compare the results to the heterogeneity-robust estimator, which shows that place-specific factors explain up to 25% of regional variant in outpatient care spending, and no more than 4% and 6% of inpatient care and prescription drug spending. Both approaches thus indicate that the impact of place-specific factors seems to be highly dependent on the category of care, with the biggest impact on outpatient care. But, the substantial variation in the estimates between the traditional TWFE and event study regressions compared with the heterogeneity-robust estimator indicates a great uncertainty in terms of the actual share of regional variation in spending explained by place-effects – an uncertainty that extends to the previous literature on this topic that has been based solely on traditional TWFE and event study regressions.

The rest of the paper is structured as follows. In section two, we describe the institutional setting, the data, descriptive statistics, and the empirical approach. Section three presents the results, and in section four, we discuss the findings.

2. Material and methods

2.1. Institutional setting

In the Swedish national health services, the provision of primary care, specialized outpatient care and inpatient care are organized in 21 regions (county councils). Long-term care is the responsibility of the 290 municipalities. Coverage is universal, and funding is based on income taxes that vary somewhat across regions and municipalities (Anell et al., 2012). The health system has a clear division between primary and specialized care. Primary care is delivered at primary care centers with salary-paid physicians and health professionals, and also function as gate-keepers for specialized care. Specialized care is primarily delivered at hospitals, where health professionals manage both in- and outpatient services. The providers are a mix of public and private care organizations and are reimbursed by their respective regions at the same rate. In the market for prescription drugs, prices are set at the national level, and physicians have no (direct) financial incentives tied to type or volume of drugs prescribed.

2.2. Analysis sample

A random sample of 1 million individuals residing in Sweden in 2007 was drawn from the Register of the total population and by unique personal identification numbers linked to individual level socioeconomic and demographic data for the years 2007–2016 (Statistics Sweden, 2019). After the exclusion of children under the age of 15, we have a total of 929,711 individuals and 8.2 million individual-year observations. The data shows some gradual loss of observations for each consecutive year due to deaths and emigration, thus we have an unbalanced panel. Our empirical strategy is based on regional migrants, defined as individuals who moved across regional borders once during 2008–2015. The sample of movers is 53,620 individuals with about 0.5 million individual-year observations. Stayers (non-movers) and individuals who moved more than once are excluded from the analyses.

Using two national healthcare registers (the National Patient Register and the Register of Prescription Drugs), we add data on utilization of healthcare for the entire period (National Board of Health and Welfare, 2019). This include inpatient stays, outpatient specialist visits and prescription drug use. Spending for inpatient care includes hospital-based drug use and spending for outpatient specialized care only includes visits to physicians. Unfortunately, primary care is not covered in a nation-wide register, which implies that we lose around 18 percent of the total volume of healthcare spending (RKA, 2021). The merging of data and research questions addressed in the study was approved by the regional ethics review board in Gothenburg, Sweden (#803–17).

The main outcome variable of our analyses is total annual healthcare spending; the sum of costs for inpatient care, outpatient specialized care and prescription drugs. For prescription drugs, the register data provides...
the cost for each prescription, which we sum up to annual spending per individual. For inpatient and outpatient specialized care, the register contains a code for Diagnosis Related Group (DRG) for each care episode based on diagnoses, treatment interventions and resource use associated with the care episode. The Swedish Association of Local Authorities and Regions (SALAR) has estimated prospective cost weights for each DRG from the Cost per patient (KPP) database (National Board of Health and Welfare, 2021). The cost for a DRG-weight of 1.00 in 2021 was €196 (€1 = 10.1449 SEK, 2021). Hence, we sum up inpatient care and outpatient specialized care episodes into annual spending per individual. Covariates that we use as controls are Charlson comorbidity index, indicators for age-gender group, individual annual disposable income, marital status, and the number of children in the household.

2.3. Variation in healthcare spending

Mean healthcare spending per capita per year over 2007–2016 was €1814, and by category of care: €993 for inpatient care, €490 for specialized outpatient care, and €330 for prescription drugs (Appendix Table A1). Movers had on average lower healthcare spending compared with stayers. Movers were also in general younger, more likely unmarried and had higher education compared with stayers (Table 1).

Regional mean healthcare spending varies across the 21 regions from €1658 per capita in Västra Götaland to €2079 per capita in Gotland, or in relative terms, −8.6% to +14.6% around the national mean (Fig. 1 & Table A2). There is not a strong correlation between average healthcare spending and the regional economic situation. In terms of regional domestic product (RDP), the top three regions of RDP have among the highest (Stockholm), average (Norrbotten), and lowest (Västra Götaland) average healthcare spending in our analysis sample. There is also a mix of urban and rural regions among regions with the highest and lowest healthcare spending – the two largest regions (Stockholm and Västra Götaland) are at opposite ends in terms of deviations around the national mean.

The size of variations and the geographical pattern varies by the category of care (Fig. 2). Inpatient care varies −7.6% to +12.9% around the national mean, while variation is larger for specialized outpatient care −23.4% to −27.2% around the national mean. Fig. 2 reveals that some regions with high spending in inpatient care do not necessarily have high spending in specialized outpatient care, while other regions have low (high) spending for both inpatient and specialized outpatient care. The correlation between inpatient and outpatient care is close to zero (Spearman’s correlation coefficient −0.02). Regional variation in prescription drug spending is slightly larger than variation in inpatient care (Fig. A1), and its correlation to inpatient (outpatient) care is positive but low 0.24 (0.09).

Tables A3 and A4 display the most common regions to move from and to move to, as well as the most common region pairs. The three most populous regions (Stockholm, Västra Götaland and Skåne) have a smaller share of movers from the region than their share of population; while several mid-size and smaller regions have a higher share of movers from (and to) the region than their share of population. The most common region pairs are moving from Västra Götaland to Stockholm, Västra Götaland to Halland, and Uppsala to Stockholm, with about three percent movers each.

2.4. Empirical approach

We determine the relative effect of place (region) and of individuals (patients) as drivers of variations by estimating how health spending changes when moving between regions. Previous studies using patient migration have estimated the place effect in two way fixed effects (TWFE) models and event studies (e.g. Finkelstein et al., 2016; Godoy and Huitfeldt, 2020; Salm and Wübker, 2020). Following the previous literature using patient migration (e.g. Johansson and Svensson, 2022), a TWFE regression equation is specified as

\[ y_{it} = D_{ij} + \theta + \tau_i + \alpha_j + \beta_x + \epsilon_{it} \]  

where the dependent variable \( y_{it} \) is the log health spending for individual \( i \) in year \( t \), defined as \( \ln(\text{spending} + 1) \). We conduct our analyses on the sum of healthcare spending and on each category of care separately; inpatient care, specialized outpatient care, and prescription drugs. Following the previous literature, the treatment (of moving) is defined as the difference in mean log spending between the region of origin and the region of destination \( D_{ij} = y_{j\text{dest},i} - y_{j\text{orig},i} \) for individual \( i \), where the regional mean log spending is the pooled mean over ten years (\( y_{j\text{dest},i} = \frac{\sum_{t=10}^{20} y_{j\text{dest},i}}{T} \) for region \( j \)). Hence, \( D_{ij} \) is a continuous variable taking 420 distinct values (21 × 20 for 21 regions). The treatment variable \( D_{ij} \) is independently defined for each outcome \( y \). The distributions of \( D_{ij} \) for each of the four outcomes indicate that moves from low-to-high regions are as common as moves from high-to-low regions (Fig. A2).

\( I_{\text{r,t}} \) is a binary indicating taking the value 1 in years after the move, else 0. Hence, \( D_{ij}I_{\text{r,t}} \) takes the value 0 for the year of the move and before, and the value of \( D_{ij} \) in years after the move. The parameter of interest is \( \theta \), representing the average treatment effect of moving to a new region with higher or lower average health spending. \( \tau_i \) is year fixed effects and \( \alpha_j \) is individual fixed effects. We include \( X_{it} \) as a vector of time-varying individual characteristics: Charlson comorbidity index, binary indicators for age-gender groups, individual disposable income, marital status and number of children in the household. \( I_{qj} \) is a vector of binary indicators with \( r \) specifying time to move, controlling for migration effects unrelated to \( D_{ij} \). Finally, \( \epsilon_{it} \) is an error term that represents unobserved individual characteristics. The identification assumption for equation (1) is that outcome trends would be identical for treated and untreated units in absence of treatment (the assumption of parallel trends).

The parameter of interest, \( \theta \), reflects the percentage change in individual health spending in each year before and after moving to a region with higher (lower) average health spending, which is interpreted as the share of variation attributed to a place (region) effect. Thus, if average regional spending does not affect variation in individual spending we would expect \( \theta \) to be zero after the move (no place effect), and if average regional spending completely predicts variation in individual spending we would expect \( \theta \) to be one in years after the move. We interpret the
remaining variation \((1 - \theta)\) as attributed to an individual-level (demand-side) effect.

As a complement to the TWFE regression equation, we estimate potential trends in years before and after the move, by year-specific \(\theta_s\), in an event study regression equation is specified as

\[
y_{it} = D_i \theta_{iR} + \tau_t + \alpha_i + \beta X_{it} + \epsilon_{it}
\]  

(2)

where \(D_i\) is interacted with the vector \(I_{R}\), estimating year-specific \(\theta_{iR}\). All other parameters are defined as previously. Both the TWFE model in equation (1) and the event study in equation (2) are estimated with a
traditional two way fixed effects regression using the standard package xtreg, fe in Stata, with robust standard errors clustered on individual level.

The study design building on individuals who move across regions with varying levels of healthcare spending implies several complicating factors compared to a standard two group-two period difference-in-differences design with a binary treatment. First, we have multiple units defined by individuals (not by regions) and multiple time periods defined by year (2007–2016), identified in both the TWFE model and the event study by individual fixed effects and year fixed effects. Second, our study design implies variation in treatment timing, since individuals move in different years. Third, the treatment variable \( D_i \) is continuous, constructed as the mean log spending difference between the individual’s region of origin and region of destination. To clarify, the regression model cannot distinguish which region an individual belongs to, the model can only take into account the mean difference between regions in healthcare spending. We assume a staggered study design where individuals can be treated (move) once, but cannot switch out of treatment (excluding individuals who move more than once).

A recent literature has criticized the use of the traditional TWFE regressions in settings with multiple units and time periods, and emphasized that TWFE models are unbiased only under assumptions of parallel trends and a constant treatment effect (Callaway and Sant’Anna, 2021; Sun and Abraham, 2021). With multiple units and time periods, the estimated average treatment effect in traditional TWFE is a convex combination of treatment effects, consisting of all possible pair-combinations of treated units (Goodman-Bacon, 2021). With variation in treatment timing (as in our case), early-treated units (individuals) will be compared to not-yet-treated units, and late-treated units will be compared to already-treated units. The last type of comparison may be problematic as it (inevitably) assigns a negative weight to some treatment effects, which in turn can lead to bias in the estimated effect (even resulting in the opposite sign of the effect, thereby coined “forbidden comparisons”) (Borusyak and Jaravel, 2017; de Chaisemartin and D’Haultfoeuille, 2022). Negative weights are not a problem as long as one can assume a constant treatment effect, but with a potentially heterogeneous treatment effect, the negative weights may lead to bias (de Chaisemartin and D’Haultfoeuille, 2022). A constant treatment effect rules out both heterogeneity over calendar time and dynamic treatment effects over individual time (individuals’ outcomes develop over time after the start of treatment).

In addition, a non-binary treatment (discrete or continuous) implies more forbidden comparisons since the traditional TWFE estimator also compares a unit with high-intensity treatment (move between regions with large difference) to a unit of low-intensity treatment (move between similar regions). Thus, even without variation in treatment timing the traditional TWFE estimator may fail to identify a convex combination of treatments effects (de Chaisemartin and D’Haultfoeuille, 2022).

In our case, there may be heterogeneity over calendar time since we cover a time period of ten years, for example if a change in policy have affected the way movers respond to a new healthcare setting, such as the national policy reform for increased patient choice in primary care 2010 (Dietrichson et al., 2020). In addition, there may be dynamic treatment effects in the sense that healthcare is a rare consumption good. Individuals may not need to seek healthcare in the first year after they have moved, or it may take some time for individuals to get settled and pursue their ordinary life after they have moved. If so, the effect of a new healthcare setting may develop over time. Empirically, most previous studies have documented no evidence of a gradual adjustment over years (e.g. Finkelstein et al., 2016; Godey and Huitfeldt, 2020), except Johansson and Svensson (2022) who estimate for Swedish pharmaceutical spending a place effect first at three to five years after the move.

In sum, with multiple units, multiple time periods and variation in treatment timing the assumption of a constant treatment effect is unlikely to hold. In addition, our treatment variable is continuously distributed, and with a non-binary treatment the traditional TWFE estimator may be biased even without varying treatment timing (de Chaisemartin and D’Haultfoeuille, 2022). As a consequence, we apply a new heterogeneity robust estimator that strictly compares groups switching to treatment in a given time period with groups not-yet-treated during the same period, thus avoiding forbidden comparisons and negative weights. This estimator specifically takes into account dynamic effects and is applicable also for continuous treatments, developed by de Chaisemartin and D’Haultfoeuille (2023, earlier versions from 2020-2022). We implement the estimator by the Stata package did_multiplegt with options for dynamic effects (as a robustness check we implement the alternative package did_multiplegt_dyn). The choice of estimator does not change our specified regression equation or the underlying assumption of parallel trends hence, we apply the heterogeneity robust estimator to the specified event study regression equation (2).

3. Results

3.1. Results using the traditional TWFE regression

In the TWFE model (equation (1)) estimated by a traditional TWFE regression, the estimated place effect \( \hat{\theta} \) for total spending is estimated to 0.777 with a confidence interval of 0.614–0.940 (Table 2). The place effect is similar in magnitude also in specifications not adjusting for comorbidity index, demographic and socioeconomic factors (Table A5). Due to many zeros in some of the outcome variables we assess the robustness of our results using the inverse hyperbolic sine transformation (arc-sinh), yielding very similar findings, also in Table A5 (Bellemare and Wichman, 2020). We find substantial differences when subcategorizing the dependent variable in inpatient care, specialized outpatient care and prescription drugs. The place effect is estimated to 0.887 for inpatient care, 7.072 for specialized outpatient care, and to 0.048 for prescription drugs.

In the event study specifications (equation (2)) estimated by a traditional TWFE regression, time-specific \( \hat{\theta} \)’s are estimated in similar magnitudes as in the traditional TWFE models. We do not find evidence of pre-trends in the years before the move. The event study figures reveal the development over time after the move and show the uncertainty around the estimated place effects, which is large for inpatient care and smaller for outpatient care (Figs. 3 and 4).

3.2. Results using the heterogeneity robust estimator

Fig. 5 shows the results of time-specific \( \hat{\theta} \)’s in the event study

<table>
<thead>
<tr>
<th>Total spending</th>
<th>Inpatient care</th>
<th>Specialized Outp. care</th>
<th>Prescription drugs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Transformation</td>
<td>In + 1</td>
<td>In + 1</td>
<td>In + 1</td>
</tr>
<tr>
<td>( \hat{\theta} ) (st.err.)</td>
<td>0.777 (0.083)</td>
<td>0.255 (0.111)</td>
<td>0.752 (0.038)</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.614; 0.940</td>
<td>0.038; 0.472</td>
<td>0.677; 0.827</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.0001</td>
<td>0.021</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>No of ind-year obs.</td>
<td>507,510</td>
<td>507,510</td>
<td>507,510</td>
</tr>
<tr>
<td>No of obs.</td>
<td>53,620</td>
<td>53,620</td>
<td>53,620</td>
</tr>
<tr>
<td>Independent var.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Years since move</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note. The regressions are run as two way fixed effects models. Controls in all specifications are comorbidity, demographic and socioeconomic factors.
specification (equation (2)) estimated by the heterogeneity robust estimator without control variables (full regression results in Table A6). For total spending and for outpatient spending, the pre-trend in time period \(-2\) is statistically significant different from zero. A joint test of the null of all pre-trends yield non-significant p-values for each of the four outcomes, indicating that we cannot reject the null hypothesis of parallel pre-trends for either of the four outcomes. We find evidence of a positive place effect after the move for total healthcare spending, driven by changes in outpatient spending. For total spending, the point estimates of the time-specific \(\hat{\theta}\)‘s in the years after the move range between 0.06 and 0.14, and with confidence intervals up to 0.21. The point estimates are higher for outpatient spending, between 0.15 and 0.25. In contrast, for inpatient and prescription drug spending, the time-specific \(\hat{\theta}\)‘s are estimated close to zero (0.04 and 0.06 at the most, with confidence intervals overlapping zero). Results are similar when including control variables (Fig. A3 and Table A7), and when using the alternative package \texttt{did multiplegt dyn} (Table A8).

### 3.3. Robustness analyses

As a robustness analysis, we investigate the outcome variables on the extensive and the intensive margin. We define extensive margin setting all positive costs to 1, else 0. To define intensive margin, we include all individual-year observations for individuals who had any spending in at least one year (excluding individuals who had 0 spending all years). That leaves us with 52,266 movers for total costs, 51,298 movers for prescription drugs, 46,359 movers for specialized outpatient care, and 22,810 movers for inpatient care. We run the analyses using the event study specification estimated by the traditional TWFE regression.

The results show the estimated place effect on the intensive margin is similar to the main results of the traditional event study, but with larger confidence intervals especially for inpatient care (Fig. 4). On the extensive margin however, the results show a place effect close to zero with very high precision, or at the most 0.10 for specialized outpatient care. The results suggest that on the extensive margin, having healthcare costs or not, is primarily driven by a patient effect. While the overall estimated place effect from our main results, is an effect on the intensive margin, i.e. the intensity of how much healthcare spending.

As a second robustness check, we assessed the potential bias from older adults moving due to a health shock, by excluding individuals older than 60 years in the traditional event study. The results are basically identical to the main results using the traditional event study (Fig. A4-A5).

### 4. Discussion

We analyze regional variation in Swedish healthcare spending exploiting cross-region migration in TWFE models and event studies using traditional TWFE regressions, as well as using a new heterogeneity robust estimator. Importantly, we find that the effect of place-specific factors is heterogeneous with respect to the category of care, irrespective of regression model. In the traditional TWFE analyses, the place effect for specialized outpatient spending is estimated to 75%, for inpatient spending 26%, prescription drug spending 5%, while the place effect for total spending is about 78%.

As previously mentioned, there are reasons to believe there is heterogeneity in regional variation by category of care. We have shown also in our descriptive data that the size and the pattern of variations differ by category of care. However, our results contrast findings from the Netherlands, where Moura et al. (2019) estimated a place effect of 27% for total healthcare spending, 21% for general practitioner, 27% for hospital care and 28% for pharmaceutical spending. Other authors have classified different types of care as “effective”, “preference-sensitive”, and “supply-sensitive” (Chandra and Skinner, 2012; Wennberg et al., 2002). In our data set, we see that only 25% of inpatient episodes were scheduled in advance, i.e. the majority of inpatient episodes were unforeseen (acute) health issues which may imply that inpatient care is less likely to be preference- or supply-sensitive. While for outpatient visits, 77% were scheduled in advance which could indicate more scope for preference and supply-sensitivity in outpatient planned care.

Compared to previous studies that have considered the effects on total healthcare spending in US Medicare and the Netherlands, our traditional TWFE model results show a larger place effect. It was estimated to about 50% in the US and 27% in the Netherlands (Finkelstein et al., 2016; Moura et al., 2019). The place-effect on total healthcare spending in Sweden is mainly driven by specialized outpatient care. Few previous studies has focused on that care category, but Salm and Wübker (2020) find that only about 10% of the variation in ambulatory care in Germany can be explained by place-specific factors, while Goday and Huittfeldt (2020) find a place effect of about 50% in outpatient and inpatient hospital spending in Norway. However, it is difficult to compare results between studies since not only the country and healthcare system differs, but also what category of care has been investigated. Regarding pharmaceutical spending we find a place-effect...
almost identical to previous estimates from Johansson and Svensson (2022), who use the same pharmaceutical data as we do, but they did not adjust for comorbidity.

The results of our analyses using the traditional TWFE regressions should be considered with great care. Our estimates using the heterogeneity robust estimator to address the recent criticisms of the TWFE approach, show large discrepancies compared with our estimates from the traditional TWFE regressions. For total healthcare spending, the traditional event study show a place effect of 70%, while the heterogeneity robust event study estimate a place effect of about 10%. The comparison of estimators in our data suggests that the results from traditional TWFE regressions in previous empirical papers on movers and regional variation may be biased (e.g. Finkelstein et al., 2016; Godøy and Huitfeldt, 2020; Salm and Wübker, 2020). Considering our study design of multiple units and time periods as well as a continuous treatment with variation in timing, which is very similar to previous studies investigating regional variation using patient migration, the arguments for implementing these up-to-date heterogeneity-robust estimators are strong. Finding that the heterogeneity robust estimator affect the point estimates considerably implies that there is reason to consider the validity of previous results in this literature solely relying on traditional TWFE regressions.

There are however, several caveats with the heterogeneity robust estimator. For total spending and for outpatient spending, one of the pre-trends is statistically significant different from zero, which may violate the assumption of parallel trends. However, a joint test of null of the pre-trends (placebos) yield a p-value of 0.146 for total healthcare spending, 0.532 for prescription drugs, 0.764 for inpatient care, and 0.171 for outpatient care.

The results of our analyses using the traditional TWFE regressions should be considered with great care. Our estimates using the heterogeneity robust estimator to address the recent criticisms of the TWFE approach, show large discrepancies compared with our estimates from the traditional TWFE regressions. For total healthcare spending, the traditional event study show a place effect of 70%, while the heterogeneity robust event study estimate a place effect of about 10%. The comparison of estimators in our data suggests that the results from traditional TWFE regressions in previous empirical papers on movers and regional variation may be biased (e.g. Finkelstein et al., 2016; Godøy and Huitfeldt, 2020; Salm and Wübker, 2020). Considering our study design of multiple units and time periods as well as a continuous treatment with variation in timing, which is very similar to previous studies investigating regional variation using patient migration, the arguments for implementing these up-to-date heterogeneity-robust estimators are strong. Finding that the heterogeneity robust estimator affect the point estimates considerably implies that there is reason to consider the validity of previous results in this literature solely relying on traditional TWFE regressions.

There are however, several caveats with the heterogeneity robust estimator. For total spending and for outpatient spending, one of the pre-trends is statistically significant different from zero, which may violate the assumption of parallel trends. However, a joint test of null of the pre-trends yield non-significant p-values, indicating that the assumption of parallel trends may still hold. Because of our continuous treatment variable, taking 420 distinct values, and the large number of units (individuals) it is computationally challenging to run the novel heterogeneity robust estimator on our data (especially in the package `did_multiplegt`). Due to restrictions on forbidden comparisons, it is not possible to run models with more than five leads and lags (despite having the data available up to eight years before and after the move). Neither is it computationally possible to use the full set of control variables in these estimations. However, the traditional models show that the inclusion of controls does not substantially alter findings.

We have argued that there may be dynamic treatment effects created by individuals’ adjustment over time to the new healthcare setting, motivating the use of event study models (traditional or heterogeneity-robust). Considering a longer time period, also individual level characteristics may change following a move. However, it is unlikely that all movers systematically experience the same type of change in individual characteristics. The move may be associated with various lifestyle changes that imply improved or deteriorated health and healthcare need.

A limitation of the methodological approach building on patient migration, is that we estimate the effect of place-specific factors in an attempt to separate the effect of supply-side factors from demand-side factors. Far from all identified place-specific effects are necessarily traced to variations in access to care or differences in provider behavior (supply-side). There are also potential inter-dependencies between place- and patient-specific factors. For example, higher environmental pollution in one geographic area may cause more prevalent health problems, leading to higher spending and utilization. Any such effects would be captured as place-effects in the empirical models (if the
pollution-triggered spending is reduced after moving to a less polluted area (with lower spending), but are also linked to objective differences in healthcare needs while living in different geographical areas. The identification of place-effects could also be used as a trigger to try to identify regional determinants in healthcare needs that causally affect variations in health-care utilization. In addition, the methodological approach implies that we estimate the place effect at a regional level and assume that the remaining variation is attributed to individual-level characteristics. This is a simplifying assumption since the analysis does not account for multiple levels of variation. Rabbe et al. (2022) showed that hospital level variation was substantially larger than region level variation for a number of medical treatments in Germany, Italy, and the Netherlands.

A limitation with relying on movers to identify place-specific factors is further that the effect is not necessarily representative for the non-mover population. Model reweighting can be used to produce externally valid results for non-movers, but requires observing all factors that impact moving, which is an assumption that is unlikely to be met. Another methodological issue is the definition of the treatment variable $D_i$, which is based on pooled regional means over the ten years study period. There are indeed several ways to define a regional mean over a longer time period, and it remains to be investigated whether that would affect the results of our analyses. Another limitation in our study is the lack of access to primary care data. Considering our results showing discrepancies by category of care, there may be scope for a more prominent place effect in primary care.

In conclusion, we estimate notable differences depending on the category of care, with place-specific factors having a significantly larger impact on variation in specialized outpatient care compared to inpatient and pharmaceutical care. In addition, we find that the empirical estimator has a substantial impact on the estimates of the place-specific effect, where the traditional two-way fixed effects regression produces much larger estimates of the place-specific effect compared to results based on a recently developed heterogeneity robust estimator. This finding indicates that previous results in this literature, based on traditional two-way fixed-effects regressions, should be interpreted with care.

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CRediT authorship contribution statement

Naimi Johansson: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.
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Mikael Svensson: Conceptualization, Data curation, Funding acquisition, Writing – original draft, Writing – review & editing.

Declaration of competing interest

Nothing to declare.

Data availability

The authors do not have permission to share data.
Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2024.116571.

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