RUHR
ECONOMIC PAPERS

Martin Salm
Ansgar Wübker

Causes of Regional Variation in Healthcare Utilization in Germany

#675

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

RWI Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #675

Responsible Editor: Jochen Kluve

ISSN 1864-4872 (online) – ISBN 978-3-86788-783-0

Ruhr Economic Papers #675

Martin Salm and Ansgar Wübker

Causes of Regional Variation in Healthcare Utilization in Germany

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788783
ISSN 1864-4872 (online)
ISBN 978-3-86788-783-0

Martin Salm and Ansgar Wübker[1]

Causes of Regional Variation in Healthcare Utilization in Germany

Abstract

Healthcare utilization varies widely between regions. Yet, the causes of regional variation are still not well understood, and they can also differ between countries and institutional settings. We exploit patient migration to examine which share of regional variation in ambulatory care use in Germany can be attributed to demand factors and to supply factors, respectively. Based on administrative claim-level data we find that regional variation can be overwhelmingly explained by patient characteristics. Our results contrast with previous results for other countries, and they suggest that institutional rules in Germany successfully constrain supply-side variation in ambulatory care use between German regions.

JEL Classification: I11, I13, H51

Keywords: Healthcare spending; regional variation; Germany

February 2017

1 Martin Salm, CentER, Tilburg University; Ansgar Wübker, RWI and RUB. – The authors thank Alexander Burstedde for excellent research assistance. We also thank Eric Roberts and Hendrik Schmitz as well as conference participants at the Annual Meeting of the German Health Economics Association in Berlin, the conference on "New empirical developments in health and labor markets" in Leuven, the American Society of Health Economics Meeting in Philadelphia, the European Health Economics Association Conference in Hamburg, the Meeting of the Health Economics Committee of the German Economic Association in Stuttgart, and the Health Policy Workshop in Den Haag as well as seminar participants at the Universities of Bochum, Duisburg-Essen, Hamburg, Lucerne, and Tilburg for their valuable comments and suggestions. We thank BKK for making the data available. Funding from the Leibniz Foundation is gratefully acknowledged. – All correspondence to: Ansgar Wübker, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: ansgar.wuebker@rwi-essen.de

1. Introduction

Healthcare utilization can vary greatly between regions in the same country (see surveys by Chandra, Cutler, and Song 2012 and Skinner 2012). Large regional disparities in healthcare utilization have been documented for many countries and for many different types of care.[1] The variation in healthcare utilization between regions in the same country is often larger than the one between countries (OECD 2014).

In this study, we focus on ambulatory care in Germany. In international comparison, utilization of ambulatory care in Germany is high, with more doctor visits per person than in most other OECD countries (OECD 2011). The average utilization of ambulatory care varies greatly between German regions (Eibich and Ziebarth 2014a, Kopetsch and Schmitz 2014). For example, average utilization is around 30% higher in Hamburg, the state with the highest utilization, than in Brandenburg, the state with the lowest utilization.

Regional variation of healthcare utilization can have many causes. Broadly speaking, these can be divided into two categories: factors that can be attributed to patients and factors that can be attributed to regional characteristics (Finkelstein, Gentzkow, and Williams 2016). The first category includes e.g. differences in patients' health and preferences whereas the second category comprises e.g. differences in the number and specialization of outpatient physicians, available equipment, and physicians' beliefs about effective treatments.[2] As a shorthand, we refer to the first category as "demand" factors and to the second category as "supply" factors.[3]

Understanding the causes of regional variation in healthcare use has important implications for policy. Different causes imply very different conclusions about optimal policies. One possible explanation for regional variation is excessive and inefficient treatment in regions with high healthcare utilization (Skinner 2012, Cutler et al. 2013). If this explanation proves true then policies restricting supply of healthcare in regions with high healthcare utilization could be beneficial. Another possible explanation is that regional variation is caused by insufficient access to care in underserved regions (Ozegowski and Sundmacher 2014). If this explanation proves true

[1] Reich et al. (2012) analyze regional variation in Switzerland, Prieto and Lago-Penas (2012) for Spain, and Bojke et al. (2013) for the United Kingdom.

[2] For example, Eibich and Ziebarth (2014b) examine differences in health between German regions. Jürges and Pohl (2012) examine regional differences in the number of physicians.

[3] This definition of "demand" and "supply" factors overlaps mostly, but not completely with the use of these terms in other settings. For example, in our use of these terms the effects of regional climate or local economic conditions are categorized as "supply" factors.

then policy should focus on increasing availability of healthcare services in regions with low healthcare utilization. A third possible explanation is that regional variation is caused by differences in patients' health and preferences. In this case, policies focusing on the supply of healthcare could be ineffective or counterproductive.

In this study we examine the relative importance of "demand" factors versus "supply" factors in explaining regional variation in ambulatory care utilization in Germany. We exploit patient migration in order to separate regional variation attributable to patients from regional variation attributable to regional characteristics. If regional variation could be entirely attributed to differences in patient characteristics then healthcare utilization should not change if patients move from an area with low healthcare utilization such as Brandenburg to an area with high healthcare utilization such as Hamburg or vice versa. If on the contrary, regional variation could be entirely attributed to differences in regional characteristics, then healthcare utilization of movers should immediately adjust to the level of healthcare use in the destination region. When the observed utilization change falls between these extremes, then the change in utilization at the time of the move allows us to identify the relative importance of "demand" factors versus "supply" factors.

We use administrative claim-level data from a group of social health insurers in Germany (Betriebskrankenkassen). Our data include observations on around 6.3 million patients of age 18+ for the period 2006-2012. We use a measure of healthcare utilization that is unaffected by regional differences in prices. Our measure of utilization is based on case-points which are set at the Federal level in Germany to determine the relative remuneration for different types of ambulatory care. We define regions in the main specification based on 2-digit postal codes with an average population of around 800,000. Thus, regions are similar in average population size to Hospital Referral Regions in the United States.

We use two related empirical approaches. The first empirical approach is an event study analysis in which we examine changes in healthcare utilization at the time of move to a region with a different level of average healthcare utilization. Specifically, we estimate how the change in utilization at the time of move varies with the difference in average healthcare utilization between the origin and destination region.

The second approach is based on a model in which ambulatory care utilization is the product of person-specific fixed-effects, binary indicators for regions, and some further control variables. The presence of movers in the sample allows disentangling region-specific effects from person-specific effects. We use decomposition techniques to study which part of the difference of healthcare variation between German regions can be attributed to “demand” factors and to “supply” factors, respectively.

We find that regional variation in ambulatory care use in Germany can be overwhelmingly explained by patient characteristics. If a person moves to a region with a 1% higher average healthcare utilization then her utilization increases by on average just 0.09% in the baseline specification. Thus, movers’ healthcare utilization tends to change very little when they move to an area with higher or lower average healthcare utilization.

Results are very similar for different age categories and if we look at the extensive instead of the intensive margin of healthcare utilization. We also find that regional variation even in supply-sensitive treatments such as imaging services can be mostly attributed to patient characteristics. However, “supply” factors play a somewhat larger role for women, for specialist care, and for patients at higher percentiles of the distribution of healthcare utilization. Yet, even in these cases “demand” factors account for the largest part of regional variation in ambulatory care use in Germany.

Our study provides important insights into the causes of regional variation in healthcare use. The existence of large regional disparities in healthcare utilization in Germany is well documented (Göpffarth, Kopetsch, and Schmitz 2016). However, the literature on causes of regional variation in healthcare use in Germany is limited to studies that explain the contribution of observed patient characteristics such as age and gender and observed regional characteristics such as physician density (Eibich and Ziebarth 2014a, Kopetsch and Schmitz 2014, Ozegowski and Sundmacher 2014). Together these factors can account for around 60 percent of regional variation in ambulatory care use in Germany (Kopetsch and Schmitz 2014). An important advantage of our approach based on patient migration is that we can also account for unobserved patient characteristics such as preferences for healthcare use as well as for unobserved regional factors such as physicians’ beliefs about the effectiveness of treatment.

A number of recent studies have used migration as a way to disentangle the effect of environmental factors from the effect of personal characteristics. For example, Bronnenberg, Dube, and Gentzkow (2012) have used this approach to examine brand preferences, Card, Heining, and Kline (2013) looked at which share of wage differentials can be attributed to workers versus firms, Chetty, Friedman, and Rockoff (2014) have examined to what degree student success can be attributed to students versus teacher. In health economics, Song et al. (2010) explore regional differences in diagnosing behavior, and Molitor (2016) follows physicians when they move to a different region. The study most closely related to ours is by Finkelstein, Gentzkow, and Williams (2016) who look at differences in healthcare utilization between regions for Medicare patients in the United States.

While large regional variation in healthcare utilization has been documented in many countries and institutional settings, the causes of regional variation can be very different. Our results suggest that regional variation in ambulatory care in Germany is mostly caused by "demand" factors. In contrast, Finkelstein, Gentzkow, and Williams (2016) find that only around 50% of regional variation in Medicare use can be explained by "demand" factors and the remaining 50% by "supply" factors.[4] Nonetheless, the amount of regional variation is very similar for ambulatory care utilization in Germany and for outpatient care utilization for Medicare patients in the United States.

Why are the causes for regional variation in ambulatory care in Germany so different from the United States? Part of the explanation might be the institutional setting for ambulatory care in Germany which has strict rules that specifically aim to restrict variation in the supply of ambulatory care. For example, there are restrictions on the number of physicians' practices in areas with high physician densities, and there are deductions on payment for physicians who provide too much treatment. There are also incentives for physicians to practice in underserved areas. Together, these rules and interventions could account for the small role of "supply" factors in regional variation in ambulatory care use in Germany.

On the other hand, regional variation in patient demand might be larger in Germany than in the United States. Regional differences in patients' health and preferences could be related to strong regional identities, historic differences between regions, and the long term effect of very different healthcare systems in East and West Germany. Furthermore, patient demand in Germany is relatively unrestricted. Patients have free choice of physicians, they can access specialists without a referral from a General Practitioner, co-payments are low, and waiting times and travel times tend to be short.

[4] For outpatient Medicare use, 35% of regional variation can be attributed to "demand" factors, and 65% to "supply" factors.

Our findings have important policy implications. Policymakers in Germany are keenly aware of large differences in healthcare utilization between regions. Recent law changes aim to reduce these differences with stronger incentives to open a physicians' practice in areas with low utilization and further restrictions on opening practices in areas with high utilization (GKV-Versorgungsstärkungsgesetz 2015). These policy changes are motivated by widespread concerns about lack of access to ambulatory care in rural regions with aging populations (Sachverständigenrat 2014). Our study contributes to this debate by showing that regional differences in ambulatory care use can for the most part be explained by "demand" factors rather than "supply" factors. Thus, lower healthcare utilization in regions such as Brandenburg can mainly be explained by patients' health and preferences, and not by a lack of access to care.

This study continues as follows. Section 2 describes the institutional background. Section 3 presents the data. Section 4 explains the empirical approach. The results are shown in Section 5, and Section 6 concludes.

2. Institutional setting

Health insurance in Germany

Around 90% of the German population are covered by public ("social") health insurance (SHI).[5] More than 100 SHI sickness funds compete for enrollees.[6] The SHI benefit packages are highly standardized under German law, and they are generally identical across sickness funds. If enrollees move to a different region they can keep their health insurance contracts without a change in contribution rates or coverage. Patient cost-sharing is very low by international standards, heavily regulated, and generally identical across sickness funds.[7] Patients are free to choose among physicians and hospitals.

Ambulatory care

In Germany, ambulatory care and inpatient care are strictly separated. The two sectors have separate rules, institutions, and budgets. Generally speaking, hospitals are not allowed to provide ambulatory care. Physicians in Germany generally work either for a hospital or in ambulatory care.

[5] The remaining 10% of the population are insured under private health insurance. The privately insured are mostly civil servants, self-employed, or high earners (above €56,250 in 2016). These groups have the right to opt out of public health insurance into private health insurance. For everyone else, participation in public health insurance is mandatory.
[6] A description of the German Healthcare system can be found at Simon (2010) and at Busse and Riesberg (2004).
[7] Throughout our study period patients had to pay a "Praxisgebühr" of €10 per quarter if they visited a physician. Many patients were exempted from this fee, for example if they had low income or chronic diseases.

The approximately 130,000 physicians in the ambulatory care sector are mostly self-employed and work in individual or small group practices. Ambulatory care physicians are organized by regional associations (Kassenärztliche Vereinigungen). These regional associations are powerful semi-public institutions. On behalf of outpatient physicians they negotiate with SHI sickness funds over the total budget for ambulatory care services in a region, and they distribute this budget among physician practices in the region.[8]

Case-points

Compensation for physicians' services is based on case-points.[9] Case-points determine the relative weights of different treatments and procedures. The number of case-points assigned to types of treatment is determined at the Federal level, and it is identical across German regions (Einheitlicher Bewertungsmaßstab). Case-points are awarded for episodes of treatment, which typically include all treatment provided by a physician practice to a patient within a quarter of a year. Case-points are converted to monetary units through a conversion factor (€/point).

Before 2009, the system operated within global budgets so that the value of the case-points (€/point) automatically fell if the budget of a regional association was exceeded. Thus, physicians in a region collectively bore the risk of exceeding the budget. They did not know the value of a case-point until the end of the year.

At the beginning of 2009 a reform of ambulatory care financing took effect which introduced fixed Euro prices for case-points. However, physicians are now subject to budget limits at the level of the individual physician practice. Each physician practice is allocated a budget limit, the so-called Regelleistungsvolumen.[10] Services performed beyond those budget limits are reimbursed at a much lower rate.

Rules to ensure uniform access to care

Health policy in Germany aims to ensure uniform access to care across regions, and it has established rules and regulations in order to achieve this aim. By law, regional associations of

---

[8] Payments from SHI sickness funds are the most important, but not the only source of financing ambulatory care. Other sources of financing are fees paid by privately insured patients, payments from work accident insurance, and payments from patients.

[9] Some services are not compensated in case-points, but directly in monetary units. An examples for such a service is skin cancer screening. For an overview see KBV (2009).

[10] The Regelleistungsvolumen (RLV) defines the maximum quantity of services that a physician can bill without discount. The RLV depends on the physician type (e.g. GP or specialists) as well as on patient characteristics such as the age structure. For a detailed description of the RLV see KBV (2009).

physicians must guarantee access to ambulatory care for all insured patients (Sicherstellungsauftrag). Guidelines set target numbers of general practitioners and specialist physicians in relation to the population (Bedarfsplanung) (Klose and Rehbein 2011). In areas where physician density is above target there are restrictions on the opening of new physician practices. In areas where physician density is below target regional associations offer incentives to open physician practices, such as cheap loans or guaranteed minimum revenues. Finally, as discussed above, payment for physicians are reduced if they provide too much treatment, i.e. treatments beyond the Regelleistungsvolumen. This limits the scope for ambulatory care physicians to increase the supply of services.

3. Data

We use administrative claims data from a large group of health insurers (*Betriebskrankenkassen*) for the period 2006–2012 covering 28 quarters.[11] The data provide information on around 6.3 million individuals above age 18, including around 203,000 movers. The data include information on ambulatory care and consist of two types of files.[12] The first type includes information on patient characteristics such as year of birth, gender, and the start and end date of insurance coverage. The second type entails claim-level information on treatments. Treatment data includes information on the number of case-points awarded for an episode of treatment, information on care providers such as whether care is provided by a general physician or a specialist, and information on procedures such as whether patients had a computer tomography (CT) scan or a magnetic resonance imaging (MRI) scan. [13] Of special importance for the identification of regional variation is information on the patient’s place of residence which is recorded for each episode of treatment.

[11] Traditionally, Betriebskrankenkassen (BKK) represented employer-sponsored health insurers where each fund represented one company. Even today, in some cases the BKK`s name identifies the company, e.g., the Audi BKK. In 2012 there exist 87 Betriebskrankenkassen in Germany. According to data of the German Socioeconomic Panel (GSOEP), household structure, education levels, occupation status (white collar, full time worker) and the health status of BKK enrollees are quite representative of the average SHI policy holder. However, their wages are slightly higher than average for SHI policy holders.

[12] In our data it is not possible to merge information on inpatient care to patient identifiers.

[13] CT and MRI are widely used tools in medical imaging, in particular for diagnostic and preventive medicine or screening for disease.

Our key outcome variable is based on the sum of case-points for each individual and quarter.[14,15] In our main specification, we define our outcome variable y_{it} as a logarithmic function of case-points plus 1 for individual i in period t: $y_{it} = \log(pts_{it} + 1)$. Following Finkelstein, Gentzkow, and Williams (2016) in the analysis of regional variation of Medicare patients in the US, we prefer a log specification economically and econometrically.[16] In robustness checks we examine alternative specifications of the functional form such as $\log(pts_{it} + 10)$, $\log(pts_{it} + 0.1)$, binary indicators on whether or not patients receive any treatment in a given quarter, and binary indicators on whether the number of case-points is above the median, or above the 75th, 90th, or 95th percentile of all observations in the same quarter. Furthermore, we consider additional outcome variables for care provided by General Practitioners, care provided by specialists, and for specific procedures such as CT- and MRI scans.

We determine a patient's place of residence based on the postal code that is most common for treatment claims of the patient in the quarter. In our baseline specification we define regions by 2-digit postal code areas. These have an average population of around 800,000, similar to a hospital referral region in the United States. In an alternative specification we define regions by states.

Figures 1 and 2 show regional variation in average case-points per person and quarter during our study period. Figure 1 shows regional variation in case-points for ambulatory care between German states. Average utilization is around 30% higher in Hamburg, the state with the highest utilization, than in Brandenburg, the state with the lowest utilization. Figure 2 displays average case-points per person and quarter for 2-digit postal code regions on a map of Germany. The map shows that ambulatory care utilization tends to be highest in metropolitan areas such as Hamburg, Berlin, and Munich, and it tends to be lowest in more rural areas, especially in Eastern Germany.

---

[14] Ca. 6% of treatment episodes have missing information on case-points. For these episodes we impute the number of case-points as the average number of case-points for all treatments.

[15] Some ambulatory care provided under selective contracts is not included in our data. From 2009 onwards health insurers could directly contract with groups of GPs circumventing the regional associations (KVs). During our study period such selective contracts were mostly confined to two states, Bavaria and Baden-Wuerttemberg. We test for possible effects of selective contracts on our results in a sensitivity analysis where we exclude these two states from our data.

[16] The logarithmic transformation of case-points reduces the positive skewness of the variable because it compresses the upper tail of the distribution while stretching out the lower tail leading to an almost symmetric and normally distributed outcome variable. Moreover, the log allows us to interpret the relationship between our main explanatory variable (see below) and the outcome variable as elasticity.

The ranking of regions in terms of ambulatory care utilization is quite stable over time.[17] The ranking of regions for BKK insured patients in our data is also similar to the ranking of regions for a representative sample of the German population. The regions with the highest and lowest outpatient care utilization in our data tend to be the same as the regions with the highest and lowest number of physician visits in the general population.[18]

We define a patient to be a mover if her 2-digit postal code changes exactly once during our study period. We drop individuals from our sample who moved twice or more.[19] It is possible that patients still visit physicians in their region of origin after a move to another region. As a robustness check we estimate a specification where we restrict the sample to individuals who move at least 100km. Travelling more than 100km for an outpatient physician visit is rare.

Our key explanatory variable for the event study analysis is the origin-destination difference in average log case-points. This variable δ_i subtracts the average log of case-points in the origin area $\bar{y}_{o(i)}$ from the average log of case-points in the destination area $\bar{y}_{d(i)}$ and is accordingly defined: $\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}$. For example, a δ_i of 0.1 implies that the average utilization in the destination region is 10% higher than in the region of origin. Figure 3 shows the distribution of δ_i. The mean value of δ_i is close to zero and the distribution is approximately symmetric, indicating that moves from high to low-utilization regions are as common as moves from low to high-utilization regions.

Table 1 reports summary statistics separately for movers and non-movers. The baseline sample of movers consists of N = 5,085,960 quarterly observations for N = 203,679 individuals and the baseline sample of non-movers consists of N = 146,803,504 quarterly observations for N = 6,137,849 individuals.[20] Movers and non-movers differ in their observed characteristics. Compared to non-movers, movers are younger on average, are more likely to be female, and utilize less ambulatory care.

---

[17] To show this we divide our study period in two sub-periods (2006-2008 and 2009-2012) and we compute a Spearman rank coefficient test for the rankings of 2-digit postal code regions in both sub-periods. The test shows a correlation of 0.7146 (p-value = 0.000).

[18] In Figures A1 and A2 in the online Appendix we show that the ranking of regions in terms of the number of outpatient visits for a representative sample of the general population (based on the GSOEP) is very similar to the ranking of regions in our data as shown in Figures 1 and 2. Figures A1 and A2 are reproduced from a study by Eibich and Ziebarth (2014) with the friendly permission of the authors.

[19] For quarters without treatments we do not know the address of the patient. If there are no treatments and correspondingly no addresses reported for periods around the time of move then we assume that the move has taken place in the middle period.

[20] We exclude people with more than one change in 2-digit postal code areas of residence (1.9 % of claims) and people who have missing values for the 2-digit postal code areas (less than 0.1 % of quarterly observations with claims).

4. Empirical Approach

4.1. Event Study Analysis

In this study we employ two related empirical approaches. The first approach is an event study analysis. In order to disentangle which part of regional variation in outpatient care utilization can be attributed to patient and regional characteristics, respectively, we follow persons as they move between regions with different levels of average outpatient care utilization. Thus, we can examine how healthcare utilization changes if the same person lives in different regions. In our empirical approach we relate the change in outpatient care utilization at the time of the move to δ_i, the difference in average outpatient care utilization between the region of origin and the region of destination.

We employ the following linear regression model with individual fixed effects for a sample of movers:

$$y_{it} = \delta_i I_{t\geq r}\theta + X_{it}\beta + I_Y + I_Q + I_R + \alpha_i + \varepsilon_{it} \tag{1}$$

where y_{it} is a measure of outpatient care utilization of person *i* in time *t*. In the baseline specification y_{it} is defined as $y_{it} = \log(pts_{it} + 1)$. δ_i is defined above. $I_{t\geq r}$ is a binary indicator variable which takes the value one for periods after the move. X_{it} is a vector of time-varying personal characteristics, which consists of binary indicators for gender-specific 5 year age categories. I_Y is a vector of binary indicators for calendar years, I_Q is a vector of binary indicators for a year´s quarter, and I_R is a vector of binary indicators for years since the move date. I_R accounts for direct effects of moving that are not related to δ_i. For instance, getting used to a different disease environment or the hassle associated with moving to a different region can have a direct effect on health and healthcare utilization. α_i is a vector of person-specific unobserved fixed effects, and ε_{it} represents time-varying unobserved individual characteristics. θ is a parameter, and β is a vector of parameters.

The main parameter of interest is θ which measures how large the change in healthcare utilization at the time of move is in relation to δ_i, the difference in average healthcare utilization between the destination region and the region of origin. If $\theta = 0$, then healthcare utilization does not change as persons move to a different region. In this case, regional variation is entirely caused by observed and unobserved patient characteristics. If on the other hand, $\theta = 1$, then healthcare utilization fully adjusts to the level of healthcare utilization in the destination region. For example, if $\theta = 1$ then for $\delta_i = 0.1$ the expected increase in healthcare utilization at the time of move is 10%. In this case, regional variation is entirely caused by regional characteristics. If θ is between zero and one then both "demand" factors and "supply" factors contribute to regional variation. We can interpret θ as the share of regional variation that can be attributed to "supply" factors, and $1-\theta$ as the share of regional variation that can be attributed to "demand" factors.

Estimates of parameter θ can be interpreted as causal effects if the exogeneity assumption below holds:

$$E(\varepsilon_{it} \mid \delta_i I_{t \geq R}, X_{it}, I_Y, I_Q, I_R) = 0 \tag{2}$$

This assumption requires that time-varying unobserved characteristics must not be related with explanatory variables such as δ_i. The assumption above is not violated if movers differ from non-movers, e.g. in age or health. Our empirical approach does not rely on comparing movers with non-movers. In the event study analysis described above we restrict our sample to movers only, and we compare movers with different values of δ_i. Likewise, the exogeneity assumption is not violated if time-constant unobserved characteristics such as patients' preferences for healthcare or longstanding chronic conditions are related with δ_i. The exogeneity assumption makes no assumptions about α_i.[21] Furthermore, the exogeneity assumption is not violated if conditions in the new region such as climate or the local unemployment rate lead to a change in health. These conditions are part of the regional characteristics examined in this study.

Yet, several possible causes can lead to a violation of the exogeneity assumption. A first possible violation arises if there are unobserved individual time trends that are systematically related to δ_i. This could, for instance, be the case if people with deteriorating health tend to move to regions with higher average healthcare utilization. We employ two alternative robustness tests for this violation. First, we interact δ_i with a vector of indicators for years before the move. This allows examining whether there are time trends in the years before the move that are related to δ_i. Second,

[21] Figure A3 in the appendix shows that movers with a higher δ_i had higher healthcare expenditures before the move relative to the mean of the population of the same age and gender in the region of origin. However, if these differences reflect differences in α_i rather than in ε_{it} then the exogeneity assumption is not violated.

we restrict the time window around the time of move to a maximum of either 3 years, 2 years or 1 year and examine whether this restriction of the sample affects estimation results.

A second violation of the exogeneity assumption can arise if the effect of δ_i on healthcare utilization is nonlinear. For example, the effect on utilization of a move to an area with lower average utilization and the effect of a move to an area with higher average utilization do not need to be symmetric. We can test for non-linear effects of δ_i by computing the change in healthcare utilization around the time of move for different ranges of δ_i and by examining whether these changes follow a linear pattern.

A third violation of the exogeneity assumption can arise if θ varies over time. The relative importance of "demand" factors versus "supply" factors could have changed for example as a result of a reform of ambulatory care financing in Germany which took effect in 2009, around the middle of our sample period. As a robustness check, we repeat our estimation for alternative sub-periods before and after the reform.

Furthermore, we also examine whether our estimation results are sensitive to the definition of the outcome variable, to the definition of regions and movers, whether results are similar when employing a balanced sample, and how results vary by age and gender.

4.2. Decomposition Analysis

The event study approach presented above relies on following persons who move to a region with different average healthcare utilization. This approach is limited by the fact that the analysis is restricted to movers. The group of persons who move to a different region is not representative for the general population. In the following, we present an alternative estimation approach which allows separating "demand" factors from "supply" factors for the general population.

For this approach we assume that healthcare utilization is the product of the effect of regional characteristics and unobserved and observed patient characteristics as well as year, quarter of year, and years since move effects.[22] If utilization is measured in logarithms, then it can be described as the sum of the above factors. Based on this assumption, we estimate the following linear regression model with individual fixed effects for a sample including both movers and non-movers:

$$y_{ijt} = \gamma_j + X_{it}\beta + I_Y + I_Q + I_R + \alpha_i + \varepsilon_{ijt} \tag{3}$$

[22] In an alternative specification we allow that the effects of regional characteristics can vary by age categories.

Where y_{ijt} measures outpatient care utilization of person *i* in region *j* in quarter *t*. In the baseline specification y_{ijt} is defined as $y_{ijt} = \log(pts_{ijt} + 1)$. γ_j is the effect on outpatient care utilization created by living in a region *j*. ε_{ijt} represents time-varying individual characteristics. All other variables are as defined above.

One challenge for our estimation approach is to separate time-constant unobserved characteristics α_i from the effect of regional characteristics γ_j. As in the event study approach our identification strategy relies on the presence of movers in our estimation sample. For non-movers neither α_i nor γ_j vary during our observation period. For movers, however, we can observe the same person in two different regions. This allows identifying regional fixed-effects γ_j. Once we know the regional fixed-effects we can also compute person-specific fixed effects α_i.

Based on estimation coefficients obtained from equation (3) we employ decomposition methods to examine to which degree differences in average healthcare utilization between any two regions or groups of regions can be attributed to "supply" factors and "demand" factors, respectively. We first need to define two groups of regions which we wish to compare. For example, we can compare 2-digit postal code regions with above average healthcare utilization to 2-digit postal code regions with below average healthcare utilization. We define the average healthcare utilization of the first group as $\bar{y}_h$ and the average healthcare utilization of the second group as $\bar{y}_l$. The difference in average utilization between the two groups is $\bar{y}_h - \bar{y}_l$.

As a next step, we compute the part of the above difference which can be attributed to regional characteristics. The average effect of regional characteristics for regions with high utilization is denoted as $\bar{\gamma}_h$. We compute $\bar{\gamma}_h$ as the weighted average of estimation coefficients $\hat{\gamma}_j$ for regions which are part of the high utilization group *h*.[23] Correspondingly, we can compute $\bar{\gamma}_l$ as the weighted average of estimation coefficients $\hat{\gamma}_j$ for regions which are part of the low utilization group *l*. $\bar{\gamma}_h - \bar{\gamma}_l$ is the difference in utilization between the two groups that can be attributed to regional characteristics.

[23] Regions are weighted by the number of observations in each region. $\hat{\gamma}_j$ are obtained from equation (3).

Finally, we compute the share of the difference in care utilization between the two groups of regions that can be attributed to "supply" factors as:

$$S_{place} = \frac{\overline{\gamma}_h - \overline{\gamma}_l}{\overline{y}_h - \overline{y}_l} \tag{4}$$

Correspondingly we can compute the share of differences in care utilization between two groups of regions that can be attributed to "demand" factors as $S_{patient} = 1 - S_{place}$.

In alternative specifications, we employ different definitions for the two groups of regions. In the baseline specification, we define the first group as regions with above median healthcare utilization, and the second group as regions with below median healthcare utilization. Alternatively, we compare regions above the 75th percentile with regions below the 25th percentile, regions above the 90th percentile with regions below the 10th percentile, and regions in West Germany with regions in East Germany.

5. Results

5.1. Event Study analysis

Estimation results for the event study approach are shown in Table 2. Our estimate of θ for the baseline specification (equation 1) is 0.090. This implies that if a person moves to a region with a 1% higher average care utilization then her care use will increase by 0.09% on average. Thus, only 9% of regional variation in outpatient care utilization can be attributed to "supply" factors, and 91% can be attributed to "demand" factors.

In the same table we also show how estimation coefficients vary between demographic groups. Most studies on regional variation of healthcare utilization in the United States examine the Medicare population of persons above age 65.[24] This makes it interesting to compare causes of regional variation for the age 65+ population with causes of regional variation for younger age groups. For both persons above age 65 and persons below age 40 estimates of θ are close to zero. For persons between age 40 and 65 the estimate of θ is somewhat higher at 0.110, and it is also somewhat higher for women than for men (0.144 vs. 0.005). For all age and gender groups regional variation can overwhelmingly be attributed to patient characteristics. Put it differently, θ is very small implying that "supply" factors play a minor role in explaining regional variation in outpatient care use.

[24] Exceptions are discussed for example in Newhouse and Garber (2013).

Next, we examine how θ varies between different types of care. First, we look at the two broad categories of ambulatory care: care by general practitioners and care by specialists. Estimates of θ are higher for specialist care than for care by general practitioners (0.322 vs. 0.074). This suggests that "supply" factors can explain a substantial share of variation in specialist care, but "demand" factors still account for the largest share. Then, we look at specific procedures. Specifically, we examine causes of variation in imaging services (CT-scans and MRI-scans). CT-scans and MRI-scans are often mentioned as examples for elective and supply-sensitive treatments (Skinner 2012). We might expect a larger role of "supply" factors for these services. However, this is not what we find. Our estimates of θ are small and do not differ significantly from zero. A possible explanation for this finding could be data limitations. Imaging services provided in hospitals during inpatient stays are not included in our data.[25]

In addition to examining changes at the intensive margin of care utilization we also analyze changes at the extensive margin. At the extensive margin, the coefficient of θ is close to zero not just for any care and GP care, but also for specialist care. This result can be explained if the decision whether or not to visit a specialist is mostly taken by the patient whereas the decision about intensity of treatment is a joint decision by the physician and the patient.

Table 3 shows results for higher percentiles in the distribution of care utilization. For these specifications we define the outcome variable as a binary indicator of whether the number of case-points for an individual in a quarter is higher than alternatively the median, the 75th percentile, the 90th percentile, and the 95th percentile of all individuals in the same quarter and year. Accordingly, δ_i is defined as the difference in the average value of these indicators between the destination region and the region of origin. The results suggest that "supply" factors become more important at higher percentiles. A possible explanation could be that while standard care is easily accessible in all German regions there could still be limitations in access to very intensive care in regions with low healthcare utilization. This explanation is also in line with our finding that the role of "supply" factors is larger for specialist care than for care provided by general practitioners. However, even at high percentiles, "demand" factors are still more important than "supply" factors.

[25] Outcome variables are binary indicators on whether a person had any CT-scan or MRI-scan in a quarter. In our data, information on procedures is stored in a separate file which cannot be matched to information on case-points for the procedure.

In the following we discuss the robustness of our results to the potential violations of the exogeneity assumption that we discussed in Section 4.1. The first potential violation is that unobserved individual time trends could be related to δ_i. In order to test for this violation we estimate a model that allows for pre-trends before the move to a different region. δ_i is interacted with binary indicators for up to five years before the move date and for up to four years after the move date:

$$y_{it} = \sum_{l=-5}^{l=4} \partial_i I_l \theta_l + X_{it}\beta + I_Y + I_Q + I_R + \alpha_i + \varepsilon_{it} \tag{5}$$

Figure 4 shows estimation coefficients of θ_l and their 95 percent confidence intervals.[26] The coefficient for the year immediately before the move is normalized to zero. We do find a small, but significant time trend before the move. If this time trend were to continue after the move then the share of variation attributed to patients would be even larger than our estimation coefficients in Table 2 suggest.

It is also interesting to look at the coefficients θ_l for years after the move. For example, a gradual adjustment to the level of care utilization in the destination region would be reflected in coefficients θ_l which increase with years since the move date. However, coefficients θ_l do not significantly differ across years in the period after the move date. Thus, we find no evidence for a gradual adjustment. At least, such an adjustment does not take place during the time window of up to 5 years after the move that we can observe.

Table 2 shows further tests for the first potential violation of the exogeneity assumption. The estimation coefficient of θ is essentially unchanged if we restrict the sample to observations for 3 years around the move, for 2 years around the move, or for 1 year around the move.

Our second concern discussed in Section 4.1 is that the effect of δ_i on healthcare utilization could be non-linear. Figure 5 shows results on non-linear effects of δ_i. We divide the sample into twenty bins of equal size according to δ_i. Subsequently we compute changes in care utilization around the time of move for each of the bins. Changes in care utilization are close to zero for all bins. If we add a regression line to connect the points in the graph then the slope of the regression line is

[26] Figure A4 in the appendix shows comparable figures for different age groups. Figure A5 shows figures separately for a move to a region with higher average healthcare utilization and for a move to a region with lower average healthcare utilization. Figure A6 shows a figure where regions are defined as states instead of 2-digit postal codes.

similar to the coefficient of θ in the baseline specification (0.048 vs. 0.090). The observation points are roughly symmetrically distributed around the regression line. Thus, we find no evidence for non-linear effects of δ_i.

Our third concern discussed in Section 4.1 is that θ is not constant over time. We estimate this coefficient separately for alternative sub-periods, the period from 2006 until 2008 and for the period from 2009 until 2012. We find that θ is similar for both sub-periods (0.097 vs. 0.087).

Table 2 shows further robustness checks. The estimation coefficient of θ is very similar to the baseline specification if we employ a balanced sample. The estimation coefficient of θ is slightly higher if we define regions by states rather than by 2-digit postal code areas (θ = 0.121) and if we exclude the two southern states of Bavaria and Baden-Wurttemberg from the sample (θ = 0.139). The estimation coefficient of θ is close to zero if we restrict the sample to persons who move at least 100km. Furthermore, estimation results are very similar if we use a different definition of our outcome variable ($y_{ijt} = \log(pts_{ijt} + 10)$ or $y_{ijt} = \log(pts_{ijt} + 0.1)$).

5.2. Decomposition analysis

Table 4 shows results for our second empirical approach, the decomposition analysis. If we compare regions with care utilization below the median with regions with care utilization above the median then around 78% of the variation between these two groups can be attributed to patient characteristics, and around 22% can be attributed to regional characteristics. The share that can be attributed to "demand" factors is 77% if we compare regions above the 75th percentile with regions below the 25th percentile, and 78% if we compare regions above the 90th percentile with regions below the 10th percentile. Furthermore, "demand" factors can account for 88% of the difference in utilization between East Germany and West Germany.[27,28]

The results from the decomposition analysis point towards a somewhat smaller role of "demand" factors compared to results from the event study analysis. In the decomposition analysis "demand" factors account for slightly less than 80% of regional variation compared to more than 90% in the event study analysis. These differences can be explained by different samples and different

[27] In appendix Table A1 we show results for a variance decomposition of log utilization. The cross-region variance due to patients is larger than the overall cross-region variance. This is possible since there is a negative correlation between average place effects and average patient effects.

[28] Robustness checks for the decomposition analysis are shown in appendix Table A2. The robustness checks are similar to the robustness checks shown in Table 2 for the event study analysis.

comparison groups. The event study analysis is based on movers only, while the decomposition analysis is based on the full population of both movers and non-movers. Overall, results from decomposition analysis support our findings based on the event study approach that regional variation in ambulatory care utilization in Germany can mainly be attributed to "demand" factors. Our results contrast to results from previous studies in other settings. For Medicare patients in the United States Finkelstein, Gentzkow, and Williams (2016) find that around 50% of regional variation can be attributed to "demand" factors and around 50% to "supply" factors, respectively. For outpatient Medicare use, around 35% can be attributed to "demand" factors and around 65% to supply factors.

Nonetheless, the total amount of regional variation is very similar for ambulatory care utilization in Germany and for outpatient care utilization for Medicare patients in the United States. The difference in log-utilization between regions with above median utilization and regions with below median utilization is 0.186 for ambulatory care in Germany and 0.193 for outpatient care for Medicare patients in the United States.

The part of variation in outpatient care that can be attributed to "supply" factors is much smaller in our study compared to Medicare patients (0.041 vs. 0.124). This could be explained by the institutional setting which specifically aims to restrict regional variation in the supply of ambulatory care in Germany. On the other hand, the part of variation in outpatient care that can be attributed to "demand" factors is much larger in our study compared to Medicare patients (0.145 vs. 0.069). We discuss possible explanations for this finding in Section 6.

"Demand" and "supply" factors are broad categories of potential causes of regional variation in healthcare utilization. Based on our research design it is not possible to identify which "demand" factors and which "supply" factors are responsible for regional variation. However, we can examine how region effects γ_j as defined in equation (3) and patient effects $\bar{y}_j - \gamma_j$ are correlated with observed regional characteristics.

Figure 6 shows coefficients from bivariate OLS regressions which relate region effects (in the right panel) and patient effects (in the left panel) to alternative regional variables. Regional variables are computed at level of 2-digit-postal code areas and include demographic characteristics (the share of people above age 65, the share of people below age 15, and the share of women), measures of health (life expectancy and the share of people who report that their subjective health status is good or better), health behaviors (smoking rate and obesity rate), supply of services (physicians per 100,000 residents and hospital beds per 10,000 residents), and economic characteristics (unemployment rate and the regional purchasing power per capita).[29] We rescale all regional variables to have a mean of zero and a standard deviation of 1. Thus, the coefficients display the association between a change in the covariate by 1 standard deviation and the outcome variable.

The coefficients on the left panel show that patient effects are negatively correlated with health. Patient demand is higher in regions with a higher share of patients above age 65, and it is lower in regions with a higher share of people in good subjective health. Patient demand is also higher in regions with a higher share of women. There are no statistically significant correlations between patient effects and supply of services, health behaviors, or economic characteristics of the region.

The coefficients in the right panel of Figure 6 show that region effects are correlated with the supply of services. There is a statistically significant positive correlation between coefficients for regions and physician density. Coefficients for regions are also positively correlated with purchasing power and good subjective health. The latter two variables could be related to the share of patients in private health insurance who are typically wealthier and in better health. Ozegowski and Sundmacher (2014) show that the share of patients with private health insurance across regions is correlated with a higher density of physicians licensed for social health insurance. Region effects are not significantly correlated with the number of hospital beds or with health behaviors.

6. Discussion

Starting with the pioneering research on the Dartmouth Atlas in the United States regional variation in healthcare utilization has been well documented for many countries and institutional settings. However, it becomes increasingly clear that the reasons for regional variation can differ across institutional settings and types of care (Newhouse and Garber 2013).

In our study we examine regional variation in ambulatory care utilization in Germany. While the overall amount of variation in care utilization between regions is similar for ambulatory care in Germany and for outpatient care for Medicare patients in the United States, the causes of regional variation are very different.

[29] Summary statistics are reported in appendix Table A3. Data sources include the Gesundheitsberichterstattung des Bundes, microm Rasterdaten, and the Inkar-database provided by the Bundesinstitut für Bau-, Stadt- und Raumforschung.

In contrast to studies in other institutional settings we find that “supply” factors account for only a small part of regional variation. One possible explanation for our finding is that rules and institutions in the ambulatory care sector in Germany successfully restrict “supply” side regional variation. For example, there are restrictions on opening additional physician practices in areas with a high physician density, and there are budget limits on individual physician practices.

On the other hand, we find that regional variation attributed to “demand” factors is larger in Germany than for Medicare patients in the United States. One possible explanation are different attitudes towards healthcare between regions that could be related to strong regional identities in Germany. Historically, Germany was divided in many small states with very different institutions. For example, Hamburg was an independent city state, while Brandenburg was a Prussian province where feudal structures persisted until the beginning of the 20th century. Before re-unification in 1990 healthcare systems differed widely between East and West Germany. There were few independent ambulatory care physician practices in East Germany.

Furthermore, there are few restrictions on demand for ambulatory care in Germany. Patients have free choice of physicians, they can access specialist care without a referral from a general practitioner, co-payments are low, and waiting times and travel times tend to be short. The ease of access to ambulatory care in Germany is reflected in the number of annual physician visits per capita which ranks among the highest in the world (OECD 2011).

“Demand” side variation could also be a response to different “supply” conditions in the past. Patients who are used to a high physician density and easy access to care might come to expect more care. However, we find no evidence for a gradual adjustment to the level of care in the destination regions within the first five years after the move. If an adjustment of “demand” factors to “supply” conditions takes place then it must become apparent only after more than five years of residence in a new region.

Our results have important policy conclusions. We show that “supply” side explanations can account for at most a small part of regional variation in ambulatory care in Germany. Thus, we can exclude some of the causes that tend to receive most attention in the public debate. Neither excessive care in regions with high utilization nor lack of access to care in regions with low utilization are the main causes of regional variation. Regional variation in ambulatory care in Germany can be mostly explained by differences in patients’ health and attitudes.

Regional variation caused by “supply” factors is often seen as inefficient and undesirable, while variation caused by “demand” factors such as patients’ health is sometimes seen as efficient and justified. However, “supply” side variation can be efficient if it is based for example on different production functions, and “demand” side variation can be inefficient if it is for example based on inaccurate beliefs about the effectiveness of care by patients.

For future research it is interesting to learn more about causes of regional variation in healthcare utilization in other institutional settings. For example, institutional rules in the German hospital care sector are very different from the rules in the ambulatory care sector. It is also interesting to learn more about causes of regional variation in other countries.

References

Bojke, C., A. Castelli, A. Street, P. Ward, and M. Laudicella (2013). Regional variation in the productivity of the English National Health Service. *Health Economics*, 22: 194–2011.

Bronnenberg, B.J., J.P.H. Dube, and M. Gentzkow (2012). The Evolution of Brand Preferences: Evidence from Consumer Migration. *American Economic Review*, 102: 2472–2508.

Busse, R., and A. Riesberg (2004). Health care systems in transition: Germany. *WHO Regional Office for Europe on behalf of the European Observatory on Health Systems and Policies*. Copenhagen.

Card, D., J. Heining, and P.M. Kline (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics*, 128: 967–1015.

Chandra, A., D. Cutler and Z. Song (2012). Who Ordered That? The Economics of Treatment Choices in Medical Care. In: Pauly, M.V., McGuire, T.G., and P.P. Barros, editors, *Handbook of Health Economics*, 2: 397–432. Elsevier: Oxford.

Chetty, R., J.N. Friedman and J.E. Rockoff (2014). Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood. *American Economic Review*, 104: 2633–2679.

Cutler, D., J. Skinner, A. Stern, and D. Wennberg (2013). Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Spending. *National Bureau of Economic Research Working Paper* 19320.

Eibich, P., and N. Ziebarth (2014a). Analyzing Regional Variation in Health Care Utilization Using (rich) Household Microdata. *Health Policy*, 114: 41–53.

Eibich, P., and N. Ziebarth (2014b). Examining the Structure of Spatial Health Effects using Hierarchical Bayes Models. *Regional Science and Urban Economics*, 49: 305–320.

Finkelstein, A., M. Gentzkow, and H. Williams (2016). Sources of Geographic Variation in Health Care: Evidence from Patient Migration. *Quarterly Journal of Economics*, forthcoming.

GKV-Versorgungsstärkungsgesetz (2015). Gesetz zur Stärkung der Versorgung in der Gesetzlichen Krankenversicherung, *Bundesgesetzblatt*, Jahrgang 2015, Teil 1, Nr. 30, Bonn.

Göpffarth, D., T. Kopetsch, and H. Schmitz (2016). Determinants of Regional Variation in Health Expenditures in Germany. *Health Economics*, 25: 801–815.

Jürges, H., and V. Pohl (2012). Medical Guidelines, Physician Density, and Quality of Care: Evidence from German SHARE Data. *European Journal of Health economics,* 13: 635–649.

KBV (2009). Erläuterungen zum Regelleistungsvolumen. https://www.kvb.de/fileadmin/kvb/dokumente/Praxis/Honorar/Weitere/KVB-RLV-Broschuere_aktualisiert.pdf (accessed: 18th January 2017)

Klose, J., and I. Rehbein (2011). Ärzteatlas. Daten zur Versorgungsdichte von Vertragsärzten. *Wissenschaftliches Institut der AOK*, editor. Berlin.

Kopetsch, T., and H. Schmitz (2014). Regional Variation in the Utilisation of Ambulatory Services in Germany. *Health Economics,* 23: 1481–1492.

Molitor, D. (2016). The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration. *National Bureau of Economic Research Working Paper* 22478.

Newhouse, J., and A. Garber (2013). Geographic Variation in Medical Services. *New England Journal of Medicine,* 386: 1465–1468.

OECD (2011). Health data 2011 – Version October 2011.

OECD (2014). Geographic Variation in Health Care: What Do We Know and What Can be Done to Improve Health System Performance? FOCUS on health. *OECD Health Policy Studies*, OECD Publishing: Paris.

Ozegowski, S., and L. Sundmacher (2014). Understanding the Gap between Need and Utilization in Outpatient Care – the Effect of Supply-side Determinants on Regional Inequities. *Health Policy*, 114: 54–63.

Prieto, D., and S. Lago-Penas (2012). Decomposing the Components of Health Care Expenditure: the Case of Spain. *European Journal of Health Economics*, 13: 19–27.

Reich, O., C. Weins, C. Schusterschitz, and M. Thöni (2012). Exploring the Disparities of Regional Health Care Expenditures in Switzerland: Some Empirical Evidence. *European Journal of Health Economics*, 13: 193–202.

Sachverständigenrat (2014). Bedarfsgerechte Versorgung: Perspektive für ländliche Gebiete und ausgewählte Leistungsbereiche. Report Submitted to the German Ministry of Health by the Advisory Council on the Assessment of Developments in the Health Care System (Sachverständigenrat zur Begutachtung der Entwicklung im Gesundheitswesen).

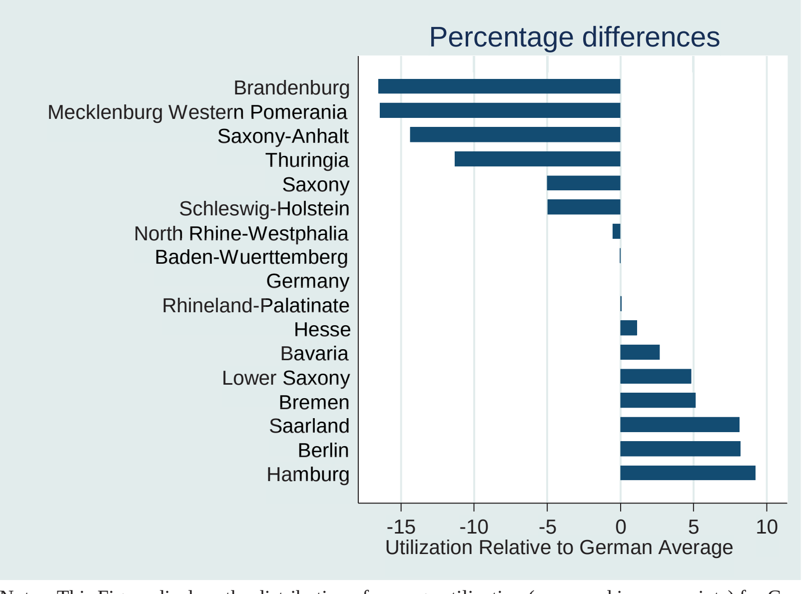
Simon, M. (2010). Das Gesundheitssystem in Deutschland: Eine Einführung in Struktur und Funktionsweise. 3rd edition, Huber: Bern.

Skinner, J. (2012). Causes and Consequences of Regional Variations in Health Care. In: Pauly, M.V., McGuire, T.G., and P.P. Barros, editors, *Handbook of Health Economics*, 2: 45–93. Elsevier: Oxford.

Song, Y., J. Skinner, J. Bynum, J. Sutherland, J.E. Wennberg, and E.S. Fisher (2010). Regional Variations in Diagnostic Practices. *New England Journal of Medicine*, 363: 45–53.

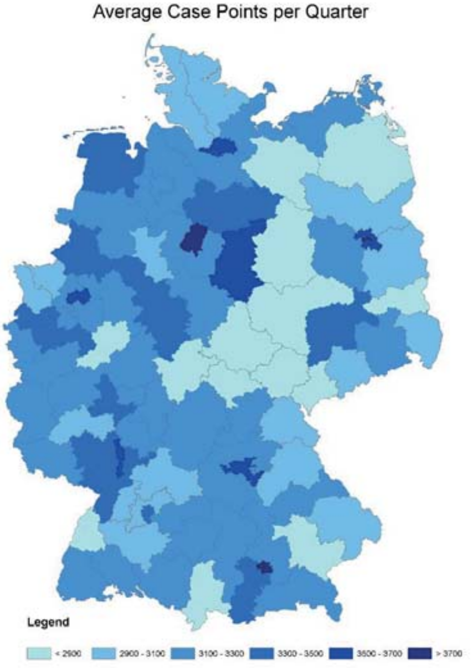
Figures

Figure 1: Regional variation in outpatient care utilization in Germany



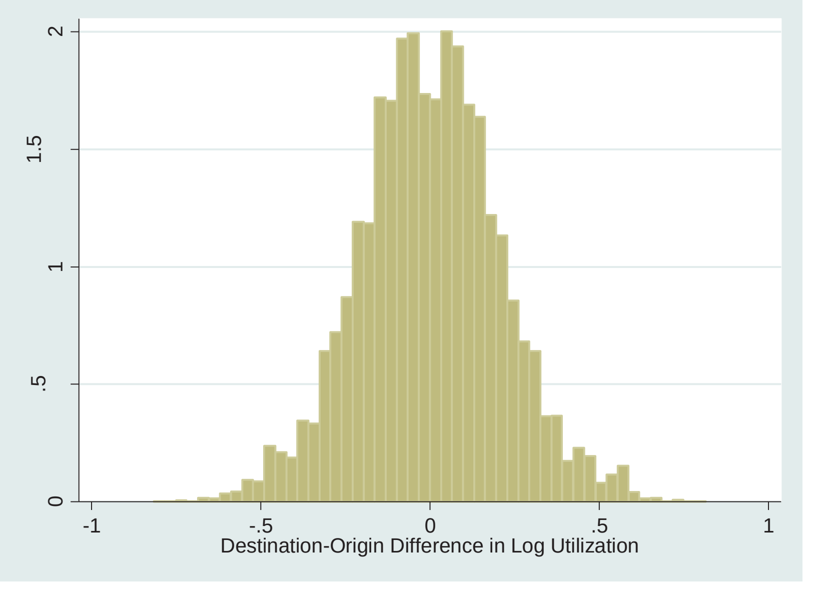
Notes: This Figure displays the distribution of average utilization (measured in case-points) for German states relative to the German average. We average utilization across individuals within states for the years from 2006 until 2012. The sample consists of N = 151,889,464 quarterly observations for N = 6,341,528 individuals.

Figure 2: Variation between regions defined by 2-digit postal codes



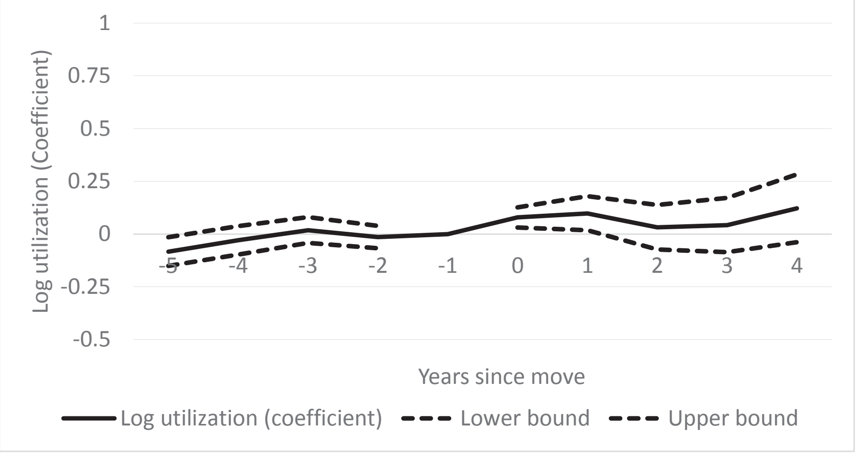
Notes: This map shows the distribution of average utilization (measured in case-points) for 2-digit-postal code areas. We average utilization across individuals within each 2-digit postal code area for the years from 2006 until 2012. The sample consists of N = 151,889,464 quarterly observations for N = 6,341,528 individuals.

Figure 3: Distribution of destination-origin difference in log utilization



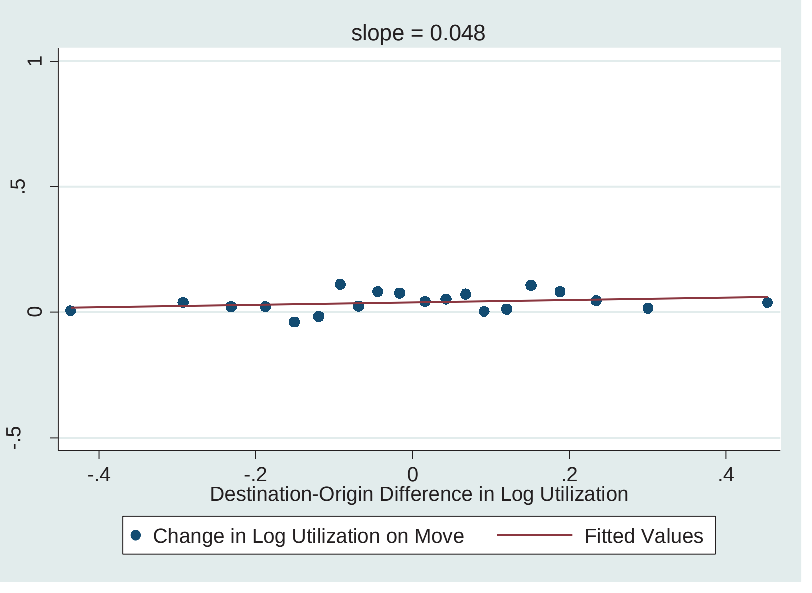
Notes: This Figure shows the distribution of δ_i, the destination-origin differences in log utilization. Origin and destination regions are defined by 2-digit postal code areas. The sample consists of all movers (N = 203,679 individuals).

Figure 4: Event study analysis



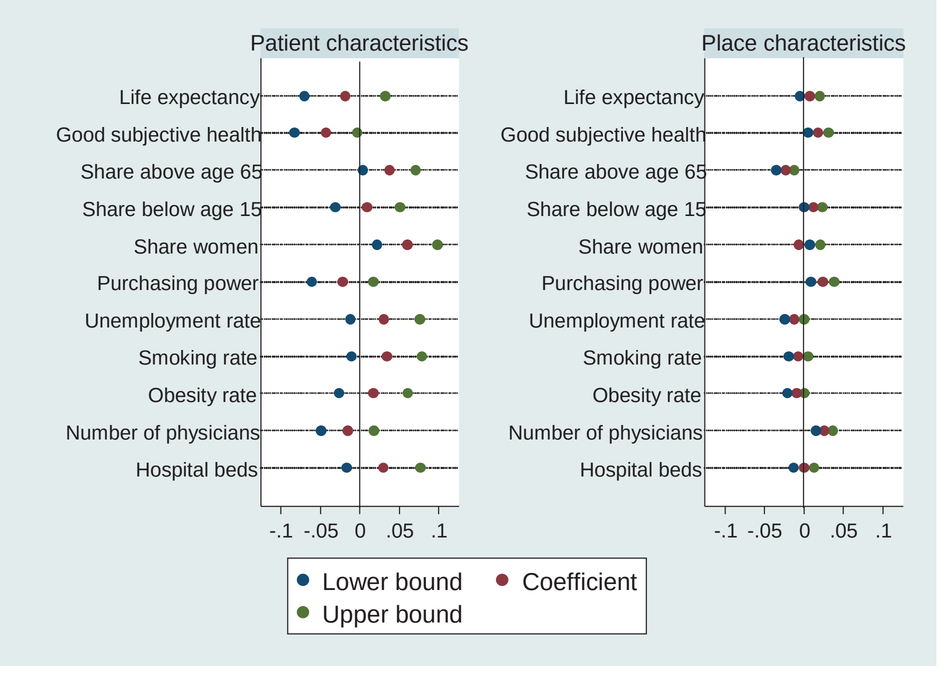
Notes: The Figure shows estimation coefficients of θ_y for years *y = -5* until y = *4* based on equation (4). The coefficient for y = *-1*, the year immediately prior to the move is normalized to 0. The drawn out line connects the estimation coefficients. The dotted lines connect the upper and lower bounds of the 95 percent confidence intervals of the estimation coefficients. The sample consists of all movers (N = 203,679 individuals).

Figure 5: Change in log utilization by size of move



Notes: We group movers into 20 bins of equal size ("ventiles") according to their δ_i. The x-axis displays the mean of δ_i for movers in each ventile. The y-axis shows the average change in log utilization for movers in each ventile. The change in log utilization is computed as the difference between the average log utilization for periods after the move and the average log utilization for periods before the move. We estimate a trend line from OLS regression using the 20 data points shown in the graph.

Figure 6: Correlates of average patient- and place effects



Notes: This Figure shows results from bivariate OLS regressions. On the right panel, the outcome variables are place effects $\hat{\gamma}_j$ for 2-digit postal code areas. On the left panel, the outcome variables are patient effects $\bar{y}_j - \hat{\gamma}_j$ for 2-digit postal code areas. Explanatory variables are regional characteristics which have been rescaled to have a mean of zero and a standard deviation of one. Each row shows an estimation coefficient and 95 percent confidence interval from a different bivariate OLS regression. The sample consists of 95 2-digit-postal code areas. Table A1 in the Appendix provides summary statistics on regional characteristics.

Table 1: Descriptive statistics of movers vs. non-movers

	Movers		Non-Movers	
	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.62	0.48	0.55	0.50
Age	40.09	17.00	51.07	18.51
Log case-points	6.05	3.48	6.34	3.35
Case-points	3476.61	5523.88	3674.21	5328.05
Any care	0.76	0.42	0.79	0.40
Any general practitioner visit	0.59	0.49	0.67	0.46
Any specialist visit	0.55	0.49	0.55	0.49
Any CT scan	0.010	0.101	0.017	0.130
Any MRI scan	0.020	0.136	0.027	0.162
Share in balanced sample	0.77	0.41	0.79	0.41
Number of individuals	203,679		6,137,849	
Number of quarterly observations	5,085,960		146,803,504	

Notes: The summary statistics refer to the estimation for the decomposition analysis in Table 4, Column 1.

Table 2: Event study analysis

	Log Case-points	
Delta baseline	0.090***	(0.025)
Heterogeneous effects		
Delta men	0.006	(0.042)
Delta women	0.144***	(0.032)
Delta age < 40	0.021	(0.070)
Delta 40 ≤ age < 65	0.111***	(0.031)
Delta age ≥ 65	0.041	(0.060)
Types of care		
Delta (outcome var.: log points GP care)	0.076***	(0.028)
Delta (outcome var.: log points specialist care)	0.323***	(0.029)
Delta (outcome var.: any CT scan)	0.001	(0.001)
Delta (outcome var.: any MRT scan)	0.0003	(0.001)
Functional form of outcome variables		
Delta (outcome var.: any care)	0.005*	(0.003)
Delta (outcome var.: any GP care)	0.010***	(0.004)
Delta (outcome var.: any specialist care)	0.038***	(0.004)
Robustness check		
Delta up to 3 years around move	0.083***	(0.025)
Delta up to 2 years around move	0.107***	(0.024)
Delta up to 1 year around move	0.075***	(0.024)
Delta early sample (sample from 2006 to 2008)	0.097	(0.065)
Delta late sample (sample from 2009 to 2012)	0.087***	(0.029)
Delta early movers (moved between 2006-2008)	0.133***	(0.050)
Delta late movers (moved between 2009-2012)	0.073**	(0.030)
Delta for balanced sample (N=140,115)	0.087***	(0.030)
Delta for moves to different states (N=106,630)	0.121***	(0.034)
Delta without southern states (N=131,223)	0.139***	(0.031)
Delta for moves of at least 100 km (N=78,565)	0.016	(0.034)
Delta (outcome var.: log case-points +10)	0.078***	(0.019)
Delta (outcome var.: log case-points +0.1)	0.103***	(0.033)
Control variables	Yes	
Number of individuals (N)	203,679	
Quarterly observations	5,085,960	

Notes: Estimations are based on equation (1). Parentheses show robust standard errors, clustered at individual level. Control variables include gender specific 5 year age categories, indicators for calendar years, indicators for quarters of the year, and indicators for years since move date. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Functional form of outcome variable

	Binary var. for case-points > median (1)	Binary var. for case-points > 75th percentile (2)	Binary var. for case-points > 90th percentile (3)	Binary var. for case points > 95th percentile (4)
Delta median	0.191***			
	(0.022)			
Delta 75th percentile		0.326***		
		(0.019)		
Delta 90th percentile			0.375***	
			(0.021)	
Delta 95th percentile				0.408***
				(0.026)
Control variables	Yes	Yes	Yes	Yes
Number of individuals	203,679	203,679	203,679	203,679
Quarterly observations	5,085,960	5,085,960	5,085,960	5,085,960

Notes: Parentheses show robust standard errors, clustered at individual level. The dependent variable is a binary indicator whether utilization is above i) the median, ii) 75th percentile, iii) 90th percentile, iv) 95th percentile of all observations in the same quarter. The main explanatory variable is the difference between the destination region and region of origin in the share of observations above i) median, ii) 75th percentile, iii) 90th percentile, iv) 95th percentile of all observations. Control variables include gender specific 5 year age categories, indicators for calendar years, indicators for quarters of the year, and indicators for years since move date. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Decomposition analysis - additive decomposition of log utilization

	Above / below Median (1)	Top & bottom 25 % (2)	Top & bottom 10 % (3)	East & West Germany (4)
Difference in average log utilization				
Overall	0.186	0.275	0.430	0.132
Due to place	0.041	0.063	0.094	0.014
Due to patient	0.145	0.212	0.336	0.116
Share of difference due to				
Patients	0.780	0.771	0.781	0.879
	(0.038)	(0.047)	(0.039)	(0.135)
Place	0.220	0.229	0.219	0.121
Control variables	Yes	Yes	Yes	Yes
Number of individuals	6,341,528	6,341,528	6,341,528	6,341,528
Quarterly observations	151,889,464	151,889,464	151,889,464	151,889,464

Notes: Results based on estimation equation (3). The columns show differences in average log utilization for 2-digit postal code areas above and below the median (column 1), among the top and bottom 25 % (column 2) and the top and bottom 10 % (column 3), as well as differences between East and West Germany (column 4). The first row shows the difference in average log utilization between the two areas, the second row reports the difference in average log utilization due to place; the third row reports the difference in log utilization due to patients. The fourth row reports the fraction of the difference in average log utilization between the two areas due to patient, as described in equation (4). We use bootstrapping with 50 repetitions drawn at the patient level to calculate standard errors (displayed in brackets). The sample consists of movers and non-movers.

Online Appendix

Table A1: Variance decomposition of log utilization

Cross-regions variance of average	
Log utilization	0.040
Due to place	0.015
Due to patient	0.072
Covariance of average place and patient effect	-0.724
Share variance would be reduced if:	
Place effects were made equal	0.625
Patient effects were made equal	-0.800

Notes: Results based on estimation equation (3) using the same specification as in Table 4. The rows show the total variance of log utilization (row 1), the variance due to place (row 2) and the variance due to patient (row 3). The fourth row shows the covariance between the average place and patient effect. Row 5 reports the fraction of the variance in 2-digit-postal code areas utilization that would be reduced if place effects would be identical between regions. Row 6 reports the according fraction of the variance if patient effects would be identical between regions. The sample consists of movers and non-movers.

Table A2: Decomposition analysis - type of care and robustness checks

Utilization measure	Mean of utilization measure (1)	Above / below median difference in utilization measure (2)	Share due to patients (3)
Types of care			
GP care	4.987	0.165	0.800
Specialist care	4.053	0.304	0.655
Any CT scans	0.017	0.001	1.013
Any MRT scans	0.027	0.003	0.767
Functional form			
Outcome var.: any care	0.792	0.015	0.867
Outcome var.: any GP care	0.671	0.024	0.792
Outcome var.: any specialist care	0.556	0.034	0.676
Robustness checks			
Up to 3 years around move	6.123	0.130	0.631
Up to 2 years around move	6.156	0.121	0.612
Up to 1 year around move	6.177	0.107	0.748
Early movers (moved between 2006-2008)	6.220	0.171	0.743
Late movers (moved between 2009-2012)	6.434	0.198	0.813
Balanced sample	6.353	0.184	0.766
Move to different states (top & bottom 25%)	6.338	0.344	0.703
Without southern states	6.394	0.209	0.878
Moves of at least 100 km	5.951	0.131	0.634
Interaction with age categories	5.951	0.130	0.651

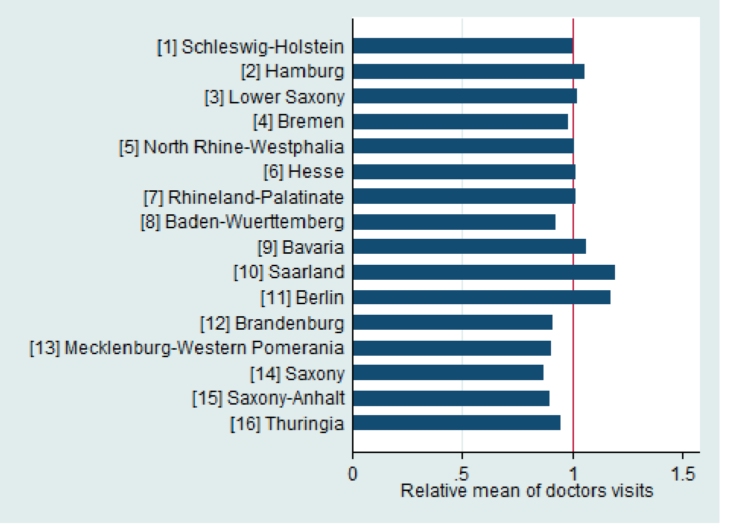
Notes: Results based on estimation equation (3). Column (1) shows the mean of the utilization measure for the given sample. Column (2) shows differences in average log utilization for 2-digit postal code areas above and below the median. Column 3 reports the fraction of the difference in average log utilization between the two areas due to patient, as described in equation (4). The sample consists of movers and non-movers.

Table A3: Descriptive statistics of regional characteristics

	Mean	Std. Dev.
Population in 2-digit postal code region	863,160	280,094
Life expectancy	77.72	0.83
Good subjective health	70.50	2.10
Share over age 65	20.38	1.96
Share under age 15	13.42	1.60
Share women	50.98	0.40
Purchasing power (in Euro per person)	19,195	2,275
Unemployment rate (percent)	7.83	3.19
Smoking rate	29.71	2.15
Obesity rate	15.94	1.09
Number of outpatient physicians per 100,000 population	160.56	33.60
Hospital beds per 10,000 population	57.46	12.37
Number of 2-digit postal code regions	95	

Notes: Information on demographic variables, purchasing power, and unemployment rates are available at 5-digit postal code level (Source: Microm), and information on number of physicians and hospital beds are available at county level (source: INKAR data provided by Bundesinstitut für Bau-, Stadt- und Raumforschung). We aggregate this information to the level of 2-digit postal code regions, using population weights. Information on smoking rate, obesity, life expectancy, and good subjective health are available at the level of 7 regions in Germany (Source: Gesundheitsberichterstattung des Bundes). We assign the variable values to 2-digit postal code regions for corresponding larger geographical units.

Figure A1: Regional variation in number of outpatient doctor visits for general population

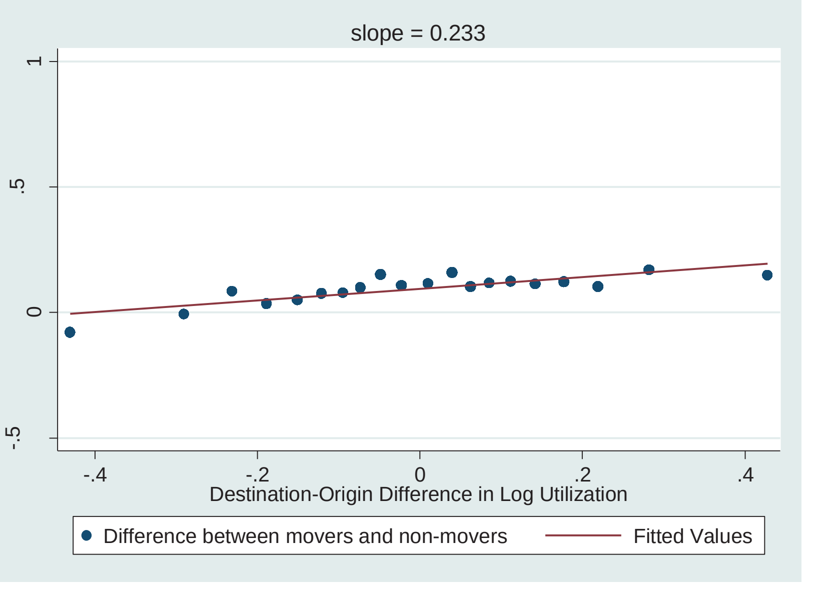


Note: This figure is reproduced from Eibich and Ziebarth (2014a) with friendly permission of the authors. It is based on survey data from the GSOEP.

Figure A2: Map for regional variation in number of outpatient doctor visits for general population

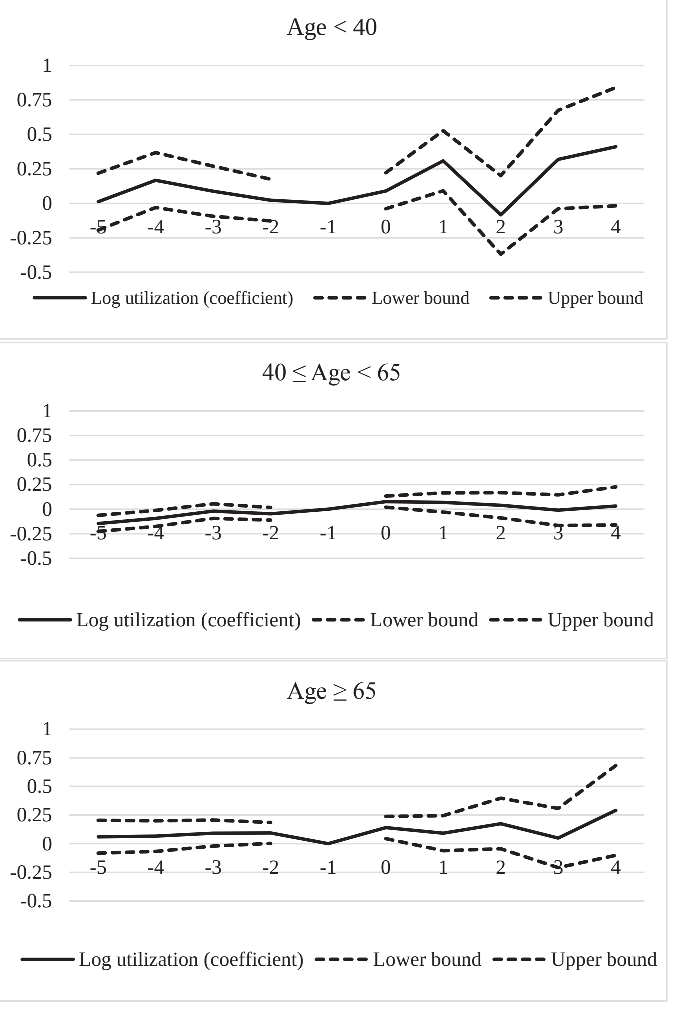
Note: This figure is reproduced from Eibich and Ziebarth (2014a) with friendly permission of the authors. It is based on survey data from the GSOEP.

Figure A3: Pre-move differences in log-utilization



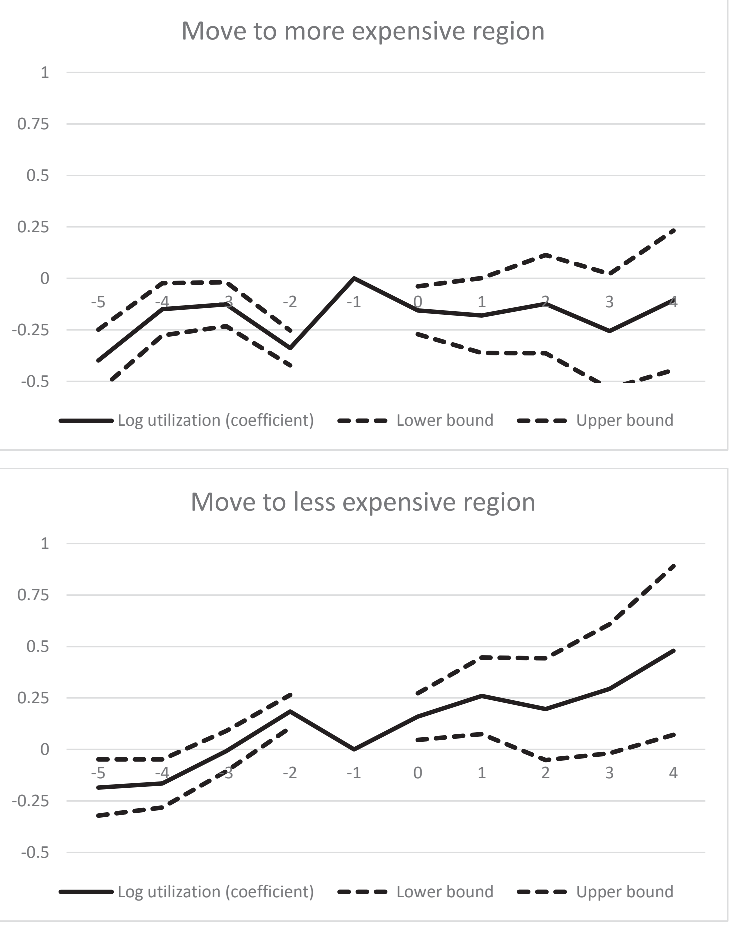
Notes: We group movers into 20 bins of equal size ("ventiles") according to their δ_i . The x-axis displays the mean of δ_i for movers in each ventile. The y-axis shows, for each ventile, the average difference in log utilization between future movers before the move and matched non-movers in the same region of origin and calendar year and with the same age and gender. We estimate a trend line from OLS regression using the 20 data points shown in the graph.

Figure A4: Event study analysis – moves by age



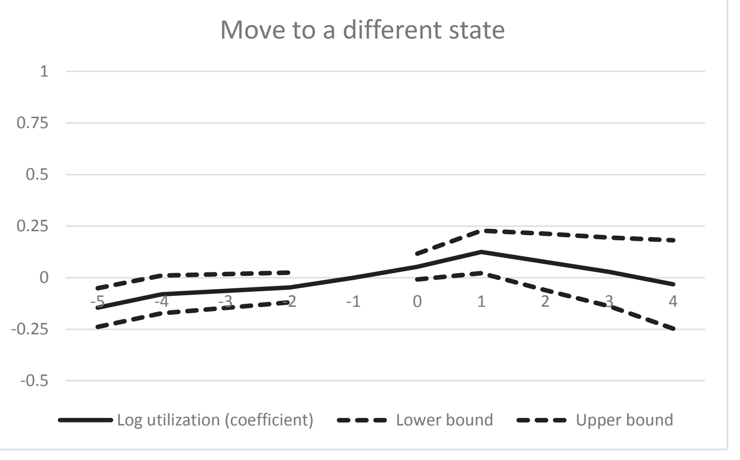
Notes: The figures show estimation coefficients of θ_y for years y = -5 until y = 4 based on equation (4) except that they are estimated on subsamples of all movers divided by age groups. The coefficient for y = -1, the year immediately prior to the move is normalized to 0. Panel (a) shows estimation coefficients for young movers (Age < 40), panel (b) shows estimation coefficients for middle aged movers (40 ≤ Age < 65), and panel (c) shows estimation coefficients for older movers (Age ≥ 65). The drawn out line connects the estimation coefficients. The dotted lines connect the upper and lower bounds of the 95 percent confidence intervals of the estimation coefficients. The sample in panel (a) consists of 30,171 movers, in panel (b) of 149,249 movers and the sample in panel (c) consists of 24,259 movers.

Figure A5: Event study analysis - move to more or less expensive region



Notes: The figures show estimation coefficients of θ_y for years y = -5 until y = 4 based on equation (4) except that they are estimated on subsamples of all movers that move to a more expensive region in panel (a) and to a less expensive region in panel (b). The coefficient for y = -1, the year immediately prior to the move is normalized to 0. A move to a more expensive region is defined to be a move to a destination 2-digit-postal code area with higher mean log utilization than the mean log utilization of the origin. A move to a less expensive region is defined to be a move to a destination 2-digit-postal code are with lower mean log utilization than the mean log utilization of the origin. The drawn out line connects the estimation coefficients. The dotted lines connect the upper and lower bounds of the 95 percent confidence intervals of the estimation coefficients. The sample in panel (a) consists of 105,421 movers and the sample in panel (b) consists of 98,258 movers.

Figure A6: Event study analysis - move to a different state



Notes: This figure shows estimation coefficients of θ_y for years y = -5 until y = 4 based on equation (4) except for a different definition of regions. Here, regions are defined by states instead of 2-digit postal code areas. The coefficient for y = -1, the year immediately prior to the move is normalized to 0. The drawn out line connects the estimation coefficients. The dotted lines connect the upper and lower bounds of the 95 percent confidence intervals of the estimation coefficients. The sample consists of 106,630 individuals who move across states.