CPB Netherlands Bureau for Economic Policy Analysis

CPB Discussion Paper | 384

Causes of regional variation in Dutch healthcare expenditures:

Evidence from movers

Ana Moura
Martin Salm
Rudy Douven
Minke Remmerswaal

Causes of regional variation in Dutch healthcare expenditures: evidence from movers[☆]

Ana Moura[a,b], Martin Salm[a,1], Rudy Douven[b,c], Minke Remmerswaal[b,a]

[a] *Tilburg University*
[b] *CPB, Netherlands Bureau for Economic Policy Analysis*
[c] *EUR, Erasmus University Rotterdam*

Abstract

We assess the relative importance of demand and supply factors as determinants of regional variation in healthcare expenditures in the Netherlands. Our empirical approach follows individuals who migrate between regions. We use individual data on annual healthcare expenditures for the entire Dutch population between the years 2006 and 2013. Regional variation in healthcare expenditures is mostly driven by demand factors, with an estimated share of around 70%. Both demographics and other unobserved demand factors, e.g. patient preferences, are important components of the demand share. The relative importance of different causes varies with the groups of regions being compared.

Keywords: Healthcare expenditures, regional variation, the Netherlands

JEL classification: I11, I13, H51

[☆]We thank Pilar García-Gómez, Leida M. Lamers, Maarten Lindeboom, Silvana Robone, and seminar participants at Tilburg University, the CPB, the 4th EuHEA PhD Student-Supervisor Conference in Lausanne, the 15th Portuguese Health Economics Conference in Coimbra, the LolaHESG in Hoenderloo, and the 12th European Conference on Health Economics in Maastricht for their valuable comments. All errors are own own. The views expressed in this study are those of the authors and do not necessarily reflect those of the CPB.

[1]Corresponding author at Tilburg University, P.O. Box 90153, 5000 LE Tilburg, The Netherlands. E-mail address: m.salm@tilburguniversity.edu. Phone number: +31 134 663 425.

1. Introduction

Regional variation in healthcare utilization and expenditures is well-documented for many countries, and it is known to persist over time (Skinner, 2012, OECD, 2014). In this study, we look at regional variation in healthcare expenditures in the Netherlands. The Netherlands is a country with a rather standardized health system. Nevertheless, individual healthcare expenditures vary by more than 20 percentage points (pp.) between provinces. In 2013, the average individual living in the province of Limburg spent €2,181 on healthcare services included in the basic health insurance package. In contrast, in the province of Utrecht the corresponding figure is €1,758.[2]

There are many possible causes of regional variation in healthcare expenditures. These causes can be grouped into demand- and supply-side factors (Skinner, 2012, Chandra and Skinner, 2012). Demand-side factors refer to anything that is related to patients, such as health status, preferences regarding healthcare use, and level of education. Supply-side factors, in turn, refer to regional characteristics such as the number of physicians in a region, their practice style, the availability of technology, but also factors such as regional climate and level of air pollution. This definition of demand- and supply-side factors is standard in the literature on regional variation and we follow it throughout our analysis.

Traditionally, the literature on regional variation emphasizes the role of differences in supply side factors such as clinical practice as main drivers of the observed variations (Phelps, 2000, Grytten and Sørensen, 2003, Chan Jr, 2016, Cutler et al. (forthcoming). Existing studies for the Netherlands focus on differences in physician remuneration schemes (Douven et al., 2015) and variations in medical practice (Westert and Groenewegen, 1999, de Jong et al., 2010, de Jong et al., 2009). Thus, policy measures implemented in the Netherlands aiming at reducing existing variations mainly tackle the supply side and, in particular, the idea that variations are caused by inefficient and excessive use of care in some regions. These

[2]These figures are based on own calculations from our data, and exclude expenditures on mental health care.

measures include, among others, issuing detailed treatment guidelines for supply-sensitive procedures, and releasing information depicting existing variations in healthcare expenditures across regions (Wammes et al., 2018). However, such policies may be failing to target some of the main causes of regional variation in healthcare expenditures, as recent studies show that demand side factors are an important source of regional variation for Medicare patients in the United States (Finkelstein et al. 2016), and for outpatient care in Germany (Salm and Wübker 2017).

In this study we examine the relative importance of demand and supply factors as causes of regional variation in healthcare expenditures in the Netherlands. Disentangling different causes is challenging. For example, supply factors such as physician density can also be a response to demand. One way to separate the effects of individual and environmental factors is to look at persons who migrate between different environments (Song et al., 2010, Grytten and Sørensen, 2003, and Molitor, 2018). Finkelstein et al. (2016) have applied this approach in the context of regional variation in healthcare utilization for the Medicare population in the US. We follow their approach, and we expand upon it.

We use two alternative empirical specifications. The first specification consists of an event-study analysis. We follow patients over time as they move between different regions in the Netherlands, and we examine how their healthcare expenditures change at the time of move. If regional variation could be entirely attributed to patient characteristics, then healthcare expenditures should not change as patients move from a region with low average healthcare expenditures such as Utrecht to a region with high average healthcare expenditures such as Limburg. If, on the other hand, regional variation can be entirely attributed to regional characteristics then we expect individual expenditures to immediately adjust to the level of expenditures in the destination region. If both patients and regional characteristics contribute to regional variation then the observed change in expenditures upon the move is informative about the relative importance of demand and supply factors.

Our second empirical specification is a decomposition analysis, which allows assessing whether the results from the event-study analysis for the sample of movers hold for the general population, and isolating the importance of demographics within the demand-side determinants of regional variation. This approach relies on a model in which healthcare expenditures are a function of regional indicators, patient demographics, individual fixed-effects, and other characteristics. The estimation sample consists of both movers and non-movers. The presence of movers in the sample allows the identification of both region and individual fixed-effects. The analysis is carried out using individual level data on healthcare expenditures for the entire Dutch population over 8 years. One advantage of our data is that it is not restricted to a certain population group as is the case for Medicare data. Additionally, the interest on the Dutch healthcare setting relates to its combination of universal coverage, private insurance, and regulated market competition. As the United States debate over options to achieve universal coverage, some of the emerging solutions, such as the Massachusetts reforms in 2006 and the Affordable Care Act, share some of the main features of the current healthcare context in the Netherlands.

Our study makes three main contributions. First, we show that patient characteristics are the main driver of regional variation in healthcare expenditures in the Netherlands, accounting for about 70% of regional variation.

Second, we further disentangle demand-side factors into demographics and other unobserved demand factors, such as patient preferences. Demographics can be seen as a source of variation that is more easily justifiable and largely unaffected by policy. We find that both demographics and other demand factors are important causes of regional variation.

Third, our analysis shows that the relative importance of different causes of regional variation greatly depends on the regions being compared. Finkelstein et al. (2016) compare regions at different points of the distribution of healthcare utilization, and they find that the demand and supply shares are similar across comparison groups. However, demand and supply shares can vary if we compare regions based on criteria other than healthcare expenditures. If we compare regions based on the share of elderly we find a higher demand share than if we compare regions based on supply characteristics.

The remainder of this paper proceeds as follows. The next section provides an overview of the main institutional features of the Dutch healthcare system. Section 3 introduces our dataset and provides descriptive evidence of existence and persistence of regional variation in healthcare expenditures in the Netherlands. The methodology is covered in Section 4 and the results are presented in Section 5. Section 6 concludes.

2. Institutional Setting

The current organization of the Dutch healthcare sector was shaped by the Health Insurance Act (Zorgverzekeringswet), which came into place in 2006.[3]

All individuals age 18 or older who live in the Netherlands are required to purchase a basic health insurance package, and those under 18 are insured through their parents. Incentives for cherry-picking of least costly individuals by insurers are reduced via a risk-equalization system, and insurers cannot reject anyone who wishes to purchase insurance from them. The basic health insurance package is highly standardized: all insurers are required to offer it and plan characteristics such as the range of services covered and the level of the mandatory deductible are defined by the Dutch government.

The range of services covered by the basic health insurance package includes GP care, maternity care, hospital care, and pharmaceuticals, among others. For services not included in the basic health insurance package (i.e. most dental care for individuals over 18, eye care, etc.), individuals can purchase supplementary insurance. Insurers are free to define all plan characteristics of the supplementary health insurance packages they wish to offer. There are nine health insurance groups operating in the Netherlands. All insurers operate at the national level. Upon moving individuals need not change their health insurance plan.

Since the Dutch healthcare system is rather standardized, one may expect little scope for

[3] An overview of the Dutch healthcare system is provided in van Kleef et al. (2014), Schut and Varkevisser (2016) (in Dutch), and Kroneman et al. (2016) (in English).

variations in healthcare expenditure across regions. Supply-side differences in healthcare expenditures can arise from different practice styles across regions, differences in the availability of technical equipment, and the concentration of healthcare providers. Another potential factor is different prices for similar services. In the Netherlands, some prices are freely negotiable between insurers and providers while others are subject to price ceilings set at the national level. For example, prices for many hospital services are subject to negotiations, while prices for GP care are regulated at the national level. Douven et al. (2018) show substantial price variation for similar hospital products between hospitals (and within a hospital for the same product across insurers). In our empirical approach, such regional differences in prices are attributed to the supply side.

3. Data

We use proprietary administrative data on individual healthcare expenditures by category of care included in the basic health insurance package for the period ranging between years 2006 and 2013. The data are available at the Netherlands Bureau for Economic Policy Analysis (CPB) and were assembled by Vektis, a private firm who receives and processes information from all health insurers operating in the Netherlands.

Due to the mandatory nature of basic health insurance in the Netherlands, we have information on the entire population living in the Netherlands for each of the years in our study period. A detailed description of the data cleaning process can be found in online Appendix B. Our final dataset comprises over 107 million observations, corresponding to about 14.5 million individuals, who are observed for at most 8 years.

For our baseline analysis, we measure total healthcare expenditures as the natural logarithm of total healthcare expenditures of individual i in year t plus one, $y_{it} = \log(\text{totexp}_{it} + 1)$. The logarithm takes into account that the distribution of healthcare expenditures is highly skewed, and adding 1 inside the logarithm operator takes into account that individuals may incur zero healthcare expenditures during a given year. Our measure of total healthcare expenditures in the basic package excludes expenditures on mental healthcare as this was added to the basic health insurance package starting from 2008.

Additionally, we look at individual healthcare expenditures on the largest categories of care and separately study GP care, hospital care, and pharmaceuticals. The outcome variables for each category of care are defined analogously to total healthcare expenditures.

We define the relevant regions as provinces. There are 12 provinces in the Netherlands, whose population size varies between 380 thousand and 3.6 million inhabitants in Zeeland and Zuid-Holland, respectively. Figure 1 provides descriptive evidence of regional variation in individual healthcare expenditures across provinces. We plot the percentage difference between the annual average individual health expenditures in each of the Dutch provinces and the national average. The figure was constructed by pooling data for all years in our sample and conveys a difference of about 20 percentage points (pp.) between provinces. The ranking of regions is stable over time, with a Spearman correlation coefficient of 0.81 between the earlier and later periods of the data (2006-09 and 2010-13, respectively).

We identify movers using individual information on the 4-digit postal code of residence at the end of the year, which we match with the corresponding province. Movers are defined as individuals who move to a new province in the Netherlands *only once* over the time horizon under analysis. According to this definition, our estimation sample contains around 0.5 million individuals who are movers, corresponding to 4 million observations.

A key variable for our empirical approach is the percentage difference in average individual healthcare expenditures between the origin and destination region of individual i. This is denoted by $\delta_i \equiv \bar{y}_{d(i)} - \bar{y}_{o(i)}$, where $\bar{y}_{d(i)}$ and $\bar{y}_{o(i)}$ are the average logarithm of individual healthcare expenditures plus one in the destination and origin province of individual i, respectively. A positive δ_i therefore means that an individual moves to a province with higher average healthcare expenditures. The larger the absolute value of δ_i, the larger the difference between the two provinces in terms of average healthcare expenditures. δ_i can take

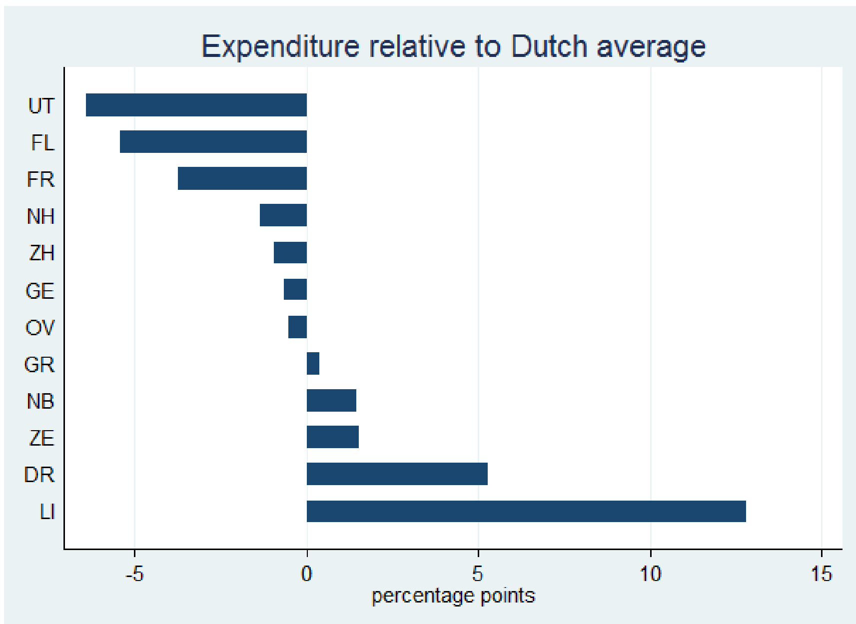


Figure 1: Average individual healthcare expenditure per province, relative to Dutch average
NOTES: The abbreviation of province names is as follows: DR, Drenthe; FL, Flevoland; FR, Friesland; GE, Gelderland; GR, Groningen; LI, Limburg; OV, Overijssel; NB, Noord-Brabant; NH, Noord-Holland; UT, Utrecht; ZE, Zeeland; ZH, Zuid-Holland. The figure displays the average individual annual health expenditure per Dutch province, relative to the Dutch average, for the period 2006-13. The sample consists of 107,364,200 observations, corresponding to 15,008,220 individuals.

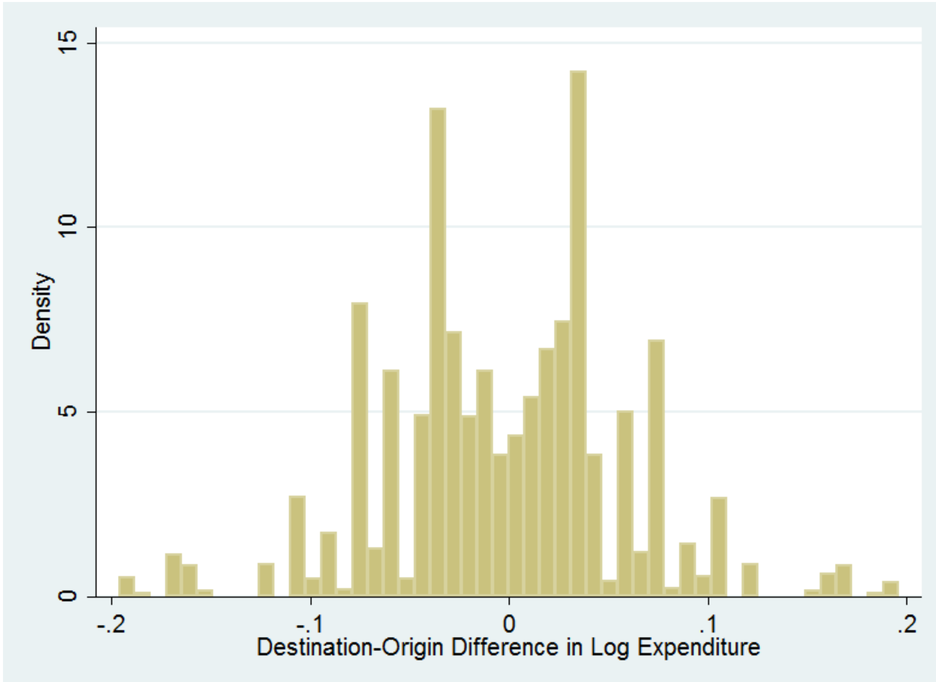


Figure 2: Distribution of destination-origin difference in log health expenditure (δ_i)
NOTES: This figure shows the histogram of δ_i, the destination-origin difference in the average log individual healthcare expenditure. Regions are defined as provinces. The histogram was built using 50 bins and the sample of all 549,500 individuals who are movers, corresponding to 4,146,945 observations.

$12 \times 11 = 132$ distinct values, corresponding to the number of possible paths a mover can take. All movers with the same path will have the same δ_i, regardless of when they move. Figure 2 shows the histogram of δ_i, which conveys the fact that moves take place both from high- to low-expenditure regions and vice-versa. The two highest bars in Figure 2 correspond to moves between Zuid- and Noord-Holland. These are the provinces where the three largest Dutch cities (Amsterdam, Rotterdam, and The Hague) are located. In specifications studying GP care, hospital care, and pharmaceuticals, δ_i is defined as the difference between the average of log healthcare expenditures plus one *in each specific category of care* in the origin and destination region of patient i. The corresponding histograms for the δ_i are not shown but exhibit a similar pattern to Figure 2.

Summary statistics for the movers and non-movers in our sample are shown in Table 1. Movers are approximately 8 years younger than non-movers, slightly more likely to be women, and exhibit lower healthcare expenditures than non-movers. They are also less likely to have

Table 1: Summary statistics for movers and non-movers

Variable	Non-movers		Movers	
	Mean	St. Deviation	Mean	St. Deviation
Age (years)	41.08	(22.95)	32.78	(18.51)
Gender (% of women)	50.93	(0.50)	52.61	(0.50)
Total Healthcare expenditures, annual (€)	1,767.70	(5,562.78)	1,305.85	(4,491,30)
of which:				
GP expenditure, annual (€)	129.76	(101.52)	116.45	(91.97)
Hospital expenditure, annual (€)	1,078.02	(4,713.46)	781.11	(3,754.96)
Pharmacy expenditure, annual (€)	308.81	(1,400.29)	203.91	(1,239.60)
Any Healthcare expenditure (%)	99.4	(0.08)	98.9	(0.11)
Any GP expenditure (%)	99.0	(0.10)	98.2	(0.13)
Any Hospital expenditure (%)	57.4	(0.49)	50.8	(0.50)
Any Pharma expenditure (%)	72.3	(0.45)	66.8	(0.47)
# individuals	14,458,720		549,500	
Average # of years observed	7.60		7.72	
# individual-years	103,217,255		4,146,945	

NOTES: Numbers for any expenditures correspond to the percentage of individuals in our dataset who incurred positive healthcare expenditures.

consumed any care than non-movers. All these differences are statistically significant at the 5% level. Finally, movers and non-movers are observed for about the same number of time periods.

4. Methods

4.1. Event-study Analysis

The idea of the event-study is to follow movers over time and use the change in healthcare expenditures upon the year of move in order to estimate the relative importance of demand and supply factors as sources of regional variation in healthcare expenditures. We specify our baseline model as follows:

$$y_{it} = \delta_i I_{t>\tau_i}\theta + X_{it}\beta + \zeta_t + I_{t-\tau_i}\kappa + \alpha_i + \varepsilon_{it}, \tag{1}$$

where y_{it}, the outcome variable, is a measure of the healthcare expenditures incurred by individual i in period t. The main explanatory variable is δ_i interacted with an indicator variable taking value 1 in periods after the move and value zero otherwise. This indicator is denoted $I_{t>\tau_i}$, where τ_i is the year of move for individual i. θ is the main parameter of interest, measuring the changes in healthcare expenditures y_{it} for years after the move. θ can be interpreted as the share of regional variation in healthcare expenditures attributed to supply-side factors.

Other independent variables included in equation (1) are year fixed-effects ζ_t; indicators for years since the year of the move, included in the vector $I_{t-\tau_i}$; [4] a vector of individual characteristics, X_{it}, including gender and age (in bins of 5 years in order to account for non-linear effects, separately for men and women); and unobservable individual fixed-effects α_i. β and κ are vectors of parameters to be estimated. Finally, ε_{it} includes time-varying individual characteristics that are unobservable. We estimate the model using fixed-effects, with robust standard errors clustered at the individual level.

Equation (1) is estimated for the sample of movers only. Identification comes from observing individuals that move at distinct points in time and have different origin and destination regions.

For the model to be valid, we need the error term to be orthogonal to the regressors: $E(\varepsilon_{it}|\delta_i I_{t>\tau_i}, X_{it}, \zeta_t, I_{t-\tau_i}) = 0$. There are several threats to this exogeneity assumption. For example, this assumption would be violated if there are underlying trends in individual healthcare expenditures that are systematically related to δ_i. Such trends can arise if individuals with deteriorating health status tend to move to regions with higher healthcare expenditures. In this case, higher healthcare expenditures after the move could be explained by trends in unobserved health and not by the higher average healthcare expenditure in the new region. In other words, we would overestimate θ. In order to assess whether there is

[4] The inclusion of indicators for years since the move accounts for direct effects of moving that might affect health and are unrelated to δ_i, such as the hassle of moving.

evidence for pre-move individual trends, we estimate the following generalization of equation (1):

$$y_{it} = \sum_{r=-6}^{6} \delta_i I_r \theta_r + X_{it}\beta + \zeta_t + I_r \kappa + \alpha_i + \varepsilon_{it}, \tag{2}$$

where we allow for θ to vary over time. That is, the subscript r on θ stands for year relative to move, ie. formally $r(i,t) \equiv t - \tau_i$. We normalize the coefficient for the year before the move to zero ($\theta_{-1} = 0$). By testing whether the estimated coefficients in periods before the move are jointly zero, one can assess whether pre-move trends are present. By looking at the estimated coefficients in periods after the move we can examine the adaptation process of individuals to the new region in the sense that they might gradually adjust their healthcare expenditures towards the average healthcare expenditure in the destination region (Bronnenberg et al., 2012). In online appendix E we discuss other threats to the validity the exogeneity assumption, and we show that our results cannot be explained by non-linear effects of δ_i on healthcare expenditures or by changes in the relative importance of demand and supply factors over time.

We carry out a battery of robustness checks to our baseline event-study specification. We assess the existence of heterogeneous effects for distinct population groups, and the robustness of our results with respect to the functional form of the outcome variable, the sample used, the definition of movers, and the definition of the relevant regions.

4.2. Decomposition Analysis

The event-study analysis is restricted to movers. However, as shown in Table 1 movers are a selected group, and the role of demand and supply factors could be different compared to the general population. Therefore, we employ an alternative estimation approach based on data for the full population, including movers and non-movers. This approach is based on the following equation:

$$y_{ijt} = \gamma_j + X_{it}\beta + \zeta_t + I_{t-\tau_i}\kappa + \alpha_i + \varepsilon_{ijt}, \tag{3}$$

where y_{ijt} is a measure of the healthcare expenditures of patient i living in province j at time t. This is a function of province indicators, γ_j, and other variables that were previously defined. ε_{ijt} is an error term.

Equation (3) is estimated based on data for the full population. Note that we can separately identify individual and region fixed effects (α_i and γ_j, respectively) due to the fact that the dataset includes movers. In case there were no movers in the dataset, then place and individual effects would be perfectly correlated. Identification of the region-specific effects γ_j comes solely from movers. As a result, we are implicitly assuming that regions affect non-movers in the same way as they affect movers.

We assess the relative importance of the different causes of regional variation using the estimates for the region-specific parameters γ_j in equation (3) in order to compare two regions or two groups of regions.[5] Regions can be grouped in many ways. For now, let us compare two groups which we label a and b. Then, the share of regional variation in healthcare expenditures coming from the supply-side is defined as follows:

$$S_{region} = \frac{\bar{\hat{\gamma}}_a - \bar{\hat{\gamma}}_b}{\bar{\hat{y}}_a - \bar{\hat{y}}_b} \equiv \frac{\Delta\bar{\hat{\gamma}}}{\Delta\bar{\hat{y}}}, \tag{4}$$

where $\bar{\hat{\gamma}}_a$ and $\bar{\hat{\gamma}}_b$ are the mean of the estimation coefficients for the regions included in groups a and b, respectively. $\bar{\hat{y}}_a$ and $\bar{\hat{y}}_b$ correspond to the average predicted outcomes based on equation (3), among individuals located in the regions included in groups a and b, respectively. Δ refers to the difference between the two groups (ie. $\Delta\bar{\hat{\gamma}} \equiv \bar{\hat{\gamma}}_a - \bar{\hat{\gamma}}_b$). The share of regional

[5]For the decomposition approach we always have to choose two regions or groups of regions which we compare. This is because the γ_j coefficient for one of the regions is normalized to zero when estimating equation (3), meaning that only the differences between γ_j's are informative.

variation attributable to patient characteristics is given by $S_{patient} = 1 - S_{region}$.

We further decompose the demand share in the share attributable to demographics and the share attributable to demand factors other than demographics. This takes the analysis a step further than Finkelstein et al. (2016). For this purpose, we estimate an additional equation which uses only demographics to explain healthcare expenditures:

$$y_{ijt} = X_{it}\rho + \mu_{ijt}, \tag{5}$$

where μ_{ijt} is an error term and ρ is a vector of parameters. We estimate equation (5) and obtain its residuals, $\hat{\mu}$. These are used to compute the share of regional variation in healthcare expenditures that is due to demographics as:

$$S_{patient}^{dem} = \frac{(\bar{\hat{y}}_a - \bar{\hat{\mu}}_a) - (\bar{\hat{y}}_b - \bar{\hat{\mu}}_b)}{\bar{\hat{y}}_a - \bar{\hat{y}}_b} = \frac{\Delta\bar{\hat{y}} - \Delta\bar{\hat{\mu}}}{\Delta\bar{\hat{y}}}, \tag{6}$$

where $\bar{\hat{\mu}}_a$ and $\bar{\hat{\mu}}_b$ are the residuals from estimating equation (5) averaged across regions in groups a and b, respectively. The share of total variation originating from demand-factors other than demographics is given by $S_{patient}^{other} = 1 - S_{region} - S_{patient}^{dem}$.

The relative importance of different causes of regional variation may depend on the choice of regions being compared. Finkelstein et al. (2016) group regions based on average healthcare utilization, for example comparing the top 25% of regions in terms of healthcare utilization with the bottom 25%, and they find that causes of variation are constant for different comparison groups. Yet, the causes of variation could be different if we chose comparison regions based on characteristics other than healthcare utilization. This can be the case if the influence of demand and supply factors is not proportional. For example, we expect a high demand share if we compare regions that differ widely in their demographic structure, but are similar in supply characteristics. In our study, we alternatively group regions based on healthcare expenditures, demographics, and supply characteristics. Specifically, we compare the following groups of regions: i. provinces above the median healthcare expenditure in the Netherlands with those below the median; ii. provinces above the 75$^{\text{th}}$ percentile of the expenditure distribution with those below the 25$^{\text{th}}$ percentile; iii. provinces above the 75$^{\text{th}}$ percentile in terms of share of elderly population (65+) with those below the 25$^{\text{th}}$ percentile and; iv. provinces above the 75$^{\text{th}}$ percentile in terms of estimated region fixed-effects ($\hat{\gamma}_j$) with those below the 25$^{\text{th}}$ percentile.[6]

The decomposition analysis is also performed for distinct categories of care, and the robustness of its results is assessed in a similar manner to the event-study.

5. Results

5.1. Event-study Analysis

We report our event-study results in Table 2, for the baseline specification and for specific categories of care. We only present the estimates for θ, the coefficient of interest. For total healthcare expenditures, the estimated coefficient of interest is 0.274, meaning that the share of regional variation attributed to supply factors is 27.4%. The remaining 72.6% correspond to the share of regional variation attributed to the demand side. This demand share is higher than the 50% share attributable to patients for healthcare utilization of Medicare beneficiaries in the United States (Finkelstein et al., 2016), but it is lower than the 80%-90% share attributable to patients for outpatient care utilization in Germany (Salm and Wübker, 2017). The relative importance of demand- and supply-side factors as sources of regional variation differs little across different categories of care.

The results from the estimation of equation (2) are summarized in Figure 3, where we plot the estimated year-specific coefficients θ_r, and their corresponding 95% confidence interval.

[6] For total expenditures, provinces above the median are Flevoland, Zuid-Holland, Noord-Brabant, Zeeland, Limburg, and Drenthe; Provinces above the 75$^{\text{th}}$ percentile are Zeeland, Limburg, and Drenthe; Provinces below the 25$^{\text{th}}$ percentile are Utrecht, Gelderland, and Friesland. Provinces above the 75$^{\text{th}}$ percentile in terms of share of elderly population are Zeeland, Limburg, and Overijssel. Provinces below the 25$^{\text{th}}$ percentile in terms of share of elderly population are Noord-Holland, Flevoland, and Utrecht. Finally, provinces above the 75$^{\text{th}}$ percentile in terms of estimated region fixed effects are Flevoland, Zeeland, and Limburg. Provinces below the 25$^{\text{th}}$ percentile in terms of estimated region fixed effects are Groningen, Drenthe, and Gelderland. See Appendix A for the relevant maps.

Table 2: Event-study Analysis: estimates of θ, baseline and by type of care

Model	Estimate	St. Error
Baseline:		
θ, Total expenditure	0.274***	0.026
By type of care:		
θ, GP expenditure	0.214***	0.027
θ, Hospital expenditure	0.266***	0.025
θ, Pharmaceutical expenditure	0.282***	0.014

NOTES: Estimates reported for the coefficient θ in equation (1). For total expenditures, the dependent variable is log(total expenditures+1). For the regressions by category of care the dependent variables are log(GP expenditures+1), log(hospital expenditures+1), and log(pharma expenditures+1) for expenditures with GP care, hospital care, and pharmaceuticals, respectively. The number of observations is 4,146,945, corresponding to all 549,500 individuals who are movers. Standard errors are robust standard errors, clustered at individual level. * significant at 10%; ** significant at 5%; *** significant at 1%.

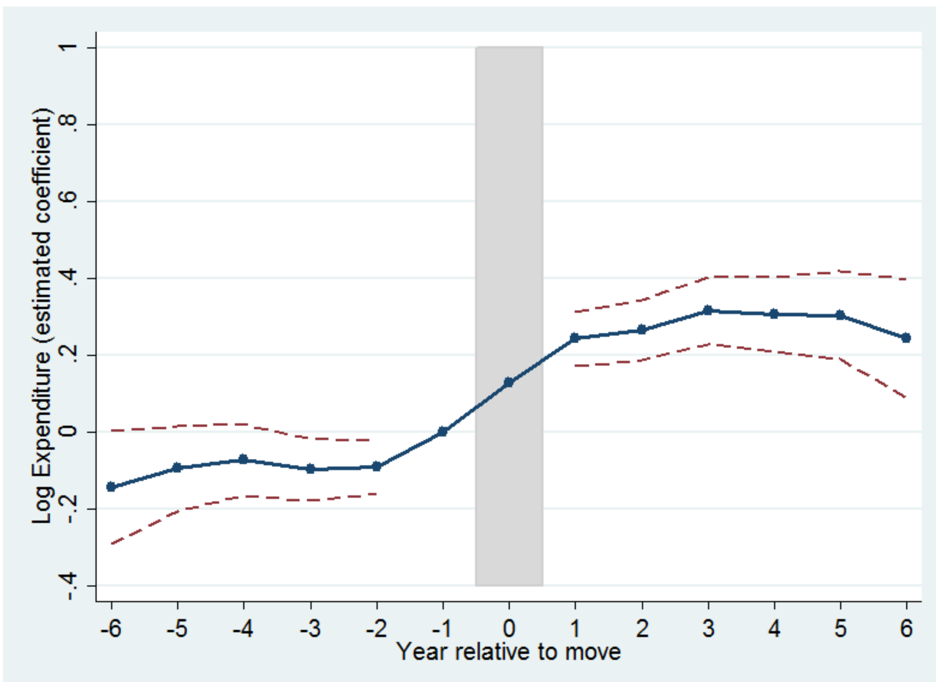
There is some evidence of a small pre-trend, with the coefficients for 2 and 3 years before the year of move being individually statistically different from zero at 5%. However, the pre-move coefficients are not jointly significant at the 5% significance level. We find no evidence for a gradual adjustment of healthcare expenditures after the move as the coefficients for periods after the move are not significantly different from each other at any conventional significance level.

Overall, our event-study results survive the robustness checks performed, with minor fluctuations of the estimated supply-side share around 0.3. For the full set of robustness checks, please check online Appendix D.

5.2. Decomposition Analysis

The results for the decomposition analysis of total healthcare expenditures are reported in Table 3. In general, our results point to the fact that most regional variation in total healthcare expenditures is driven by demand, rather than supply-side characteristics. Demand explains about 70% of the difference in healthcare expenditures between provinces in the top and bottom 25% of the expenditure distribution. This is consistent with our findings from the event-study analysis. When comparing provinces above and below the median of the

Figure 3: Assessment of pre- and post-move trends



NOTES: The figure plots the estimated coefficients θ_r based on equation (2). The coefficient for the year just before the move, $r = -1$, was normalized to zero. The solid line connects all estimated coefficients and the dashed lines connect the upper and lower bounds of their 95% confidence intervals. The sample consists of all 549,500 individuals who are movers.

expenditure distribution, patients explain only 56% of the variation. While demographics are an important component of the demand share, there is still a substantial part of the demand share that is left to unobserved factors, such as patients health status, or their preferences. The estimated shares of demand and supply vary widely with the choice of comparison regions. If we compare regions based on the share of elderly population in the region, we find that 87% of regional variation can be attributed to the demand side, with 66% of total variation being attributed to demographics. The remaining 21%(=87-66) of total variation originating from the demand side reflect patient unobservables such as health status, socioeconomic background, and preferences. In contrast, when comparing regions with large differences in supply characteristics only 18% of total variation is explained by demand-side factors, with 13% corresponding to demographics and 5% to patient unobservables. These results quantify how the relative importance of different causes of regional variation depends on the choice of comparison regions.

Table 3: Additive decomposition of log total healthcare expenditures

	Above/below median expenditure	Top/bottom 25% expenditure	High/Low share elderly	High/ Low $\hat{\gamma}$
Difference in overall log total expenditure				
Overall ($\Delta\bar{y}$)	0.068	0.139	0.129	0.107
Due to place ($\Delta\bar{\hat{\gamma}}$)	0.030	0.044	0.017	0.087
Due to patients	0.038	0.095	0.112	0.020
of which:				
Demographics ($\Delta\bar{\hat{y}}^1 - \Delta\bar{\hat{\mu}}$)	0.011	0.065	0.085	0.014
Share of difference due to				
Place	0.444	0.313	0.129	0.816
Patients	0.556	0.687	0.871	0.184
	(0.042)	(0.036)	(0.149)	(0.044)
95% CI for Patient share	[0.474, 0.638]	[0.616, 0.757]	[0.579, 1.163]	[0.098, 0.270]
of which:				
Demographics	0.166	0.465	0.659	0.132
	(0.004)	(0.004)	(0.033)	(0.005)

NOTES: Results based on equation (3) with y_{it} =log(total expenditure+1). The columns indicate the groups of provinces being compared. The first row shows the difference in average log expenditure between the two groups of provinces; the second and third rows report the difference in average log expenditure due to place and patients, respectively; row 4 reports the difference in average log expenditure due demographics; rows 5 and 6 report the estimated shares attributable to supply (place) and demand (patients), respectively; rows 7 and 8 show the standard errors for the patient share and the corresponding 95% confidence interval; finally, rows 9 and 10 report the estimated share of total variation that is due to demographics and the corresponding standard error. The standard errors for the patient and demographics shares are obtained by bootstrapping with 50 repetitions drawn at the individual level. The sample consists of movers and non-movers and excludes the year of move, amounting to 106,814,700 observations.

Results for the decomposition analysis by type of care are similar to those of the event-study analysis. In almost all specifications the demand share dominates the supply share, and the groups of regions being compared keep playing an important role. Detailed results from the decomposition analysis by type of care are presented in online Appendix F. Further robustness checks such as using a balanced sample, restricting the analysis to early and late sample periods, and to 1, 2, and 3 years around the move yield similar results.[7]

The results from the event-study analysis and the decomposition analysis are generally similar, but not exactly the same. This is due to the fundamentally distinct nature of these two approaches. The event-study analysis is restricted to movers, focuses on the change in expenditures upon the move, and averages the patient share across all movers. In contrast, the decomposition analysis makes use of the full sample of individuals, is based on all pre- and post-move years and compares the patient share between two groups of regions.

6. Conclusion

In this study, we exploit patient migration in order to examine the relative importance of different causes of regional variation in healthcare expenditures in the Netherlands. We use two alternative empirical approaches, an event-study analysis and a decomposition analysis. Our results from the event-study analysis suggest that variation is mostly demand driven, with an estimated demand share of around 0.7. Overall, the decomposition analysis conveys a similar picture, with demand-side factors accounting for a larger share of regional variation in most of our specifications.

Our study contributes to the Dutch policy debate. We aim to contribute to the Dutch policy debate by raising awareness that demand-side differences account for the largest share of the observed variations. Our findings imply that the potential of supply-side policies that have been implemented to reduce regional variation is limited to around 30% of total variation.

We further show that the relative importance of different factors depends on the regions being

[7] Results available upon request.

compared. Demand factors are more important if we compare regions with large differences in the share of older people, whereas supply factors are more important if we compare regions with large differences in supply characteristics.

In summary, our results add to the evolving understanding that causes of regional variation in healthcare expenditures can vary by context and institutional setting.

References

Bart J Bronnenberg, Jean-Pierre H Dubé, and Matthew Gentzkow. The evolution of brand preferences: evidence from consumer migration. American Economic Review, 102(6): 2472–2508, 2012.

David C Chan Jr. Informational frictions and practice variation: evidence from physicians in training. National Bureau of Economic Research. Working Paper 21855, 2016.

Amitabh Chandra and Jonathan Skinner. Technology growth and expenditure growth in health care. Journal of Economic Literature, 50(3):645–680, 2012.

David Cutler, Jonathan Skinner, Ariel Dora Stern, and David Wennberg. Physician beliefs and patient preferences: a new look at regional variation in health care spending. American Economic Journal: Economic Policy, (forthcoming).

Judith de Jong, Peter P Groenewegen, P Spreeuwenberg, Gert P Westert, and Dinny de Bakker. Do decision support systems influence variation in prescription? BMC Health Services Research, 9, 2009.

Judith de Jong, Peter P Groenewegen, Peter Spreeuwenberg, François Schellevis, and Gert P Westert. Do guidelines create uniformity in medical practice? Social Science & Medicine, 70:209–216, 2010.

Rudy Douven, Remco Mocking, and Ilaria Mosca. The effect of physician remuneration on regional variation in hospital treatments. International Journal of Health Economics and Management, 15(2):215–240, 2015.

Rudy Douven, Monique Burgera, and Erik Schut. Does managed competition constrain hospitals' contract prices? Evidence from the Netherlands. CPB Discussion Paper 378, 29 March 2018, 2018.

Amy Finkelstein, Matthew Gentzkow, and Heidi Williams. Sources of geographic variation in health care: evidence from patient migration. Quarterly Journal of Economics, 131(4): 1681–1726, 2016.

Jostein Grytten and Rune Sørensen. Practice variation and physician-specific effects. Journal of Health Economics, 22(3):403–418, 2003.

Madelon Kroneman, Wienke Boerma, Michael van den Berg, Peter Groenewegen, Judith de Jong, and Ewout van Ginneken. Netherlands: health system review. Health Systems in Transition, 18(2):1–239, 2016.

David Molitor. The evolution of physician practice styles: evidence from cardiologist migration. American Economic Journal: Economic Policy, 10(1):326–356, 2018.

OECD. Geographic variations in health care: what do we know and what can be done to improve health system performance? OECD Publishing, 2014.

Charles E Phelps. Information diffusion and best practice adoption. In Anthony J. Culyer and Joseph P. Newhouse, editors, Handbook of Health Economics, volume 1, pages 223–264. Elsevier, 2000.

Martin Salm and Ansgar Wübker. Causes of regional variation in healthcare utilization in Germany. RUHR Economic Papers 675, 2017.

Erik Schut and Marco Varkevisser. Economie van de gezondheidszorg. Springer Media B.V., 2016.

Jonathan Skinner. Causes and consequences of regional variations in health care. In Mark Pauly Thomas G. McGuire and Pedro P. Barros, editors, Handbook of Health Economics, volume 2, pages 45–93. Elsevier, 2012.

Yunjie Song, Jonathan Skinner, Julie Bynum, Jason Sutherland, John E. Wennberg, and

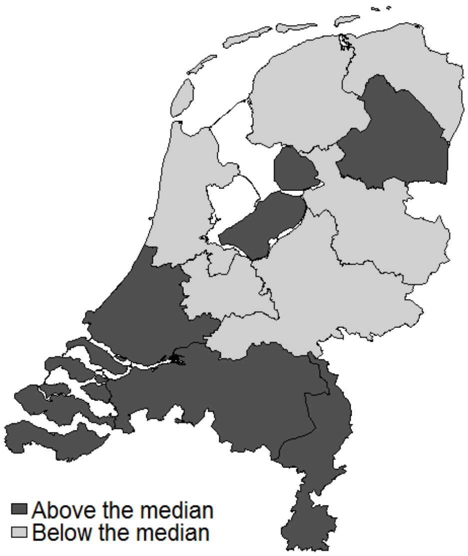
Elliott S. Fisher. Regional variations in diagnostic practices. New England Journal of Medicine, 363(1):45–53, 2010.

Richard van Kleef, Erik Schut, and Wynand van de Ven. Evaluatie zorgstelsel en risicovereveing acht jaar na invoering zorgverzekeringswet: succes verzekerd? iBMG Erasmus Universiteit Rotterdam, 2014.

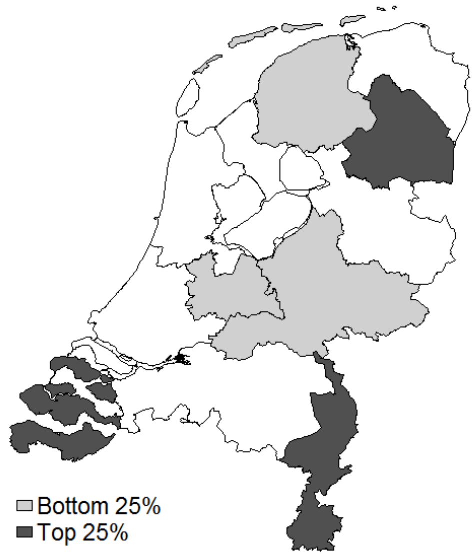
Joost Wammes, Femke Atsma, Yvonne de Mann, Stef Groenewound, and Gert Westert. De zorg is niet overal hetzelfde; het reduceren van ongewenste verschillen in kwalliteit en kosten in Nederland. In Patrick Jeurissen, Hans Maarse, and Marit Tanke, editors, Betaalbare zorg, pages 311–332. Sdu Uitgevers, 2018.

Gert P Westert and Peter P Groenewegen. Medical practice variations: changing the theoretical approach. Scandinavian Journal of Public Health, 27:173–180, 1999.

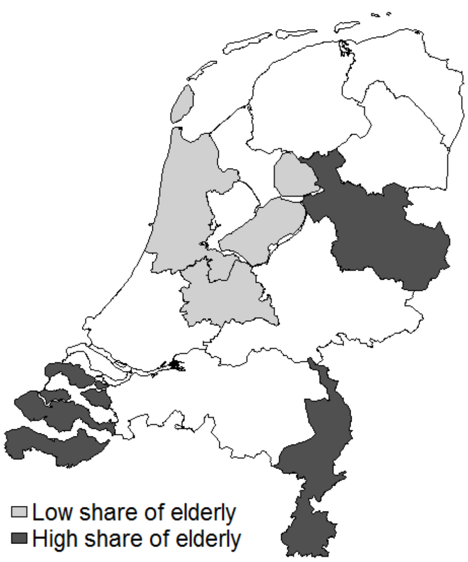
A. Regions being compared in the decomposition analysis



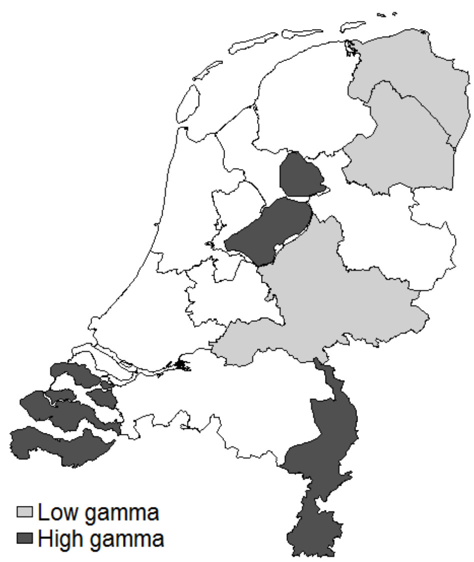
(a) Provinces above and below the median average healthcare expenditure



(b) Provinces in the top and bottom 25% in terms of average healthcare expenditure



(c) Provinces in top and bottom 25% in terms of share of elderly population



(d) Provinces in the top and bottom 25% of the (estimated) region fixed-effect

B. Details on the dataset and data cleaning process

Hereby we detail the data cleaning process that yielded the dataset used in the baseline analysis. We make clear how many observations were lost at each step of the process.

The original raw dataset covered 133,060,196 observations, with the number of individual observed each period varying between 15.8 and 17.1 millions for 2006 and 2013, respectively. In the paragraphs below, the term observation refers to a given line in the dataset and the term individual refers to all observations associated with a given individual identifier.

To begin with, we exclude 1,619,384 (1.2%) observations with invalid postal codes. These were due to the fact that some postal code areas are very small, thus raising privacy concerns. Then, we drop 1,008,072 (0.8%) observations whose registration time was above 1 year and 42,107 (0.0%) with no individual identifier.

Some individuals exhibited impossible age patterns over time and therefore were excluded from the dataset. In that case we deleted all the observations associated with that individual, resulting in the exclusion of 8,647,602 (6.5%) observations.

Additionally, some individuals had more than one observation per year. This can be due to several reasons, such moving to a new postal code area, switching insurers, etc. If their individual characteristics (age and gender) are not consistent, these observations were excluded from the dataset. For the individuals whose personal characteristics are consistent, we summed the registration times for all the lines corresponding to the same year. In case the total registration is above 1 year, the observation was dropped. In case the postal code varied between the multiple entries for an individual within a given year t, then we checked which of the postal codes corresponded to the destination region by looking and the next time period and attributed that postal code to year t. Because all the information in the dataset refers to December 31 of each year, this is an harmless procedure. After fixing these issues, we summed the expenditures for each category of healthcare over the multiple lines for the same individual within a given year. Finally, we dropped duplicated observations in terms of individual ID, year, gender, age, postal code, registration time and expenditure amounts, resulting from the procedure.

We dropped all observations whose total registration time is below 1 year (4,569,467, corresponding to 3.4% of the initial number of observations). Note that, since we had already excluded all observations with registration time above 1 year, this implies only observations with one year registration time are kept.

A few individuals exhibited negative expenditures in some categories of care. This is due to adjustments and reimbursements between the insurer and the insured that span across distinct years. We dropped 35,223 observations corresponding to such situation.

Furthermore, we dropped 6,522,126 observations corresponding to individuals who exit and then re-enter the dataset, as such situations can also be related to moving (that is, we dropped non-consecutive observations within individuals). The fact that a given individual is not observed in a certain year can, to some extent, be a result of some the procedures described in the previous paragraphs which lead to the exclusion of some observations for a given individual.

Finally, we drop individuals who moved for more than once during the time horizon under analysis (3,099,792 observations, corresponding to 2.3% of the initial number of observations). This is done in order to ensure we observe enough pre- and post-move years for each mover, which is needed for our decomposition analysis. In addition, this allows to clearly identify the change in healthcare expenditures upon the move, which is crucial for our event-study analysis. Individuals moving in 2013, the last period of our sample, are not considered as movers. The reason for this is that our empirical strategy requires that we observe healthcare expenditures both before and after the move.

Additional minor restrictions imposed in the data resulted in the exclusion of 187,446 observations.

There are a few observations with very high expenditures at certain points in time. Vektis specifically checked that those costs indeed were incurred. Thus, we keep them in our analysis. This results in a final dataset consisting on 107,364,200 observations, where all observations have 1 year registration time, each individual is observed only once a year and individuals are observed continuously over time (though not over the same number of periods - ie. the panel is unbalanced).

Finally, we excluded expenditure variables on the categories of mental health. Therefore, our concept of total healthcare expenditure excludes expenditure with mental healthcare services. This is because mental healthcare services were only included in the basic insurance package starting from the year 2008.

C. Percentiles of expenditure distributions

Table C.1: Percentiles of expenditure distributions (€)

Variable	p50	p75	p90	p95	n. observations
Total expenditure	397.51	1,346.38	3,969.76	7,227.53	107,364,200
GP expenditure	98.28	152.65	230.39	299.02	107,364,200
Hospital expenditure	57.9	564.20	2,237.96	4,818.48	107,364,200
Pharma expenditure	42.48	212.33	740.95	1,302.11	107,364,200

D. Additional analysis using the event-study framework

D.1. Heterogeneous effects across distinct population groups

In order to assess whether the demand and supply shares vary across different population groups, we extend our baseline event-study analysis to allow for heterogeneous effects based on gender, and age.

Specifically, our variable of interest, $\delta_i I_{t>\tau_1}$ was interacted with group indicators. For the gender case, we include two binary indicators, one for men and another for women, denoted I_m and I_w, respectively. Thus, instead of equation (1), the estimated equation now takes the following form: $y_{it} = \delta_i I_{t>\tau_i} I_w \theta_w + \delta_i I_{t>\tau_i} I_m \theta_m + X_{it}\beta + \zeta_t + I_{t-\tau_i}\kappa + \alpha_i + \varepsilon_{it}$. In terms of reference groups, note that $I_{t>\tau_i}$ ensures these variables only take positive values after the move. Thus, instead of the traditional men vs. women comparison, we compare men (women) with other men (women) who move at different points in time and to different destinations. The benchmark is therefore the pre-move of each of the groups.

The remaining regressions looking at heterogeneous effects follow the same approach. The age groups considered are individuals under 19, between 19 and 40, between 41, and 64 and above 64.

The results for the analysis of heterogeneous effects are presented in Table D.1.

We do not find statistically significant differences between men and women. Nevertheless, differences are found when looking at distinct age groups: the supply-side share of regional variation is higher among individuals between 19 and 40 than among those between 41 and 65. Among those under 19 and the elderly one cannot reject the null hypothesis that all regional variation is demand-driven, though precision is lost due to the low share of movers in these age groups.

D.2. Difference functional forms of the outcome variable

We now assess the robustness of our baseline results to the functional form assumed for the outcome variable.

Table D.1: Event-study Analysis: estimates of θ, heterogeneous effects

Model	Estimate	St. Error
By gender:		
θ, men	0.247***	0.038
θ, women	0.298***	0.036
By age group:		
θ, age ≤ 18	0.065	0.058
θ, $18<$ age ≤ 40	0.377***	0.033
θ, $40<$ age < 65	0.157***	0.054
θ, age ≥ 65	0.158	0.107

NOTES: Estimates are based on equation (1) with dependent variable being log(total expenditure + 1). The number of observations is 4,146,945, corresponding to 549,500 movers. Standard errors are robust standard errors, clustered at individual level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Different functional forms of the outcome variable yield the results shown in Table D.2. Changing the functional form of the outcome variable to the logarithm of total healthcare expenditures plus 10, the logarithm of total healthcare expenditures plus 0.1 or the logarithm with base 10 instead of the natural logarithm leaves the baseline estimates unchanged. Finally, changing the outcome variable to an indicator variable for whether an individual's expenditure is at the top percentiles of the cost distribution, yields a share of supply side factors that is similar or even somewhat lower than in the baseline case.

D.3. Robustness checks to the baseline sample

We further assess the robustness of the estimates obtained for the baseline regression to the sample used. More specifically, we restrict the estimation of the event-study equation to a balanced sample, we exclude the most common move paths, and we redefine movers to include all individuals moving distances long enough to minimize the chance that after the move individuals still seek care in the same health care facilities and are treated by the same physicians which they visited before the move. This is would mean they would not be exposed to different supply conditions. Finally, we redefine the relevant regions to the 25

Table D.2: Event-study Analysis: estimates of θ, alternative forms of outcome variable

Model	Estimate	St. Error
Distinct functional form of outcome variables:		
θ, Log(total expenditure + 10)	0.267***	0.023
θ, Log(total expenditure + .1)	0.272***	0.029
θ, Log_{10}(total expenditure + 1)	0.274***	0.026
θ, Expenditure > median	0.290***	0.018
θ, Expenditure > percentile 75	0.196***	0.021
θ, Expenditure > percentile 90	0.218***	0.033
θ, Expenditure > percentile 95	0.180***	0.047

NOTES: Estimates are based on equation (1). In the specifications using the distribution percentiles, the dependent variable is an indicator for whether the individual is above a given percentile of the expenditure distribution of all observations in a certain year; The number of observations is 4,146,945 , corresponding to 549,500 movers. Standard errors are robust standard errors, clustered at individual level. * significant at 10%; ** significant at 5%; *** significant at 1%.

GHOR regions instead of 12 provinces.[8]

The results of these robustness checks are shown in Table D.3. Our baseline results are robust to estimating the model in a balanced sample of movers and to excluding the most common move paths, between Noord- and Zuid-Holland. When restricting the sample to individuals moving further than a minimum distance between their origin and destination postcode, estimates of the supply-side share are of similar magnitude to our baseline results. The model estimates also are robust to an alternative definition of regions. Using GHOR regions to identify movers leads to slightly smaller supply shares for all types of care than the use of provinces. GHOR regions are smaller than provinces, so this result may be reflecting the fact that more individuals keep visiting health providers in their old region after having moved.

[8]GHOR stands for Geneeskundige Hulpverleningsorganisatie in de Regio (Regional Medical Emergency Preparedness and Planning) and it is responsible for the coordination and management of medical aid in case of disasters and crises. The GHOR also provides advice to governments and other organizations. There are 25 GHOR offices in the Netherlands and each of them is responsible for a specific territorial area. In this robustness check, we thus consider as movers individuals who move to a new GHOR region once and only once during the time period under analysis. Using GHOR regions results in 724,952 movers, corresponding to 5,458,133 observations. Among GHOR regions, differences in terms of healthcare expenditures are even higher than those among provinces, reaching 30 percentage points over our sample period.

Table D.3: Event-study Analysis: estimates of θ, additional robustness checks

Model	Estimate	St. Error	N. Obs.
Sample restrictions:			
θ, balanced sample	0.299***	0.027	3,611,944
θ, excluding moves between NH and ZH	0.278***	0.026	3,823,868
θ, moves > 75km	0.349***	0.031	2,166,909
θ, moves > 100km	0.285***	0.035	1,544,721
GHOR regions:			
θ, log(total expenditure+1)	0.190***	0.019	5,458,133
θ, log(GP expenditure+1)	0.189***	0.018	5,458,133
θ, log(hospital expenditure+1)	0.223***	0.016	5,458,133
θ, log(pharma expenditure+1)	0.228***	0.012	5,458,133

NOTES: Estimates are based on equation (1). For the specifications with sample restrictions, we use $\log(\text{tot exp}_{it} + 1)$ as dependent variable. The number of mover-year observations varies according to the restriction imposed, as shown in the last column of the table. For the GHOR regions, the dependent variables are $\log(\text{tot exp}_{it} + 1)$ for total expenditures, $\log(\text{GP}_{it} + 1)$ for GP care, $\log(\text{Hospital}_{it} + 1)$ for hospital care, and $\log(\text{Pharma}_{it} + 1)$ for pharmacy care. The number of observations in this case corresponds to the number of mover-years using GHOR regions to define movers. Standard errors are robust standard errors, clustered at individual level. * significant at 10%; ** significant at 5%; *** significant at 1%.

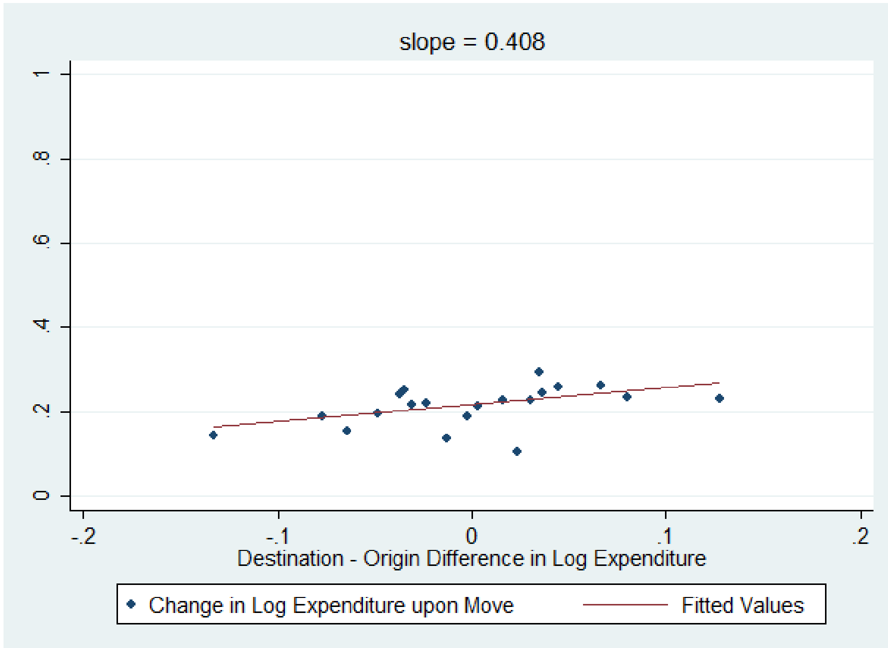
E. Assessment of possible violations of the exogeneity assumption

Besides the existence of unobserved individual times trends that are systematically related to the δ_i, which is discussed in the main text, there are other threats to the exogeneity assumption required by our baseline model. In this section, we discuss the plausibility of our assumptions of linear effects of δ_i on healthcare expenditures, and a time-invariant θ.

Our baseline model specification assumes that the change in healthcare expenditures at the time of the move is linear in δ_i. This assumption would be violated for example if individuals respond differently to positive and negative δ_i's, i.e. the effect of moving to a 10% more expensive region can be different in magnitude from that of moving to a 10% less expensive region. In order to test whether assuming a linear effect of δ_i on healthcare expenditures is reasonable, we divide the sample of movers into 20 equally sized bins according to δ_i and, for each of the bins, compute the average change in healthcare expenditures upon the move (i.e. the average of the difference between average annual expenditure after the move and before the move). We then assess the plausibility of the assumption that the effect of δ_i is linear using a visual approach. Figure E.1 plots the 20 equally sized bins of movers according to δ_i on the horizontal axis and the associated average change in individual healthcare expenditure around the move on the vertical axis. These are the 20 points in the plot. The line is a regression line connecting all 20 points. One can see that the points lie close to the regression line and the figure does not suggest the existence of non-linear effects of δ_i. Note that the slope of the regression line connecting all 20 points is 0.4, which is above our estimated θ in the baseline regression. This is due to the fact that this plot is only assessing a correlation and no covariates are being accounted for.

Another key assumption of our baseline model specification is that θ is time-invariant. This implies that the event-study equation (1) assumes the relative importance of demand and supply-side factors as drivers of regional variations in healthcare expenditures to be constant over time. As previously mentioned, on January 1$^{\text{st}}$ 2006, the Dutch healthcare system was subject to a systematic reform, which introduced managed competition and a

Figure E.1: Testing the linearity assumption on δ_i



NOTES: This figure was constructed by grouping movers into 20 equally sized bins according to their δ_i. The horizontal axis measures the average change in log expenditure for movers in each bin upon the move. The trend line was estimated by OLS using the 20 data points shown. The sample consists of all 549,500 individuals who are movers.

single compulsory health insurance scheme for all individuals. Simultaneously, 2006 is the first year contained in our dataset. Thus, it may well be that in the years after the reform many adjustments were taking place as patients, physicians, hospital managers, and other agents in the healthcare sector learned the new rules of the game. This could result in θ varying over time. In order to assess the stability of θ over time, we estimate the event-study regression separately in two distinct time periods (the early period between 2006-2009, and the late period between 2010-2013). Additionally, we estimate the event-study equation distinguishing individuals who moved in the first and the second half of our study period. In each of the cases, testing the equality of the θ coefficients allows assessing whether θ is time-invariant. The corresponding results are shown in Table E.1 and suggest that our assumption of a time-invariant θ is reasonable. When distinguishing between the early and late sample periods, or estimating the baseline model among a sample of either early movers or late movers, we find no statistically significant differences in the estimated coefficients at the 5% significance

Table E.1: Event-study Analysis: estimates of θ, assessing model assumptions

Model	Estimate	St. Error	N. Obs.
Early vs. Late sample:			
θ, sample from 2006 to 2009	0.209***	0.050	2,051,943
θ, sample from 2010 to 2013	0.226***	0.042	2,095,002
Early vs. Late movers:			
θ, individuals who moved between 2006 and 2009	0.235***	0.035	4,146,945
θ, individuals who moved between 2010 and 2013	0.329***	0.039	4,146,945

NOTES: Estimates are based on equation (1), using $\log(\text{tot exp}_{it} + 1)$ as dependent variable. The number of observations varies according to each restriction imposed, as shown in the last column of the table. Standard errors are robust standard errors, clustered at individual level. * significant at 10%; ** significant at 5%; *** significant at 1%.

level.

F. Decomposition Analysis per type of care

Table F.1: Additive decomposition per type of care, GP and Hospital

	Above/below median	Top/bottom 25%	Old/ Young	High/ Low $\hat{\gamma}$
Difference in overall log GP expenditure				
Overall ($\Delta\bar{y}$)	0.048	0.079	0.069	0.054
Due to place ($\Delta\bar{\hat{\gamma}}$)	0.015	0.021	0.008	0.031
Due to patients	0.033	0.059	0.061	0.023
of which:				
Demographics ($\Delta\bar{\hat{y}} - \Delta\bar{\hat{\mu}}$)	0.006	0.013	0.026	0.006
Share of difference due to				
Place	0.312	0.260	0.112	0.573
Patients	0.688	0.740	0.888	0.427
of which:				
Demographics	0.117	0.161	0.381	0.112
Difference in overall log Hospital expenditure				
Overall ($\Delta\bar{y}$)	0.182	0.216	0.136	0.178
Due to place ($\Delta\bar{\hat{\gamma}}$)	0.073	0.082	-0.023	0.134
Due to patients	0.109	0.134	0.160	0.044
of which:				
Demographics ($\Delta\bar{\hat{y}} - \Delta\bar{\hat{\mu}}$)	0.036	0.025	0.154	-0.036
Share of difference due to				
Place	0.400	0.379	-0.167	0.753
Patients	0.600	0.621	1.167	0.247
of which:				
Demographics	0.198	0.115	1.127	-0.201
Difference in overall log Pharma expenditure				
Overall ($\Delta\bar{y}$)	0.205	0.353	0.353	0.297
Due to place ($\Delta\bar{\hat{\gamma}}$)	0.056	0.112	0.112	0.139
Due to patients	0.149	0.242	0.242	0.158
of which:				
Demographics ($\Delta\bar{\hat{y}} - \Delta\bar{\hat{\mu}}$)	0.047	0.160	0.160	0.118
Share of difference due to				
Place	0.273	0.316	0.316	0.468
Patients	0.727	0.684	0.684	0.532
of which:				
Demographics	0.229	0.454	0.454	0.398

NOTES: the provinces belonging to the groups of expenditure percentiles being compared in columns 1, 2, and 4 are not constant across types of care. Indeed, the rank of provinces in terms of GP expenditure can be very different from that in terms of hospital expenditure and the same applies to the estimated region fixed-effects. Thus, we use the specific expenditure in the type of care under analysis in order to determine which provinces belong to the groups of percentiles being compared. This analysis uses all movers and non-movers and excludes the year of move, amounting to 106,800,653 observations.

Publisher:

CPB Netherlands Bureau for Economic Policy Analysis
P.O. Box 80510 | 2508 GM The Hague
T (088) 984 60 00

October 2018