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ABSTRACT

Does Population Sorting through Internal Migration Increase Healthcare Costs and Needs in Peripheral Regions?*

Large regional disparities in health and healthcare costs prevail in many countries, but our understanding of the underlying causes is still limited. This study shows for the case of the Netherlands that population sorting through internal migration can explain a substantial share, around 28%, of regional variation in healthcare costs. Internal migration during the 1998-2018 period increases average healthcare costs in peripheral provinces by up to 3%. Most of this effect can be attributed to selective migration. We find similar results for risk scores, a measure of healthcare needs. The Dutch risk equalization scheme compensates only partially for these effects.

JEL Classification: H51, I14, R23

Keywords: regional variation in healthcare costs, internal migration, movers approach, regional disparities

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1 Introduction

In many countries, health and healthcare costs differ widely between regions (Currie & Schwandt, 2016; OECD, 2014; Skinner, 2011). Such regional disparities can have different explanations. One possible explanation is that some region-specific characteristics determine average health and longevity (Atella et al., 2019; Deryugina & Molitor, 2020, 2021; Finkelstein et al., 2021; Johnson & Taylor, 2019) or healthcare costs (Cutler et al., 2019; Molitor, 2018). A second possible explanation is that individuals sort themselves into regions according to their health and healthcare needs via internal migration. Thus, young and healthy persons move to regions with good average health and low average healthcare costs, and old and sick persons move to or remain in regions with poor average health and high average healthcare costs.

These two possible explanations for regional disparities in health and healthcare costs have very different policy implications. If regional disparities are caused by region-specific characteristics then we should try to influence these characteristics in an effort to obtain desirable outcomes such as good health and efficient healthcare provision. However, if internal migration causes differences in average healthcare needs across regions then we should try to accommodate these needs even if this increases regional disparities in average healthcare costs.

The aim of our study is to assess the effect of population sorting through internal migration on two outcome variables: average healthcare costs and average healthcare needs, as measured by risk scores, in different regions. Hence, we compare outcomes in regions based on their current population with counterfactual outcomes in the same regions, had there been no internal migration. In order to compute such counterfactual outcomes we need to overcome two empirical challenges. First, we need to assign individuals to regions where they have lived in the past. Second, we need to estimate what healthcare costs and needs of internal migrants would have been if they had stayed in their region of origin.

Our empirical approach addresses these challenges based on administrative data from the Netherlands. While the Netherlands is a relatively small country, it faces stark contrasts between a booming Randstad region in the Western part of the country which includes the major cities of Amsterdam, Rotterdam, and The Hague, where average healthcare costs are low and the population is growing fast, and a number of provinces at the periphery of the country with higher average healthcare costs and a population that is growing slowly or even shrinking. Based on the Dutch population register, we know individuals' current and past places of residence over an extended period. Thus, for essentially the entire population of the Netherlands in the year 2018 we know their province of residence in, for example, the year 1998 if they have already been alive and a resident in the Netherlands in this year.

Both healthcare costs and needs can be influenced by an individual's region of residence, e.g. due to regional differences in pollution, living conditions, or physician practice style. We refer to the combined effect of local conditions on outcome variables as place effects. By following individuals over time who move between regions, we can assess how an individual's region of residence affects her healthcare costs and needs. This approach allows estimating place effects for each province in the Netherlands.[1] We then use estimated place effects to compute what healthcare costs and needs of an individual in the year 2018 would have been if she had stayed in the province where she lived in the year 1998.

[1] The movers approach to separate environmental effects from individual effects was first developed by Abowd et al. (1999) in the context of firms and workers. Our empirical specification to estimate place effects for healthcare costs closely follows Finkelstein et al. (2016) who estimate such place effects for Medicare patients in the United States and Moura et al. (2019) who estimate place effects in healthcare costs for provinces in the Netherlands.

We find that population sorting through internal migration increases average healthcare costs included in the basic health insurance package for provinces in the periphery by up to 3%, and it decreases average healthcare costs for provinces in the Randstad region by up to 3.5%. Internal migration exacerbates regional inequality in healthcare costs. 28% of the difference in average healthcare costs between provinces in the year 2018 can be attributed to the effects of internal migration between the years 1998 and 2018. Our results are robust to province-specific pre-move and post-move trends, heterogeneous place effects, and other alternative specifications. Furthermore, we show in a decomposition analysis that our findings can mostly be attributed to selective migration: in peripheral provinces healthcare costs are substantially higher for in-migrants than for out-migrants, while in Randstad provinces healthcare costs are substantially lower for in-migrants than for out-migrants.

As second outcome variable, we use a measure of healthcare needs, individual risk scores. In their construction, we follow the Dutch risk equalization scheme (Layton et al., 2018; McGuire & Van Kleef, 2018) as closely as possible with the available data. Results for healthcare costs and risk scores are similar. 26.5% of the difference in average risk scores between provinces in the year 2018 can be attributed to internal migration during the 1998-2018 period.

Finally, we show that effect sizes remain sizable even after adjusting healthcare costs for differences in either demographics or risk scores. Thus, the Dutch risk equalization scheme compensates only partially, but not fully for the effect of internal migration on regional differences in healthcare costs.

Our study contributes to the literature both on regional variation in healthcare costs and on regional variation in health. Traditionally, the literature on regional variation in healthcare costs emphasizes the role of differences in physician practice style and other supply-side factors (Cutler et al., 2019; Molitor, 2018; Phelps, 2000).

This also applies to studies on regional variation in the Netherlands (Douven et al., 2015; Westert & Groenewegen, 1999). However, several recent studies demonstrate based on a movers approach that patient characteristics can explain a large share of regional variation in healthcare use for various countries. This share is 50% for Medicare patients in the United States (Finkelstein et al., 2016) and for healthcare utilization in Norway (Godøy & Huitfeldt, 2020), 70% for healthcare costs in the Netherlands (Moura et al., 2019), and 90% for outpatient care in Germany (Salm & Wübker, 2020).[2] Yet, the reasons why patient demand varies so much across regions are still not well understood.

One possible explanation is population sorting through internal migration. Our study demonstrates that population sorting can explain a substantial share, around 28% in the Netherlands, of regional variation in healthcare costs. This is to the best of our knowledge a new result that has not been shown before, neither for the Netherlands nor for any other country.[3]

Large regional disparities prevail not just for healthcare costs (OECD, 2014; Skinner, 2011), but also for health and mortality (Banks et al., 2021; Chetty et al., 2016; Currie & Schwandt, 2016). A growing literature documents the role of place effects in explaining such disparities (Atella et al., 2019; Deryugina & Molitor, 2020, 2021; Finkelstein et al., 2021; Johnson & Taylor, 2019). In these studies, population sorting and selective migration is not an object of interest, but a potential source of bias that needs to be controlled for by careful research designs. Our study complements this literature by quantifying the effect of population sorting on regional differences in

[2]These shares refer to the combined effect of all observed and unobserved individual characteristics that don't change when patients move to a different region.

[3]Darlington et al. (2016) argue that internal migration can contribute to regional variation in healthcare costs based on theoretical considerations, but they don't quantify this effect.

healthcare needs, as measured by risk scores.[4] In order to better understand regional variation in health within countries it is important to know not just the contribution of place effects that make people healthy or sick, but also the contribution of population sorting, since both explanations have very different policy implications.

Our findings for the Netherlands might also apply to other countries. Many countries experience a brain-drain of highly educated persons away from economically disadvantaged regions to prosperous urban centers (Dahl, 2002; Diamond, 2016; Greenwood, 1997). Such a brain drain can be accompanied by a *health drain* if persons who move for example from rural to urban regions are positively selected on health, as Vaalavuo and Sihvola (2021) show for the case of Finland. Such a health drain might have a noticeable impact on healthcare costs and needs in peripheral or economically disadvantaged regions not just in the Netherlands, but also in other countries.

Our findings have important policy implications. First, increased healthcare needs that result from population sorting through internal migration should be accommodated. Medical facilities, e.g. hospitals, need to be and remain available, physicians and other medical staff need to be convinced to work in peripheral provinces, and there needs to be sufficient funding for addressing increased healthcare needs. Secondly, our results indicate that the Dutch risk equalization scheme only partially compensates for the effect of internal migration on regional differences in healthcare costs. It might be desirable to adjust the risk equalization scheme in order to more fully compensate affected provinces for the effects of population sorting through internal migration.

This study proceeds as follows. Section 2 describes the institutional setting.

[4] Risk scores can be seen as a proxy variable for health. Health has many dimensions which are often difficult to quantify. Risk scores combine elements of health such as chronic health conditions with information on factors that are closely correlated with health such as age and socio-economic conditions.

Section 3 presents our data and descriptive evidence. Methods are explained in Section 4, and in Section 5 we show our estimation results. Section 6 concludes.

2 Institutional Setting

The Netherlands have a system of managed competition in healthcare markets (A description of the Dutch healthcare system can be found in Kroneman et al. (2016)). Residents of the Netherlands are obliged to purchase a basic health insurance package from one of several competing health insurers. The contents of the basic health insurance package are set by law. It includes care by general practitioners and medical specialists, hospital care, pharmaceuticals, mental health care, and medical devices such as protheses and wheelchairs. In addition to the basic health insurance package, individuals can purchase supplementary insurance, e.g. for dental care. In our study, we focus on care included in the basic package.

Health insurance is paid for by a combination of income-dependent employer contributions and insurance premiums paid by individuals, in about equal parts.[5] For the basic health insurance package, health insurers have to accept all applicants, and insurance premiums are community rated. Thus, they do not depend on the health of insurance holders.[6] Individuals have the option to change their insurance contract at the beginning of each year.

Importantly for our study, individuals keep their health insurance contract if they move to a different province. All health insurers operate nationally, even though their market shares differs widely across regions.[7] Insurers negotiate with care providers

[5]Insurance premiums for children under the age of 18 are paid by the government.
[6]Group discounts of up to 10% are allowed.
[7]The map depicted in Figure A1 in the online Appendix shows for each region the health insurer

about prices, quality, and quantity of care, within the framework set by law.

The Netherlands have a risk adjustment scheme that compensates health insurers for differences in their risk pools. Compensation is based on risk scores that are assigned to each individual. Among other factors, risk scores depend on neighborhood characteristics such as the share of immigrants from non-Western countries, urbanization rate, and the average distance to a General Practitioner.[8] Yet, this regional component of the risk score is directed primarily at compensating for additional healthcare needs in poor neighborhoods in large cities, and it is not explicitly focused on compensating for additional healthcare needs in peripheral regions that result from internal migration.[9]

3 Data and Descriptive Statistics

We use administrative data provided by Statistics Netherlands (CBS). Our data combine information on healthcare costs, current and past places of residence, demographic characteristics, education, and predictors of risk scores including pharmaceutical use, income, and neighborhood characteristics. These data are assembled by Statistics Netherlands from various sources.[10]

In our baseline analysis, we restrict our data to individuals who reside in the

with the highest market share.

[8]Variables in the Dutch risk adjustment scheme are described in more detail in Section B1 in the online Appendix.

[9]By the measures included in the risk score, neighborhood characteristics for poor villages in peripheral regions and for wealthy suburbs of large cities tend to be similar.

[10]Data on individual healthcare expenditures included in the basic healthcare insurance package is obtained from Vektis, a private firm commissioned by the Dutch government to assemble information from health insurers. Data on current and past places of residence and basic personal characteristics come from the personal records database maintained by municipalities. Information on household income are provided by the tax administration. Information on education degrees are collected from various education registers and a series of professional population surveys.

Netherlands at the beginnings of both the years 1998 and 2018. This allows us to examine the effects of population sorting through internal migration over a 20 year period. 1998 is one of the first years for which the population register in the Netherlands is (almost) complete, and 2018 is the last year in our data set. The population of the Netherlands in the year 2018 was about 17.2 million. After excluding individuals with missing information on either healthcare costs, place of residence, or predictors of risk scores we are left with around 17 million observations. Furthermore, since we are looking at individuals who reside in the Netherlands in both the years 1998 and 2018, we exclude around 4.8 million individuals who were either not born before the year 1998 or immigrated to the Netherlands after the year 1998, which leaves us with an analysis sample of around 12.2 million observations. A detailed description of data availability is presented in Table A1 in the online Appendix.

We use two outcome variables in our analysis. The first outcome variable is annual healthcare costs of an individual for care which is covered by the basic health insurance package.[11] The second outcome variable is individual risk scores. The official purpose of computing risk scores in the Dutch risk equalization scheme is to account for differences in healthcare needs between persons covered by separate health insurance plans. In line with this purpose, we use risk scores as a measure of healthcare needs.

In computing risk scores, we emulate the Dutch risk equalization scheme in the year 2015, as described by Layton et al. (2018) and McGuire and Van Kleef (2018). First, we estimate predicted healthcare costs by linearly regressing actual healthcare costs of individuals on their age, gender, neighborhood characteristics, diagnoses for chronic conditions based on prescribed medicines, main source of income, income deciles, and medical spending in previous years. Then, we compute risk scores as

[11] Healthcare costs include both care paid by insurers and deductible payments made by patients.

the ratio of predicted healthcare costs for each individual and the average healthcare costs in the population.[12] For example, a risk score of 1.2 implies that predicted healthcare costs of an individual are 20% above the national average. While we follow the Dutch risk equalization scheme as closely as possible with the available data, we deviate from the risk equalization scheme in two ways. First, we use a different definition of neighborhood to compute neighborhood characteristics.[13] Second, while we include diagnoses for chronic conditions based on prescribed medicines, we do not include diagnoses based on hospital admissions and information on use of durable equipment in our estimation model due to data limitations. Nonetheless, we expect that differences between our predicted risk scores and actual risk scores are small.

Throughout our analysis we define regions by provinces. The Netherlands has 12 provinces with populations ranging from 380,000 to 3.7 million in the year 2018. We know the province of residence for the entire population of the Netherlands at each point of time based on the personal records database.[14] In our baseline analysis, we define movers as individuals whose province of residence on the first day of the year 1998 was different from their province of residence on the first day of the year 2018. Our definition of movers includes individuals who move at least once in the period between 1998 to 2018, and it does not include individuals who move back to the province where they were residing at the beginning of the year 1998. According to our definition, there are around 1.6 million movers in our sample. We denote the remaining population in

[12]Section B1 in the online Appendix describes our computation of risk scores in detail.

[13]In the risk equalization scheme, neighborhoods are defined by 4-digit ZIP codes. In our study, neighborhoods follow the definition of a neighborhood by Statistics Netherlands. The average size of neighborhoods is comparable for both definitions. In the year 2018, there were 4066 4-digit ZIP codes and 3086 neighborhoods according to the definition of Statistics Netherlands.

[14]When a person changes her address of residence, she has to notify the municipality. If a person fails to notify the municipality about a change of address then the municipality can impose a penalty. Registration is also necessary to obtain various municipal services such as for example parking permits

our sample as stayers.

Table 1 presents summary statistics separately for movers, stayers, and the entire sample. Healthcare costs are on average 21.8% lower for movers than for stayers, and risk scores are on average 22.3% lower.[15] This indicates that movers are on average healthier than stayers. The table also shows that compared to stayers, movers are on average younger, and better educated. Moreover, they are more likely to have work as main source of income, and they have higher average household incomes. However, movers are less likely to own their home.[16]

The maps displayed in Figure 1 show regional variation in healthcare costs (panel a) and risk scores (panel b) across provinces in the year 2018. In addition to provinces, the maps show only one city, Amsterdam. Average healthcare costs and risk scores are closely correlated across provinces.[17] Provinces in the Randstad region that are close to Amsterdam tend to have lower healthcare costs and risk scores, whereas provinces in peripheral regions far away from Amsterdam and the Randstad region tend to have higher healthcare costs and risk scores. Average healthcare costs in Limburg, a province in the South-Eastern corner of the Netherlands, are 23.6 percent higher than in Flevoland, a province directly to the East of Amsterdam. Risk scores are on average 18.8 percent higher in Limburg than in Flevoland. Figure A3 in the online Appendix presents a map of the Netherlands that shows the names and location of all provinces.

The maps presented in Figure 2 show population growth rates and internal mi-

[15]The average risk scores in our sample is 1.18. Since we exclude children born after the year 1998 from our sample who tend to have very low risk scores, the average risk score in our sample is above the population average of 1.

[16]We do not know the motives of movers in our sample. However, according to a representative survey of the Dutch population in the year 2021 the most common reasons to move house are changes in household composition (27%), a better home or location (21%), and employment (7%) (Stuart-Fox et al., 2022)

[17]Figure A2 in the online Appendix plots average risk scores against average healthcare costs across provinces. The R-squared is 0.961.

gration balances across provinces. Panel (a) shows population growth rates over the period 1998-2018 across provinces. Population tends to grow fast in provinces in the Randstad region close to Amsterdam, and it tends to grow slowly or, in the case of Limburg, even decline in peripheral provinces. Panel (b) shows net in-migration rates over the period from 1998 to 2018 as a share of the population in the year 1998. Patterns for population growth rates and internal migration balances tend to be similar.[18] Provinces in the Randstad region close to Amsterdam tend to have positive internal migration balances, e.g. more people are moving in than moving out, while provinces in peripheral regions tend to have negative migration balances, e.g. more people are moving out than moving in.

4 Methods

To assess the effect of internal migration on average healthcare costs of provinces, we compare actual average healthcare costs in provinces based on their current population with counterfactual average healthcare costs in the same provinces if there had been no internal migration. In the same way, we assess the effect of internal migration on healthcare needs, as measured by risk scores. We denote the effect of internal migration during the 1998 to 2018 period for a province j by TE_j. This effect can be written as the difference between a factual and a counterfactual average outcome:

$$TE_j = \bar{y}_j^F - \bar{y}_j^{CF} \tag{1}$$

[18]One exception is the province of Zuid-Holland to the South of Amsterdam, which combines fast population growth, a negative internal migration balance, and a strongly positive external migration balance.

Here, $\bar{y}_j^F$ is the average of the outcome variable in the year 2018 for the population that resided in province j on the first day of the year 2018, or formally

$$\bar{y}_j^F = \frac{1}{N_{j,2018}} \sum_i y_{i,2018} I_{j,2018} \tag{2}$$

where $N_{j,2018}$ is the population of province j on the first day of the year 2018, $y_{i,2018}$ is the outcome variable, either healthcare costs or risk score, of individual i in the year 2018, and $I_{j,2018}$ is a binary indicator that takes the value one if individual i lived in province j on the first day of the year 2018. We can calculate $\bar{y}_j^F$ directly from our data.

Similarly, $\bar{y}_j^{CF}$ denotes the average of the outcome variable for province j in the year 2018 without internal migration, or formally

$$\bar{y}_j^{CF} = \frac{1}{N_{j,1998}} \sum_i y_{i,2018}^{CF} I_{j,1998} \tag{3}$$

where $N_{j,1998}$ is the population of province j on the first day of the year 1998, $y_{i,2018}^{CF}$ is the counterfactual outcome of individual i in the year 2018 in the absence of internal migration, and $I_{j,1998}$ is a binary indicator that takes the value one if individual i lived in province j on the first day of the year 1998.

To compute the counterfactual average outcome $\bar{y}_j^{CF}$ we need to overcome two empirical challenges. First, we need to assign movers to the province in which they have resided on the first day of the year 1998. For stayers, their provinces of residence in the years 1998 and 2018 are the same.

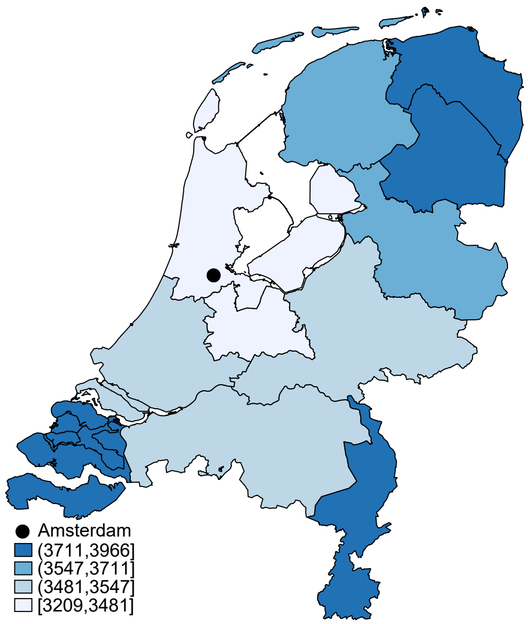
Table 1: Summary statistics

Variable	Movers		Stayers		Full Sample	
	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Healthcare Cost	2855.13	(9602.14)	3652.95	(10651.73)	3546.61	(10521.37)
Risk Score	0.94	(1.52)	1.21	(1.80)	1.18	(1.76)
Age	44.18	(15.97)	53.70	(18.03)	52.43	(18.06)
Female	0.52	(0.50)	0.51	(0.50)	0.51	(0.50)
Household Size	2.53	(1.36)	2.50	(1.28)	2.51	(1.29)
Household Income	52721.88	(72002.26)	49023.22	(62157.80)	49516.23	(63570.57)
Main Source of Income						
Employment and Self Employment	0.79	(0.41)	0.63	(0.48)	0.65	(0.48)
Social Benefits	0.07	(0.26)	0.08	(0.26)	0.08	(0.26)
Pensions	0.13	(0.33)	0.29	(0.45)	0.27	(0.44)
Students Grant	0.01	(0.11)	0.00	(0.04)	0.00	(0.05)
Capital Income	0.01	(0.08)	0.01	(0.08)	0.01	(0.08)
Home Ownership						
Own House	0.61	(0.49)	0.68	(0.47)	0.66	(0.48)
Rent without Housing Allowance	0.27	(0.44)	0.21	(0.40)	0.21	(0.41)
Rent with Housing Allowance	0.10	(0.31)	0.12	(0.32)	0.12	(0.32)
Institutional	0.02	(0.13)	0.02	(0.13)	0.02	(0.13)
Education Level†						
Basic Education	0.03	(0.18)	0.08	(0.27)	0.07	(0.26)
Vocational Training	0.39	(0.49)	0.58	(0.49)	0.55	(0.50)
College Degree	0.57	(0.50)	0.34	(0.47)	0.38	(0.49)
Number of Observations	1,620,746		10,538,474		12,159,220	

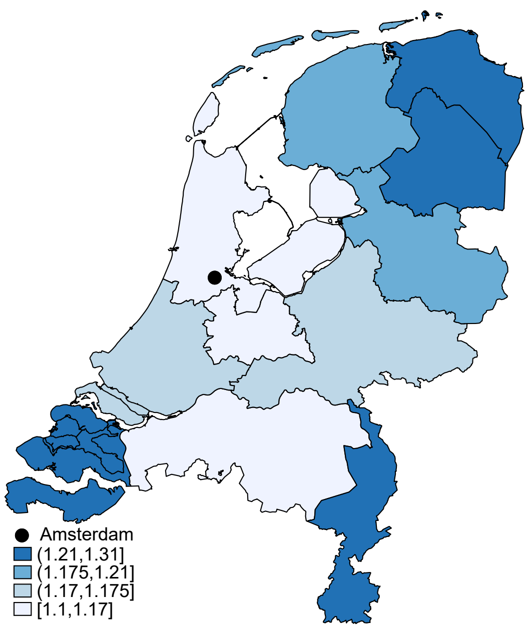
Note: Values are for the year 2018. Sample includes individuals whose data are available for the two years 1998 and 2018. Healthcare costs and household incomes are in Euro. Female, source of income, house ownership, and education level are binary indicators. †Education Level is not known for 5,107,652 individuals.

Figure 1: Regional variation in healthcare costs and risk scores in 2018

(a) Average healthcare costs



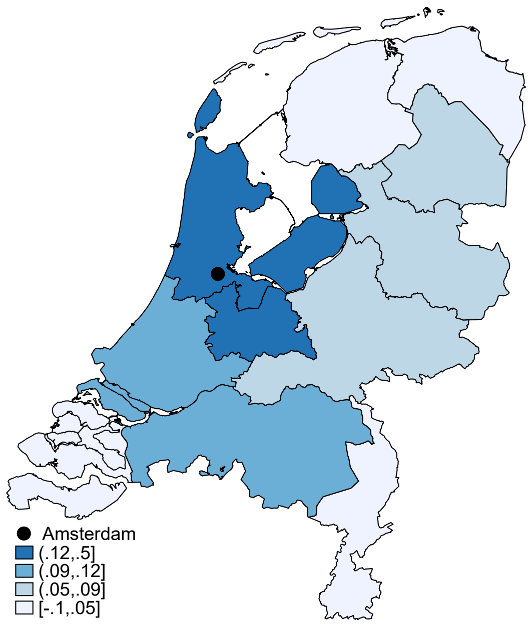
(b) Average risk score



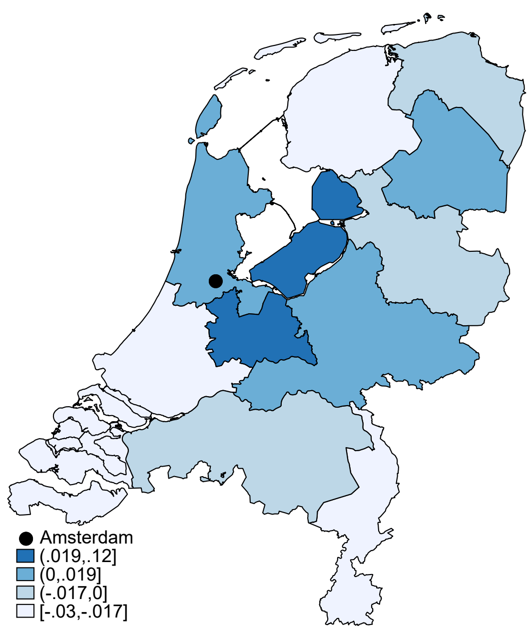
Note: The sample has 12.2 million observations. Values are for the year 2018. Healthcare costs are in Euro.

Figure 2: Population growth rate and net in-migration over the period 1998 to 2018

(a) Population growth rate (1998 - 2018)



(b) Net in-migrants as a share of 1998 population



Note: In panel (a) we use the entire population of provinces in the years 1998 and 2018 and the number of observations in panel (b) is 12.2 million.

Secondly, we need to compute $y_{i,2018}^{CF}$ for all individuals i. $y_{i,2018}^{CF}$ denotes what the counterfactual outcome of individual i in the year 2018 would have been if she had stayed in the province where she had resided at the beginning of the year 1998. Imagine a person who moved from Limburg to Flevoland. Then this move might have affected her healthcare costs by exposing her to a different practice style of local physicians, different access to medical facilities, and different health due to for example more local air pollution or better economic opportunities. Thus, the same person would incur different healthcare costs if she lived in a different province. Similarly, her risk score might also be affected by some of these factors, for example those that affect her health.

We refer to the combined effect of local conditions on outcome variables as place effects, and we denote γ_j as the place effect for province j. In order to compute the counterfactual outcome variable $y_{i,2018}^{CF}$ for individual i we need to adjust for place effects:

$$y_{i,2018}^{\mathrm{CF}} = y_{i,2018}(1 + \gamma_o - \gamma_d) \tag{4}$$

Here, $y_{i,2018}$ is the healthcare cost (or risk score) of individual i in year 2018. We denote the province of origin where i lived on the first day of the year 1998 as $j = o$, and the province of destination where i lives on the first day of the year 2018 as $j = d$. Outcome $y_{i,2018}$ depends on the place effect for province d, the individual's current place of residence. However, for estimating what the outcome variable for an individual would have been if she had stayed in her province of origin we need to adjust the outcome variable by subtracting place effects of the province of destination (γ_d) and adding the place effects of the province of origin (γ_o). For example, for a person who moved from Limburg to Flevoland, we need to subtract the place effect for Flevoland, and we need to add the place effect for Limburg. For non-movers, d and o are the same. Note that place effects in Equation 4 refer to place effects in the year 2018, not to place effects for example in the year of move.

Place effects cannot be directly observed. Thus, we need to estimate place effects γ_j for all provinces j in order to compute $y_{i,2018}^{CF}$ and ultimately TE_j, our main object of interest. We estimate place effects using an empirical approach employed by Finkelstein et al. (2016) and Moura et al. (2019) based on following persons who migrate across regions. We specify the estimation equation

$$\log(y_{it}) = \alpha_i + \gamma_j + \lambda_t + X_{it}\beta + I_{t-\tau_i}\zeta + \varepsilon_{it} \tag{5}$$

where y_{it} is either healthcare costs or risk score of individual i in year t, where $t \in [2010, ..., 2018]$. We add 1 to healthcare costs inside the logarithm operator since some individuals incur zero healthcare cost in a given year.[19] Individual fixed-effects (α_i) account for unobserved individual characteristics that do not change over time and are not affected by moving to a different province. Province fixed-effects (γ_j) represent place effects that affect all individuals living in province j. The province of residence j is defined as the province where an individual resides on the first day of year t. λ_t are year fixed-effects. Individual characteristics (X_{it}) include age and gender.[20] $I_{t-\tau_i}$ are indicators for the year relative to the year of move, where τ_i is the year in which individual i moved from one province to another. These indicators account for the direct impact of moving on outcome variables. For non-movers, the relative year of move is set to zero. The error term ε_{it} includes time-varying unobserved individual characteristics. In our estimation, we account for robust standard errors, clustered at the individual level.

[19] 515,153 out of 41.8 million observations (1.2%) have zero healthcare costs.

[20] Age is categorized in bins of 5 years. Gender and age interaction terms are included to account for non-linear effects of age, separately for men and women.

We can separately identify individual fixed-effects (α_i) and place effects (γ_j) because of the presence of movers in our sample. Only for movers, we observe the same individual in two different provinces. Place effects measure how outcome variables change if individuals move to a different province. The log specification of outcome variables in Equation 5 implies that α_i and γ_j shift outcome variables proportionally. Thus, we assume that place effects shift healthcare costs by the same factor for all individuals.[21] We also assume that γ_j are constant over time.[22]

In order to obtain unbiased estimates of place effects γ_j the exogeneity assumption below must be satisfied:

$$E(\varepsilon_{it}|\gamma_j, \alpha_i, \lambda_t, X_{it}, I_{t-\tau_i}) = 0 \tag{6}$$

Thus, ε_{it}, the time-varying individual-specific error term, must be mean-independent of α_i and all observed covariates. We discuss the exogeneity assumption and explore the robustness of our results in Section 5.2.

The sample used for estimating Equation 5 is not the same as shown in Table 1. For healthcare costs as outcome variable, we use a panel data set with annual observations for the period 2010 to 2018.[23] The sample consists of all movers and a 25 percent random sample of non-movers among the individuals who reside in the Netherlands in a given year with information on healthcare costs and province of residence.[24]

[21] We relax this assumption in robustness checks presented in Section 5.2.

[22] We use place effects for movers in the period between the years 2010 and 2018 to estimate the place effect in Equation 4, which refers to the year 2018. We relax this assumption in a robustness check presented in Section 5.2.

[23] 2010 is the first year for which individual healthcare costs are available in our data. We adjust healthcare costs for inflation with 2018 as base year, using the inflation adjustment deflator for healthcare cost in the Netherlands provided by EUROSTAT.

[24] The definition of movers for estimating Equation 5 is different from the definition of movers in Table 1. In the sample for estimating place effects, movers are defined as persons who change their province of residence exactly once during the estimation period. Movers who change their province of residence more than once are omitted from the sample.

Our estimation sample consists of 41.8 million observations. For risk scores as outcome variable, we use a panel data set with annual observations for the period 2013 to 2018. The sample consists of all movers and non-movers who reside in the Netherlands in a given year with information on healthcare costs and province of residence. The sample consists of 96.3 million observations. The estimation period is shorter for risk scores than for healthcare costs, since for computing risk scores we need information on healthcare costs in the three previous years.

Table 2 shows estimates of place effects γ_j and their standard deviation for our two outcome variables, healthcare costs and risk scores. The provinces with the lowest place effects, Noord-Brabant for healthcare costs and Zeeland for risk scores, serve as reference category. For healthcare costs, provinces in the Randstad area close to Amsterdam (Flevoland, Noord-Holland, Utrecht, and Zuid-Holland) have higher place effects than provinces in peripheral regions. Flevoland has the highest place effect of 0.103, which implies that moving from Noord-Braband, the reference category, to Flevoland increases healthcare costs by 10.3%. It is remarkable that place effects tend to be highest for provinces with low average healthcare costs.[25] One possible explanation for this finding is that people in Randstad provinces tend to be very healthy, but conditional on their health they receive more healthcare services than people in peripheral provinces. For risk-scores as outcome variable, coefficients tend to be smaller, and patterns are less easily interpretable. Place effects are highest for the provinces of Groningen, Overijsel, and Zuid Holland. Thus, living in these provinces tends to increase risk scores the most.

[25] Average healthcare costs of provinces are shown in Table 3.

Table 2: Place effects for provinces

Province	Place Effects for Log Healthcare Cost	Place Effects for Log Risk Score
Drenthe	0.035	0.028
	(0.008)	(0.005)
Flevoland	0.103	0.021
	(0.007)	(0.004)
Friesland	0.038	0.028
	(0.007)	(0.004)
Gelderland	0.015	0.018
	(0.005)	(0.004)
Groningen	0.031	0.071
	(0.007)	(0.004)
Limburg	0.039	0.015
	(0.006)	(0.004)
Noord-Brabant	-	0.016
	-	(0.004)
Noord-Holland	0.064	0.024
	(0.005)	(0.004)
Overijssel	0.043	0.034
	(0.006)	(0.004)
Utrecht	0.068	0.030
	(0.005)	(0.004)
Zeeland	0.042	-
	(0.008)	-
Zuid-Holland	0.071	0.032
	(0.005)	(0.004)

Note: Column 1 presents estimates of province fixed-effects (γ_j) using logarithm of (healthcare cost +1) as outcome variable in Equation 5. Column 2 presents estimates of province fixed-effects (γ_j) using logarithm of risk score as outcome variable in Equation 5. Robust standard errors, clustered at the individual level, in parenthesis. The lowest value of place effects is chosen as the base category for the two regressions. The province of Noord-Brabant is the base category in Column 1 and the province of Zeeland is the base category in Column 2. Number of observations for column 1 is 41.8 million, and for column 2 it is 96.3 million.

5 Results

5.1 Effects on healthcare costs

Figure 3 presents the main results for our baseline analysis for healthcare costs. Results for risk scores are presented in Section 5.4. The horizontal axis in the figure represents average healthcare costs per person for care included in the basic health insurance package in the year 2018. The vertical axis shows the effect of internal migration during the 1998 to 2018 period on average healthcare costs in the year 2018, computed based on Equation 1. The dots shown in the scatterplot represent the 12 provinces of the Netherlands and one dot for the entire country.

Internal migration tends to increase average healthcare costs in provinces in the periphery of the Netherlands, and it tends to decrease average healthcare costs in provinces in the Randstad region. The province with the highest positive effect on the vertical axis is Zeeland, a province in the periphery of the Netherlands. Average healthcare costs in Zeeland in the year 2018 are Euro 110.30 (or 3.0% of total costs) higher than they would have been in the absence of internal migration during the 1998 to 2018 period. The province with the strongest negative effect is Flevoland, a province in the Randstad region. Average healthcare costs in Flevoland in the year 2018 are Euro 111.15 (or 3.5% of total costs) lower than they would have been in the absence of internal migration.[26]

Internal migration increases regional inequality in healthcare costs. If we fit a regression line through the dots for provinces in Figure 3, the resulting slope parameter is 0.28.[27] Thus, for a province with Euro 100 higher average healthcare costs,

[26]Effect sizes and their standard deviations for all 12 provinces are presented in Table 3.

[27]In computing parameters for the regression line, we do not take the dot for the entire country into account, neither in Figure 3 nor in other figures.

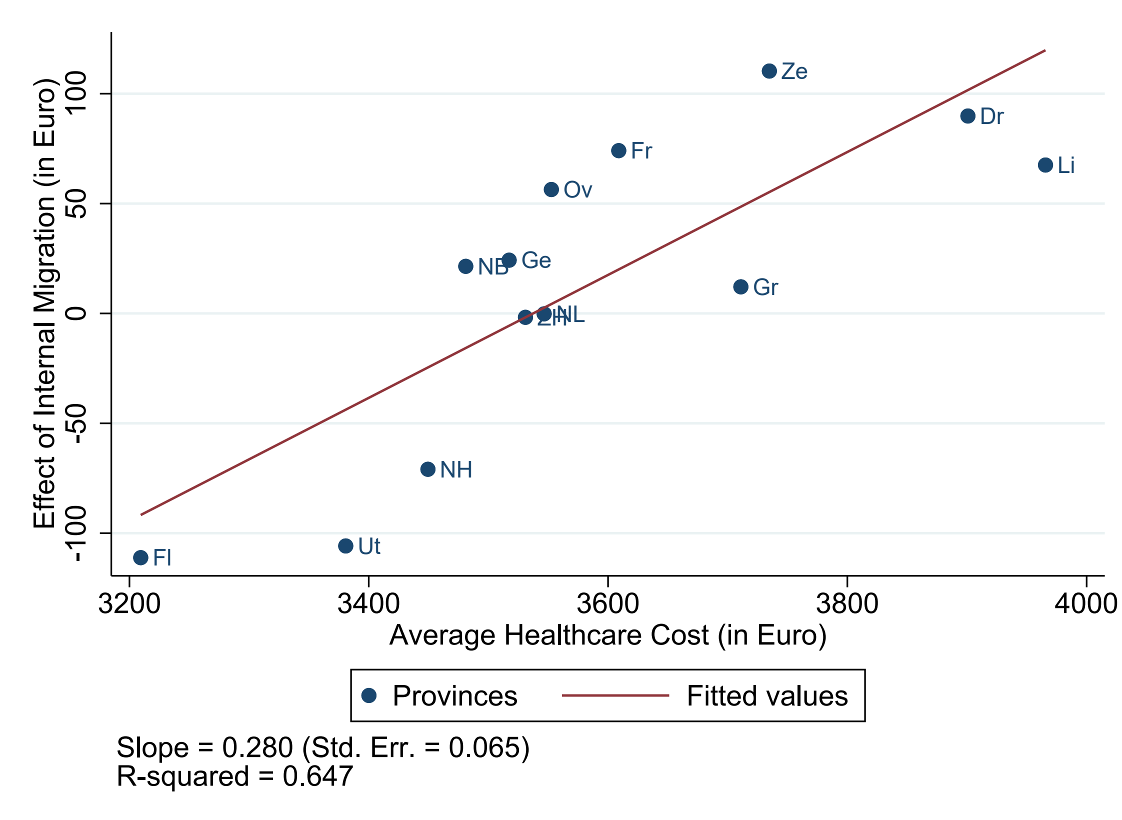
the predicted effect of internal migration is Euro 28. Hence, 28% of the difference in average healthcare costs between provinces in the year 2018 can be attributed to internal migration between the years 1998 and 2018. The slope of the regression line is significantly different from zero at the 1 percent level,[28] and the R-squared of the regression line is 0.647, indicating a close fit between average healthcare costs and the effects of internal migration on healthcare costs across provinces.

5.2 Robustness

In this subsection we discuss whether the assumptions underlying our empirical approach are plausible and whether our results are robust to alternative specifications of our empirical model. Specifically, we first discuss whether the exogeneity assumption is satisfied, and we then explore the robustness of our results if we allow for heterogeneous place effects, for province-specific post-move trends, and for alternative specifications of place effects and the outcome variable. Subsequently, we examine the effects of internal migration during a shorter time period, between the years 2010 and 2018, and finally we explore for this shorter time period whether our results are sensitive to the inclusion of spillover effects of internal migration on stayers. We find that our results are robust to all alternative specifications.

[28] When computing standard errors for the slope parameter of the regression line, we need to take into account that the effect of internal migration for each province is an estimate and thus a random variable. Therefore, we correct standard errors based on a method suggested by Hanushek (1974). The method is explained in Section B2 in the online Appendix. Standard errors with and without correcting for the randomness of the effect of internal migration are almost the same. This holds for all results presented in this study. Critical values for determining statistical significance are based on a t-distribution with 10 degrees of freedom.

Figure 3: Effect of internal migration on average healthcare costs



Note: Number of observations is 12.2 million. Average healthcare cost is based on the year 2018. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Exogeneity assumption

In order to obtain unbiased estimates of place effects, the exogeneity assumption stated in Equation 6 must be satisfied. Thus, the time-varying individual-specific error term must be mean independent of unobserved individual fixed-effects and observed covariates, including province fixed-effects, year fixed-effects, age, gender, and year relative to the year of move. This exogeneity assumption is not violated if movers are healthier than stayers or if healthy people tend to move to specific provinces, as long as unobserved individual-specific health (or other unobserved individual-specific determinants of healthcare costs) are constant over time.

However, the exogeneity assumption can be violated if the decision to move is correlated with changes in unobserved individual-specific characteristics, e.g. if people with declining health are more (or less) likely to move. In order to account for possible pre-trends of movers we estimate a specification of Equation 5, in which we account for years relative to the year of move not only for years after, but also for years before the move. Results are shown in panel (a) of Figure A4 in the online Appendix, and they are very similar compared to the baseline specification in Figure 3.

While this specification accounts for pre-trends that differ between movers and stayers, it does not account for pre-trends that differ between movers to and from specific provinces. In order to examine whether such different pre-trends affect our estimation results, we apply two robustness checks. In a first robustness check, we compare outcome variables after the move with outcomes alternatively 1, 2, or 3 years before the move.[29] In this way we examine whether our results are robust to the point of time at which we measure pre-move outcomes. Results are shown in Figure A4 panel (b) to (d) in the online Appendix, and they are similar to the baseline specification.

In a second robustness check, we estimate alternative specifications where we restrict data for movers to observations within a time window of 1, 2, or 3 years around the year of move. If we restrict data to a shorter time window around the year of move, then observations dating from many years before the move will not be considered in our estimation, and province-specific pre-trends will have less influence on our estimates of place effects. Results are shown in Figure A4 panel (e) to (g) in the online Appendix, and they are also similar to the baseline specification.

[29] The estimation equation for these specifications is identical to Equation 5, but we restrict the sample for movers to all periods after the move and alternatively 1, 2, or 3 years before the move.

Heterogeneous place effects

In Equation 5 we assume that place effects are identical for all individuals in the same province. However, it is possible that place effects differ, for example between young and old people or between persons with and without a chronic health condition. For example, if patients with chronic health conditions receive more intensive treatment in one province compared to other provinces, then this does not necessarily imply that patients without chronic health conditions also receive more intensive treatment in this province. In order to test whether our results are robust to specifications with heterogeneous place effects, we estimate the following model that adds an interaction term between place effects and a group indicator to Equation 5:

$$y_{it} = \alpha_i + \gamma_j + \gamma_j \times G_i + \lambda_t + X_{it}\beta + I_{t-\tau_i}\zeta + \varepsilon_{it} \tag{7}$$

Variables are defined in the same way as in Equation 5. The only addition is an interaction term between place effects and a group indicator ($\gamma_j \times G_i$). G_i is a binary indicator whether individual i belongs to a specific group. In our analysis, we consider the following groups: 1) Persons above age 50 and persons age 50 or below in the year 2018, 2) Persons with above and below median healthcare costs in the year 2010 (or the first year that they are in our data) relative to their province of residence in this year, and 3) persons with and without chronic health conditions based on the use of pharmaceuticals in the year 2018. We estimate group-specific place effects, and we use these group-specific place effects to compute counterfactual outcomes for movers according to Equation 4. Scatter plots showing the effect of internal migration on healthcare costs allowing for heterogeneous place effects are presented in Figure A4, panel (h) to (j) in the online Appendix. Results are similar to the baseline specification.

Direction of move

Place effects might differ not only between groups in the population, but they can also depend on the direction of move and the specific combination of the province of origin and the province of destination. For example, persons who move from Limburg to Flevoland might be different from persons who move from Flevoland to Limburg, and their corresponding place effects might also differ. We extend the model presented in Equation 5 by including indicators for specific combinations of provinces of origin and destination:

$$y_{it} = \alpha_i + \gamma_{od} + \lambda_t + X_{it}\beta + I_{t-\tau_i}\zeta + \varepsilon_{it} \tag{8}$$

Here, γ_{od} is a binary indicator that takes value 1 after individual i has moved from province o to province d. Other variables are defined as in Equation 5. Using estimated values of γ_{od}, we adjust healthcare costs for movers similar to Equation 4, and we compute the effect of internal migration on average healthcare costs in all provinces.[30] We present these results in panel (k) of Figure A4 in the online Appendix. Results are similar to the baseline specification.

Province-specific post-move trends

Our baseline model in Equation 5 includes indicators for the year relative to the year of move. This accounts for the direct effect of moving on healthcare costs in the year of move or thereafter, as long as this effect does not depend on the specific province of destination. However, it is possible that movers adjust only slowly to the new conditions in the province of destination. In order to account for province-specific post-move trends, we estimate an alternative model which includes interaction terms

[30] Equation 4 is replaced by $y^{\mathrm{CF}}_{i,2018} = y_{i,2018}(1 - \gamma_{od})$.

between province fixed-effects and indicators for the year relative to the year of move, $\gamma_j \times I_{t-\tau_i}$.[31] Results are shown in Figure A4 panel (l) in the online Appendix, and they are similar to the baseline specification.

Movers after the year 2015 only

In the baseline specification, we employ all persons who move to a different province between the years 2010 and 2018 to estimate place effects for the year 2018 that we insert in Equation 4. In a robustness check, we estimate place effects only based on persons who move to a different province in the year 2015 or later, and thus close to the year 2018. Results are shown in Figure A4 panel (m) in the online Appendix, and they are similar to the baseline specification.

Alternative specification of outcome variable

As additional robustness check, we estimate Equation 5 using the level of healthcare costs instead of the logarithm of healthcare costs as outcome variable. Instead of assuming that place effects shift healthcare costs proportionally by a constant factor, we now assume that place effects shift healthcare costs by a constant amount.[32] A scatter plot using these estimates is shown in Figure A4 panel (n) in the online Appendix. Results are similar to the baseline specification.

Migration during shorter period

Next, we examine the effect of internal migration during a shorter period, between the years 2010 and 2018, on average healthcare costs of provinces. Hence, we assign movers

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[31] For persons who move between provinces several times during the 1998-2018 period, we assign the years since move for the last move. For persons who live in the same province in both years 1998 and 2018 there is no adjustment for place effects, as in Equation 4.

[32] For this specification, we replace Equation 4 by $y_{i,2018}^{\mathrm{CF}} = y_{i,2018} + \gamma_o - \gamma_d$.

to the province where they resided at the beginning of the year 2010, the first year for which individual healthcare costs are available in our data. Fewer persons move between provinces during a shorter time period, and hence we expect that effect sizes are smaller if we study migration during a shorter time period. This is also what we find in panel (o) of Figure A4 in the online Appendix. Otherwise, our results show similar patterns for internal migration during the 2010-2018 and the 1998-2018 periods. For both periods, internal migration tends to increase healthcare costs in peripheral provinces, and it tends to decrease healthcare costs in Randstad provinces.

Spillover effects on stayers

Our research question focuses on the effect of population sorting through internal migration on average healthcare costs of provinces. This does not include spillover effects of migration on the local population of stayers.[33]

However, we explore in a robustness check whether our results are sensitive to the inclusion of spillover effects from internal migration. For this, we examine the effect of internal migration during the 2010-2018 period since individual healthcare costs are available in our data only starting from the year 2010. We start with regressing changes in average healthcare costs of stayers during the 2010 to 2018 period across provinces on net in-migration rates of provinces as a share of their 2010 population. Results are shown in Figure A5 in the online Appendix. There is only a weak and insignificant negative correlation between net internal in-migration rates and changes in healthcare costs of stayers across provinces.

In the next step, we adjust healthcare costs of stayers in each province based on

[33]For example, Aygün et al. (2021) and Giuntella et al. (2018) estimate spillover effects of external migration on the native population.

the changes predicted by the fitted regression line in Figure A5 in the online Appendix. Results are shown in Figure A4 panel (p) in the online Appendix. Results are overall similar to the baseline specification for the short migration period in panel (o). This suggests that our results are robust even if we account for the correlation between changes in healthcare costs of stayers and net internal migration balances.

Summary of robustness checks

In summary, our results are remarkably robust to alternative specifications. For example, slope coefficients of fitted regression lines for specifications that examine the effect of internal migration during the 1998 to 2018 period (panels (a) to (n) of Figure A4 in the online Appendix) range from 0.252 to 0.286, which is similar to the slope coefficient in the baseline specification of 0.280. Thus, different approaches to estimate place effects make little difference for our results. Smaller effect sizes for internal migration during the 2010 to 2018 period do not imply a lack of robustness, but a weaker response to a smaller dose of the treatment.

5.3 Decomposition Analysis

Next, we examine the underlying mechanisms why population sorting through internal migration affects average healthcare costs in provinces. There can be two possible mechanisms: 1) Movers are on average healthier than stayers, as seen in Table 1. Therefore, net in-migration tends to decrease average healthcare costs in a province, while net out-migration tends to increase average healthcare costs. 2) There can be selective migration: in some provinces, in-migrants have lower average healthcare costs than out-migrants, while in other provinces, in-migrants have higher average healthcare costs than out-migrants.

Formally, we can decompose the total effect of internal migration into the effect of net in-migration and the effect of selective migration based on the equation below:

$$\bar{y}_j^F - \bar{y}_j^{CF} = \frac{N_j^{\text{IN}} - N_j^{\text{OUT}}}{N_{j,1998}}(\bar{y}_j^{\text{IN}} - \bar{y}_j^F) + \frac{N_j^{\text{OUT}}}{N_{j,1998}}(\bar{y}_j^{\text{IN}} - \bar{y}_j^{\text{OUT}}) \tag{9}$$

where $\bar{y}_j^F - \bar{y}_j^{CF}$ is the total effect of internal migration on healthcare costs in province j, as in Equation 1. N_j^{IN} is the number of persons who move into province j from another province during the period from the year 1998 to 2018. N_j^{OUT} is the number of persons who move out of province j to another province during the period from the year 1998 to 2018. $N_{j,1998}$ is the population in province j in the year 1998. $\bar{y}_j^{\text{IN}}$ are average healthcare costs in the year 2018 of in-migrants in province j. $\bar{y}_j^{\text{OUT}}$ are average healthcare costs in the year 2018 of out-migrants out of province j. Healthcare costs of out-migrants are adjusted according to Equation 4.

The first summand in Equation 9 is the net in-migration rate times the difference in average costs between in-migrants and the full population. We denote this term as the effect of net in-migration. The second summand in Equation 9 is the out-migration rate times the difference between the average healthcare costs of in-migrants and the adjusted average healthcare costs of out-migrants. We denote this term as the effect of selective migration.

Table 3 shows average healthcare costs, the total effect of internal migration, the effect of net in-migration, and the effect of selective migration for all 12 provinces. The effect of selective migration tends to dominate the effect of net in-migration. For example, for the the province with the largest positive total effect, Zeeland, the total effect is Euro 110.30, of which Euro 106.72 can be attributed to the effect of selective migration and Euro 3.58 Euro to the effect of net in-migration. For the province with the strongest negative total effect, Flevoland, the total effect is minus Euro 111.15, of which minus Euro 78.90 can be attributed to the effect of selective migration, and minus Euro 32.25 can be attributed to the effect of net in-migration. Compared to effect sizes, their standard deviations tend to be very small.[34]

Figure 4 provides more evidence on selective migration. The horizontal axis in the figure represents average healthcare costs in the year 2018. The vertical axis shows the difference in average healthcare costs in the year 2018 between in-migrants and out-migrants, $\bar{y}_j^{\mathrm{IN}} - \bar{y}_j^{\mathrm{OUT}}$, for persons who moved to another province during the 1998 to 2018 period. The dots shown in the scatterplot represent the 12 provinces of the Netherlands plus one dot for the entire country. Figure 4 shows that $\bar{y}_j^{\mathrm{IN}} - \bar{y}_j^{\mathrm{OUT}}$ tends to be positive for provinces with above average healthcare costs, and it tends to be negative for provinces with below average healthcare costs. Selection effects can be very large. For example, for Zeeland average healthcare costs are Euro 715.24 higher for in-migrants than for out-migrants. In contrast, for Noord Holland, average healthcare costs are Euro 484.22 lower for in-migrants than for out-migrants.[35]

In summary, the results of our decomposition analysis suggest that selective migration of high-cost individuals into provinces with high average healthcare costs and of low-cost individuals into provinces with low average healthcare costs is the main mechanism behind the effect of internal migration on regional inequality in healthcare costs.

[34] TE_j is a linear combination of observed variables and estimated place effects for the province of origin and the provinces of destination, $\hat{\gamma}_o$ and the $\hat{\gamma}_d$'s. Thus, the variance of TE_j is a linear combination of the variance of $\hat{\gamma}_o$, the variances of the $\hat{\gamma}_d$'s, and their covariances. We weight the $\hat{\gamma}_d$'s according to the number of movers out of province o who migrated into province d. The standard deviation of the effect of selective migration is the same as the standard deviation of TE_j, and the effect of net in-migration is not a random variable.

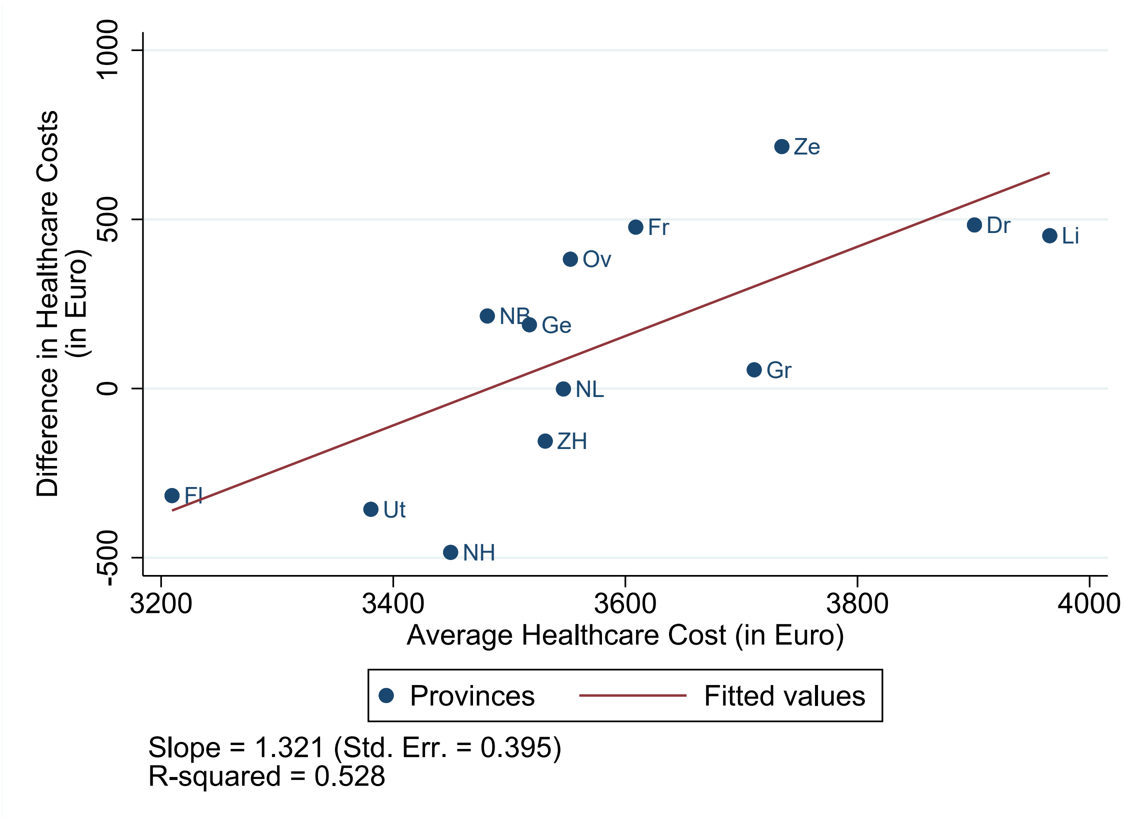
[35] Numbers are presented in Table A2 in the online Appendix.

Table 3: Decomposition analysis for healthcare cost

Province	**Average Healthcare Cost (2018)**	**Total Effect (Std. Dev.)**	**Effect of Net In-Migration (Std. Dev.)**	**Effect of Selective Migration (Std. Dev.)**
Drenthe	3900.76	89.84 (0.00141)	-7.48 (-)	97.32 (0.00141)
Flevoland	3209.42	-111.15 (0.00169)	-32.25 (-)	-78.90 (0.00169)
Friesland	3608.95	74.08 (0.00102)	6.78 (-)	67.30 (0.00102)
Gelderland	3517.33	24.24 (0.00071)	-3.39 (-)	27.63 (0.00071)
Groningen	3711.00	12.10 (0.00129)	1.10 (-)	11.00 (0.00129)
Limburg	3965.62	67.53 (0.00065)	23.67 (-)	43.86 (0.00065)
Noord-Brabant	3481.07	21.42 (0.00051)	0.71 (-)	20.71 (0.00051)
Noord-Holland	3449.45	-70.93 (0.00061)	-11.96 (-)	-58.97 (0.00061)
Overijssel	3552.64	56.39 (0.00082)	3.55 (-)	52.84 (0.00082)
Utrecht	3380.75	-105.82 (0.00097)	-32.81 (-)	-72.01 (0.00097)
Zeeland	3734.82	110.30 (0.00127)	3.58 (-)	106.72 (0.00127)
Zuid-Holland	3530.97	-1.77 (0.00054)	15.60 (-)	-17.37 (0.00054)

Note: Values are in Euro. The standard deviation for the total effect is the same as that of the effect of selective migration because only the effect of selective migration is a random variable. The effect of net in-migration is not a random variable. The sample includes 12.2 million observations.

Figure 4: Difference in healthcare costs between in-migrants and out-migrants by province



Note: The vertical axis shows the difference between average healthcare costs of in-migrants and adjusted average healthcare costs of out-migrants. The sample includes 1,620,746 observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

5.4 Effects on risk scores

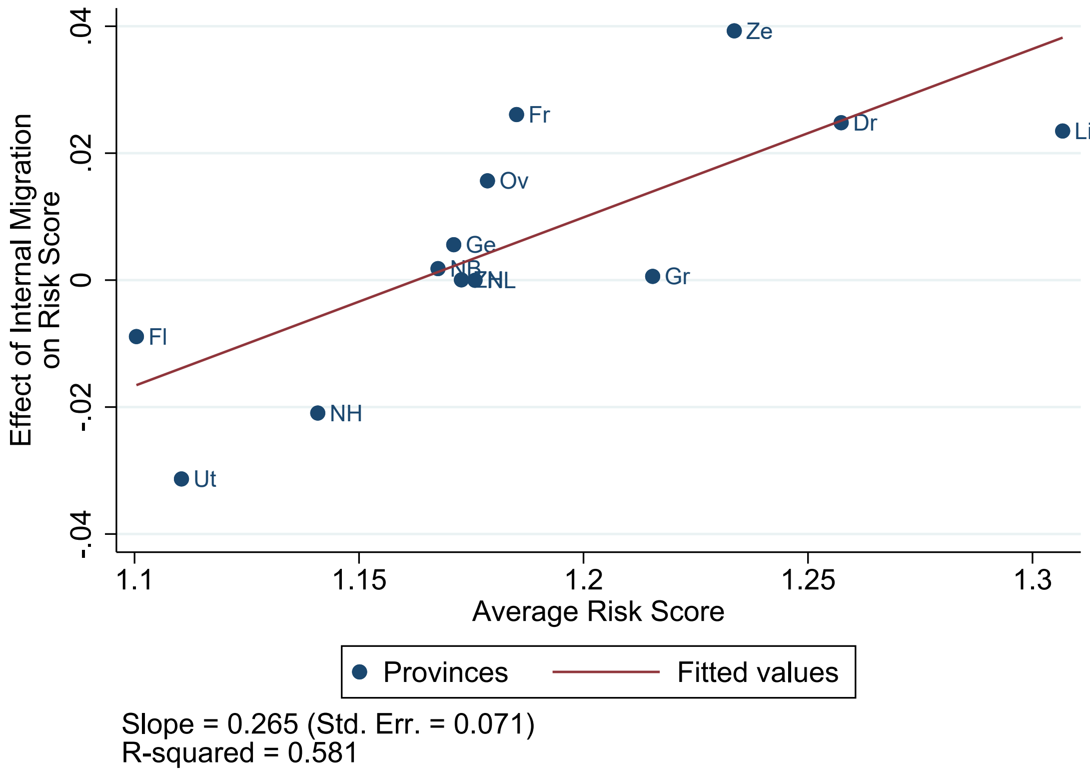
After showing results for healthcare costs, we now turn to our second outcome variable, risk scores. Figure 5 presents results. The horizontal axis represents average risk scores. The vertical axis shows the effect of internal migration on risk scores, computed according to Equation 1. The dots shown in the scatterplot represent the 12 provinces of the Netherlands plus one dot for the entire country.

Results for risk scores are overall similar to results for healthcare costs shown in Figure 3. Internal migration tends to increase risk scores in provinces with above average risk scores, and it tends to decrease risk scores in provinces with below average risk scores. If we fit a regression line through the dots for provinces in Figure 5, the resulting slope coefficient is 0.265, which is significantly different from zero at the 1 percent level. Thus, 26.5% of regional variation in risk scores across provinces can be attributed to internal migration during the 1998-2018 period.

Robustness checks for risk scores as outcome variable are shown in Figures A6 and A7 in the online Appendix. These robustness checks are the same that we discussed for healthcare costs as outcome variable in Section 5.2. Our results are robust to alternative specifications. For example, slope coefficients in Figure A6 range from 0.245 to 0.269 for internal migration during the 1998-2018 period.

Table A3 in the online Appendix shows results for our decomposition analysis with risk scores as outcome variable. The effect of selective migration dominates the effect of net in-migration not only for healthcare costs, but also for risk scores as outcome variable. Additional results for the components of the decomposition analysis are shown in Table A4 and Figure A8 in the online Appendix.

Figure 5: Effect of internal migration on average risk scores



Note: The sample includes 12.2 million observations. Average risk scores are computed for the year 2018. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

5.5 Does the Dutch risk equalization scheme compensate for the effects of internal migration?

Finally, we assess to what degree the effects of internal migration can be explained by demographics, e.g. the age and gender of movers to different provinces, and whether the Dutch risk equalization scheme is able to compensate for the effect of internal migration on regional differences in healthcare costs. For this purpose, we adjust healthcare costs either for age and gender, or for differences in risk scores, and we estimate the effect of internal migration on adjusted healthcare costs. To obtain adjusted healthcare costs we use residuals from regressing individual healthcare costs on either 1) indicators for 5-year age bins interacted with gender, or 2) risk scores. We then repeat our analysis based on these adjusted healthcare costs as outcome variable.[36]

Figure 6 presents the effects of internal migration during the 1998-2018 period on adjusted healthcare costs. Panel (a) shows results after adjusting healthcare costs for age and gender. The slope coefficient of the fitted regression line is 0.143 which is significantly different from zero at the 1 percent level. Thus, the share of variation in healthcare costs across provinces that can be attributed to internal migration over the 1998 to 2018 period is 14.3% after adjusting healthcare costs for demographics, compared to 28% for unadjusted healthcare costs (see Figure 3). Hence, demographics can explain around half of the effect of internal migration on regional variation in healthcare costs, whereas the other half is explained by individual characteristics of movers other than age and gender.

[36]Formally, we replace Equation 4 by $y^{\mathrm{CF}}_{i,2018} = (\bar{y}^F + \hat{\epsilon}_{i,2018})(1 + \hat{\gamma}_o - \hat{\gamma}_d)$, where $\bar{y}^F$ is the national average of healthcare costs in the year 2018, $\hat{\epsilon}_{i,2018}$ is a residual from regressing individual healthcare costs $y_{i,2018}$ on either 1) indicators for 5-year age bins interacted with gender, or 2) risk scores, and other variables are as defined in Section 4. Place effects are the same both in the analysis with adjusted healthcare costs and with unadjusted healthcare costs.

Panel (b) of Figure 6 shows results after adjusting healthcare costs for risk scores. Even after adjusting for risk scores, internal migration tends to increase healthcare costs in provinces with above average healthcare costs, and it tends to decrease healthcare costs in provinces with below average healthcare costs. The slope coefficient of the fitted regression line is 0.085 which is significantly different from zero at the 5 percent level.

Table 4 presents effects of internal migration during the 1998-2018 period separately for each province. Outcome variables are alternatively standard healthcare costs, healthcare costs adjusted for age and gender, and healthcare costs adjusted for risk score. Patterns differ between provinces. For some provinces, adjustment for risk scores reduces effect sizes, but they remain sizable even after adjustment (e.g. Drenthe and Utrecht). For other provinces, effect sizes are close to zero after adjustment for risk scores (e.g. Friesland and Limburg). For yet other provinces, effects become stronger after adjusting for risk score (e.g. Noord-Brabant and Zuid-Holland), or the sign of the effect reverses (e.g. Groningen).

If the Dutch risk equalization scheme would fully compensate for the effects of internal migration then the remaining effects after adjusting for risk scores should be zero for all provinces. However, this is not the case, and effect sizes remain sizable for several provinces. Even after risk adjustment, internal migration increases costs in provinces such as Drenthe and Noord-Brabant, and it decreases costs in provinces such as Flevoland and Utrecht. Thus, the Dutch risk equalization scheme compensates only partially, but not fully for the effect of internal migration on regional differences in healthcare costs.

The Dutch risk equalization scheme already includes a regional component. Our findings suggest that this regional component could be further improved in an effort to more fully compensate for the effects of internal migration. This would require redirecting funds from provinces in the Randstad regions to some provinces outside the Randstad region.

6 Conclusion

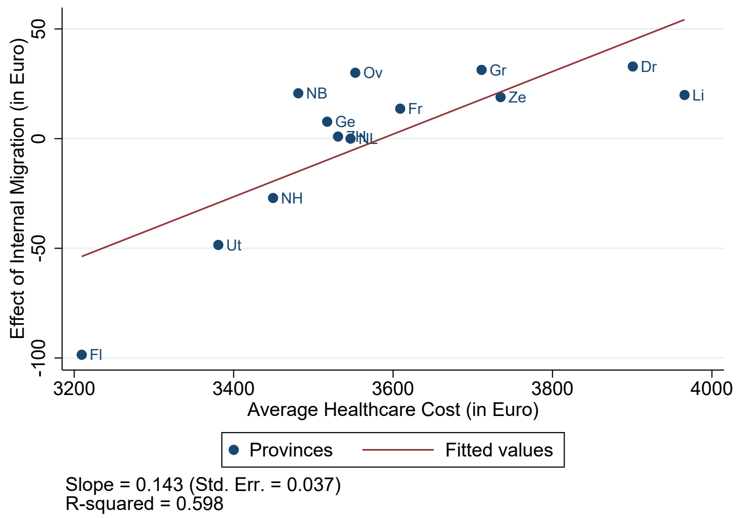
Large regional disparities in health and healthcare costs are well documented in many countries, but the underlying causes why such disparities arise are still not fully understood. In this study, we show, for the case of the Netherlands, that population sorting through internal migration can explain a substantial share of this variation. This is a new explanation that, to the best of our knowledge, has not been provided before.

We compute the effect of population sorting through internal migration on average healthcare costs and average healthcare needs in Dutch provinces by comparing actual outcomes with counterfactual outcomes if there had been no internal migration. To compute counterfactual outcomes, we assign persons to provinces where they have lived in the past, and we estimate what healthcare costs and needs of movers would have been if they had stayed in their province of origin by adjusting their outcomes for place effects. We estimate place effects based on a movers approach.

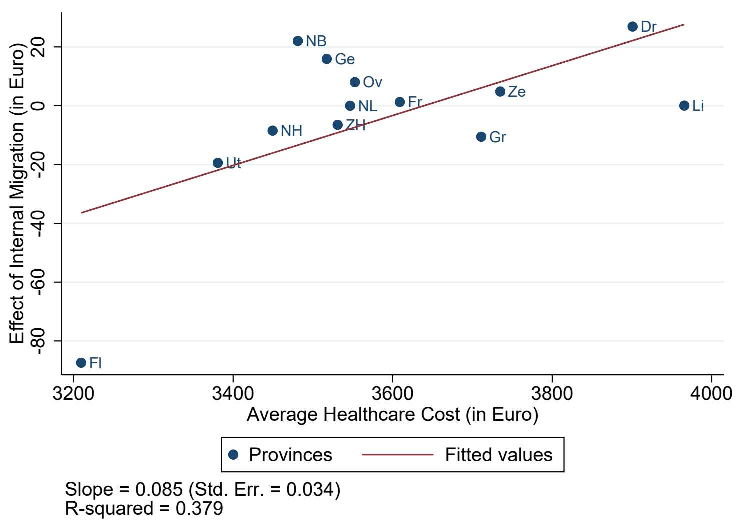
We find that internal migration increases average healthcare costs for provinces in the periphery by up to 3%, and it decreases average healthcare costs for provinces in the highly urbanized Randstad region by up to 3.5%. These effects can mainly be attributed to selective migration: in peripheral provinces, healthcare costs are substantially higher for in-migrants than for out-migrants, while in Randstad provinces, healthcare costs are substantially lower for in-migrants than for out-migrants. Internal migration during the 1998-2018 period explains 28% of regional variation in healthcare costs. We find similar results for risk scores, a measure of healthcare needs.

Figure 6: Effect of internal migration during the 1998 to 2018 period on healthcare costs after adjusting for demographics and risk score

(a) After adjusting for age and gender



(b) After adjusting for risk score



Note: The sample includes 12.2 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Table 4: Effect of internal migration during the 1998 to 2018 period on healthcare costs, adjusting for age & gender and risk score

Province	Total Effect (a)	Effect after adjusting for Age and Gender (b)	Ratio after adjusting for Age and Gender (b)/(a)	Effect after adjusting for Risk Score (c)	Ratio after adjusting for Risk Score (c)/(a)
Drenthe	89.84 (0.00141)	32.89 (0.00141)	0.37	26.93 (0.00141)	0.30
Flevoland	-111.15 (0.00169)	-98.55 (0.00169)	0.89	-87.41 (0.00169)	0.79
Friesland	74.08 (0.00102)	13.65 (0.00102)	0.18	1.27 (0.00102)	0.02
Gelderland	24.24 (0.00071)	7.73 (0.00071)	0.32	15.92 (0.00071)	0.66
Groningen	12.10 (0.00129)	31.33 (0.00129)	2.59	-10.54 (0.00129)	-0.87
Limburg	67.53 (0.00065)	19.91 (0.00065)	0.30	0.04 (0.00065)	0.00
Noord-Brabant	21.42 (0.00051)	20.67 (0.00051)	0.97	22.03 (0.00051)	1.03
Noord-Holland	-70.93 (0.00061)	-27.05 (0.00061)	0.38	-8.48 (0.00061)	0.12
Overijssel	56.39 (0.00082)	30.02 (0.00082)	0.53	8.01 (0.00082)	0.14
Utrecht	-105.82 (0.00097)	-48.46 (0.00097)	0.46	-19.44 (0.00097)	0.18
Zeeland	110.30 (0.00127)	18.93 (0.00127)	0.17	4.83 (0.00127)	0.04
Zuid-Holland	-1.77 (0.00054)	0.95 (0.00054)	-0.54	-6.49 (0.00054)	3.66

Note: The effects are in Euro. Number of observations is 12.2 million. Standard deviations in parenthesis.

Finally, we find that effect sizes remain sizable even after we adjust healthcare costs for demographics or risk scores. Our results are robust to alternative specifications.

Our study has important policy implications. Internal migration increases healthcare costs and needs in peripheral provinces in the Netherlands. Addressing such needs imposes challenges on the delivery of healthcare services. Equipment, facilities, and personnel need to be procured, and funding for healthcare services needs to be provided. Our results indicate that the Dutch risk equalization scheme only partially compensates for the effect of internal migration on regional differences in healthcare costs. It might be desirable to adjust the regional component in the Dutch risk equalization scheme in order to direct more funding to some provinces outside the Randstad region to more fully compensate for the effects of internal migration.

While our study focuses on the Netherlands, the patterns we document might be equally or even more important in other countries. Many countries experience a brain drain away from economically disadvantaged regions such as East Germany, Southern Italy, Northern England, or West Virginia and Mississippi in the United States to prosperous urban centers. Our results show that population sorting through internal migration can have a noticeable impact on healthcare needs in economically disadvantaged regions, and they highlight the importance of addressing these needs even if average healthcare costs in economically disadvantaged regions are already above the national average.

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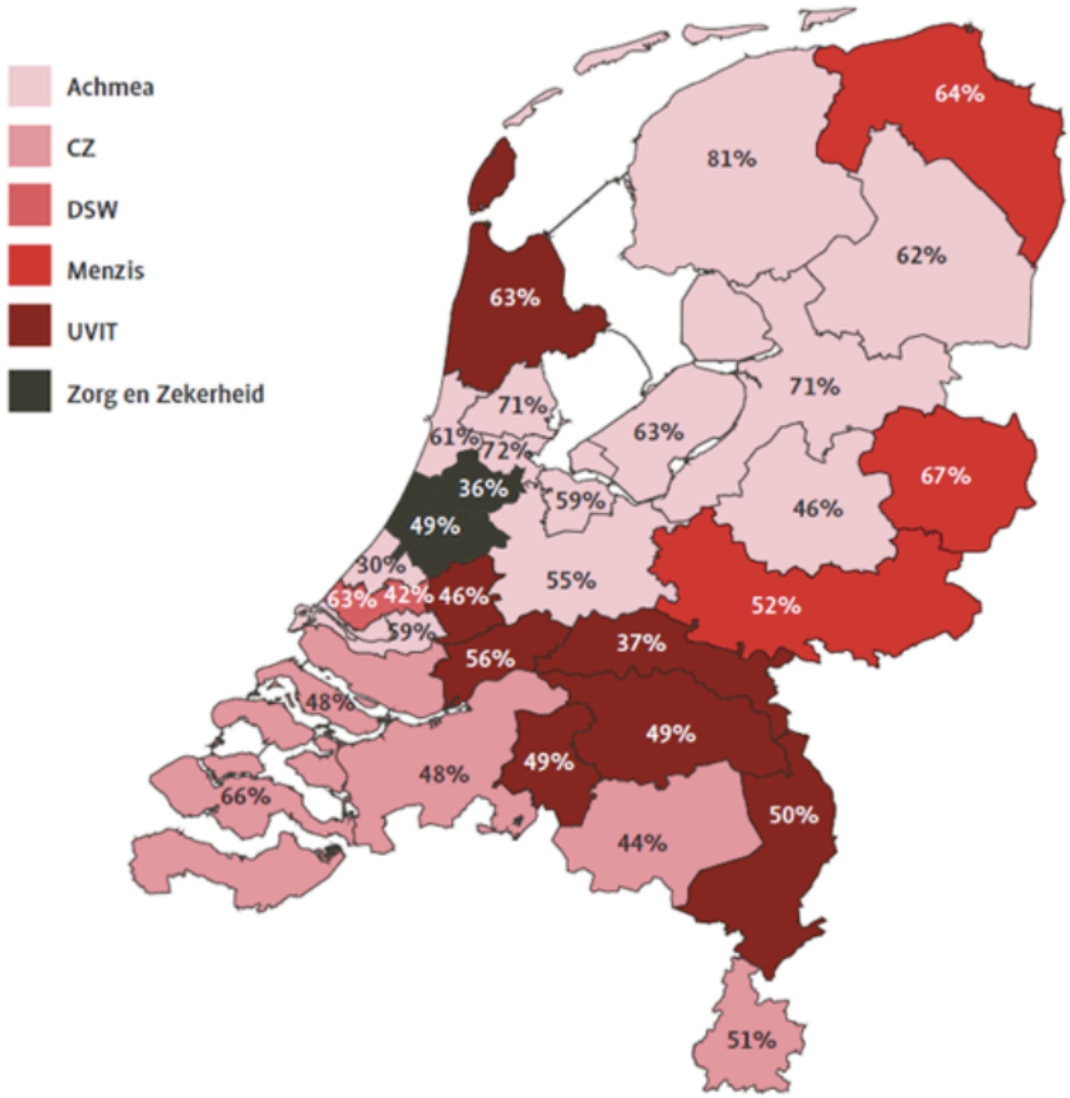
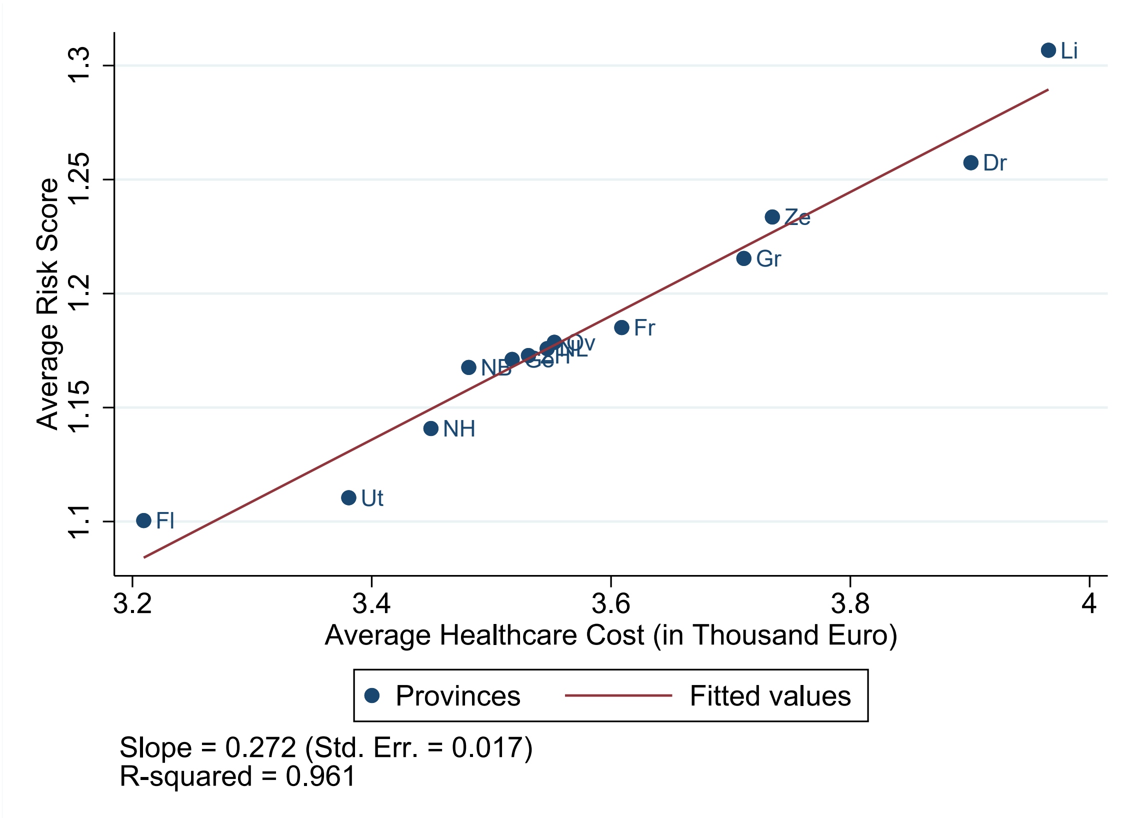
Appendix A

Figure A1: Insurers with largest market share in the region



Source: Pharmaceutical Key Figures Foundation, Pharmaceutical Weekly (2011), Volume 146 No. 46/47

Figure A2: Correlation between average healthcare costs and average risk scores across provinces in the year 2018



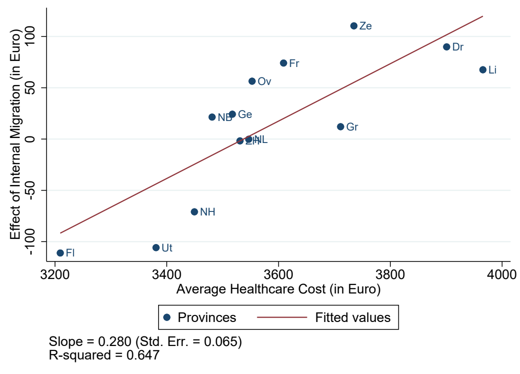
Note: The sample includes 12.2 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Figure A3: Map with location of provinces

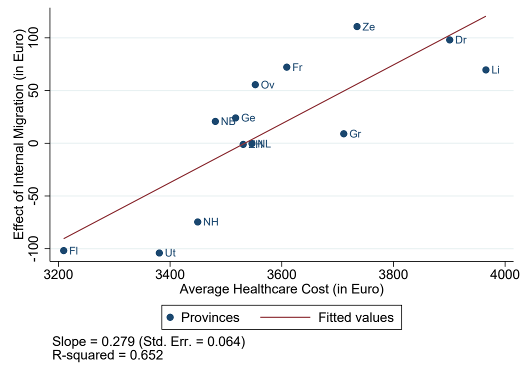
Note: Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Figure A4: Effect of internal migration on average healthcare cost

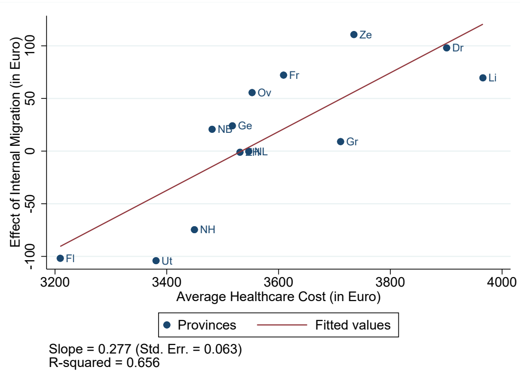
(a) Place effects calculated including pre-trends



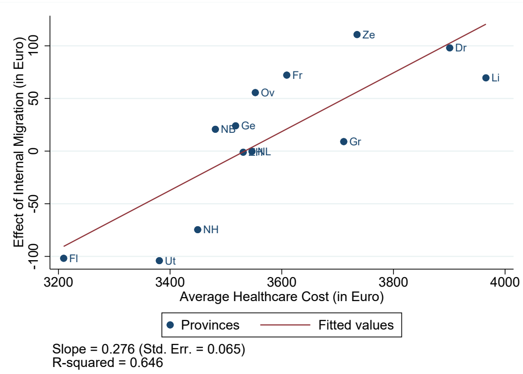
(b) Place effects calculated by including pre-trends for 1 year before the move



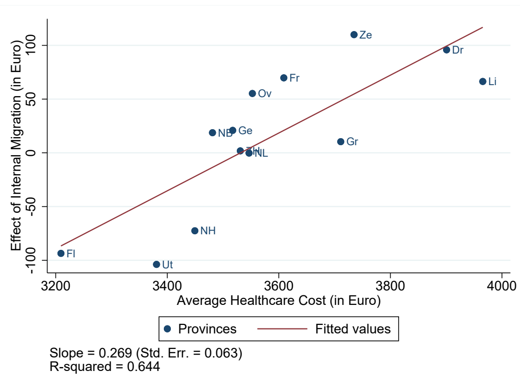
(c) Place effects calculated by including pre-trends for 2 years before the move



(d) Place effects calculated by including pre-trends for 3 years before the move



(e) Place effects calculated by restricting sample for movers to 1 year around the move



(f) Place effects calculated by restricting sample for movers to 2 years around the move

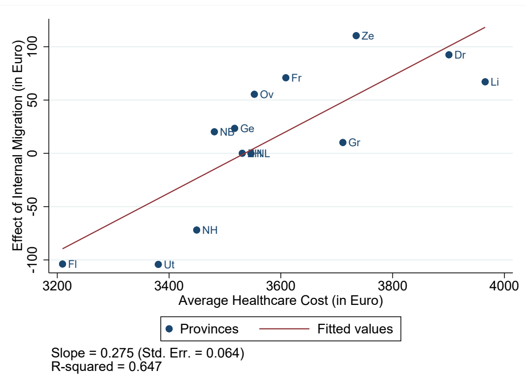
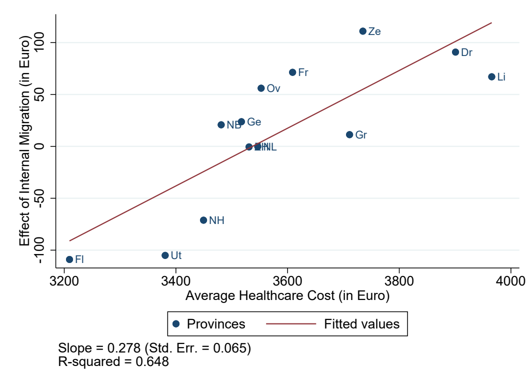
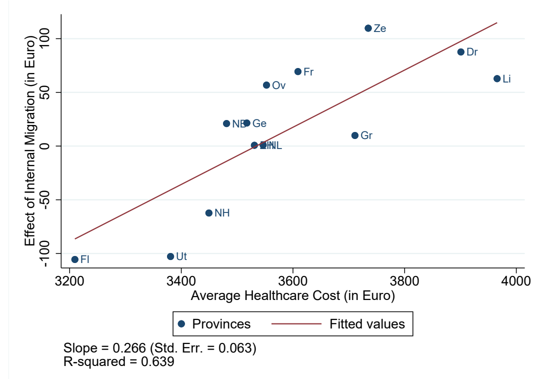


Figure A4: Effect of internal migration on average healthcare cost (contd.)

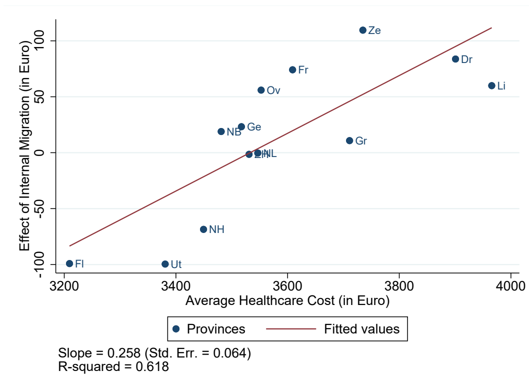
(g) Place effects calculated by restricting sample for movers to 3 years around the move



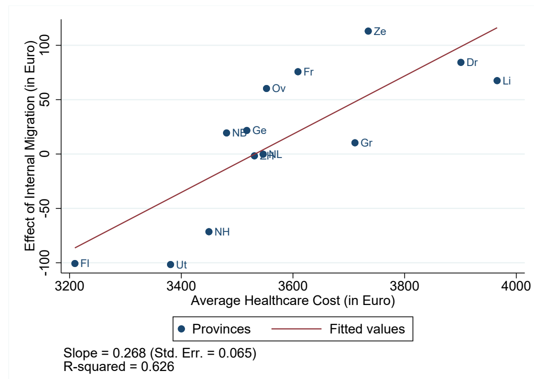
(h) Heterogeneous place effects by age above and below 50



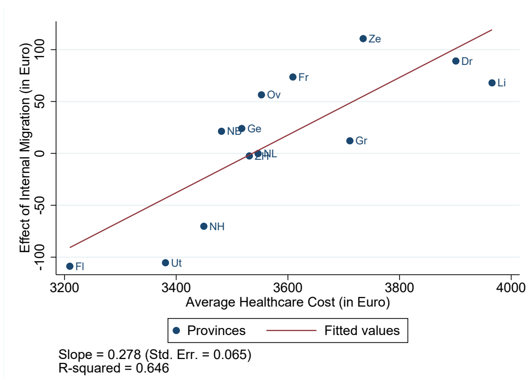
(i) Heterogeneous place effects by healthcare costs above and below median



(j) Heterogeneous place effects for patients with and without chronic health conditions



(k) Adjusted for direction of move



(l) Place effects based on province-specific post-trends

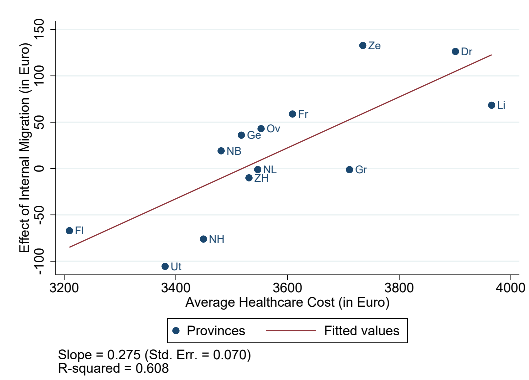
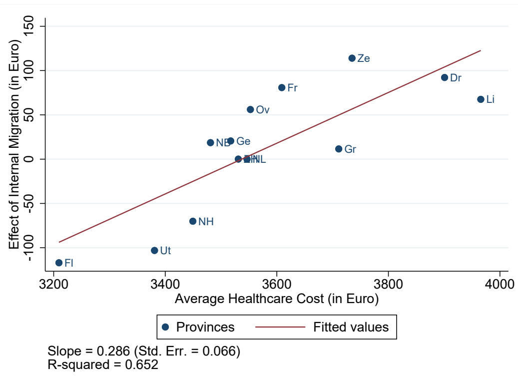
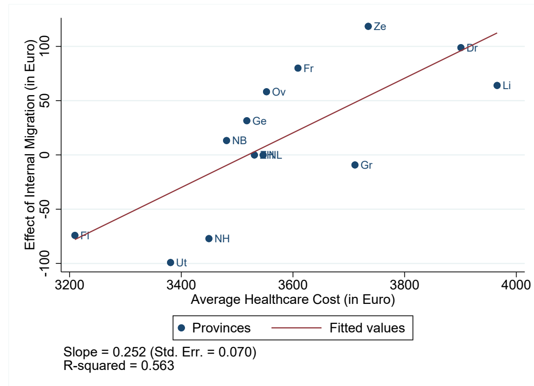


Figure A4: Effect of internal migration on average healthcare cost (contd.)

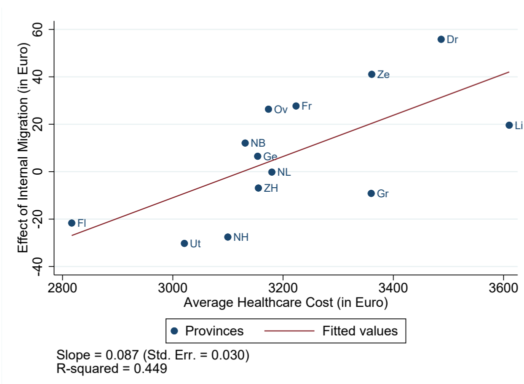
(m) Place effects based on movers post 2014



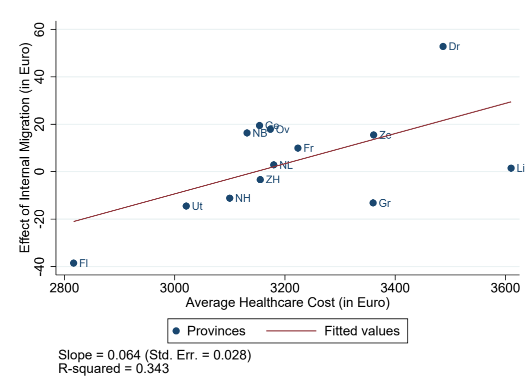
(n) Place effects based on level regression



(o) Effect of internal migration during 2010 to 2018 period

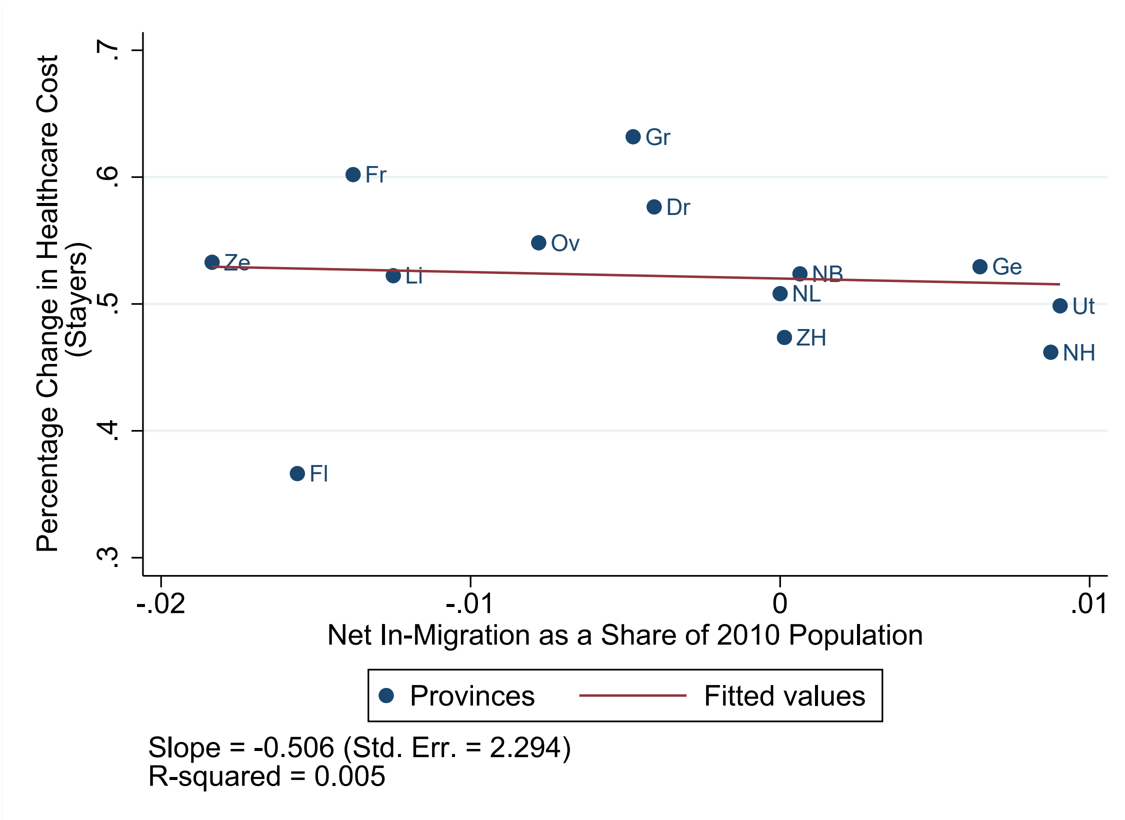


(p) Adjusted for spillover effect during 2010 to 2018 period



Note: Sample comprises of 12.2 million observations, except for panel (o) and (p) which are constructed for a sample of 14.7 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

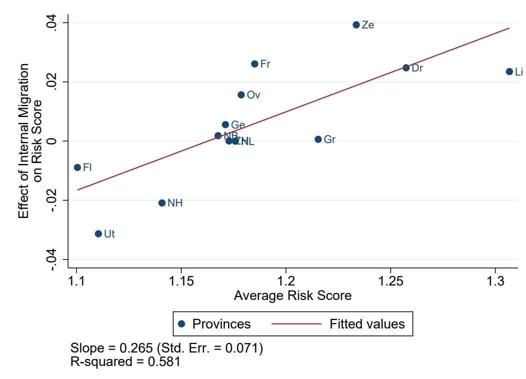
Figure A5: Correlation between the percentage change in healthcare costs of stayers from 2010 to 2018 and the net in-migration rate of provinces during the 2010 to 2018 period as a share of 2010 population



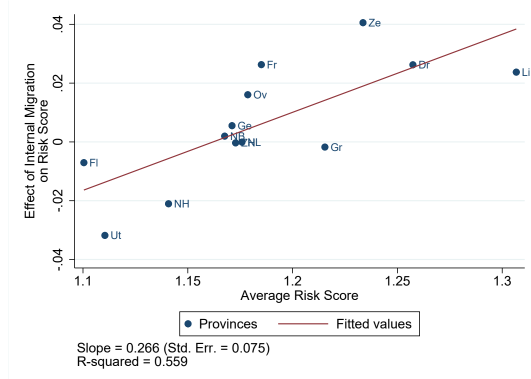
Note: The sample includes 14.7 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Figure A6: Effect of internal migration on average risk score

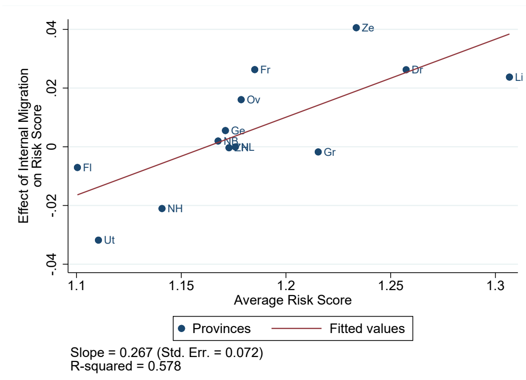
(a) Place effects calculated by including pre-trends



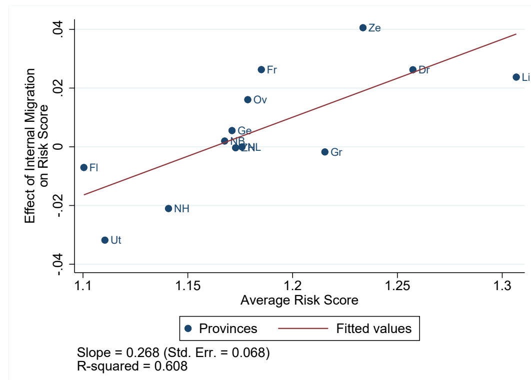
(b) Place effects calculated by including pre-trends for 1 year before the move



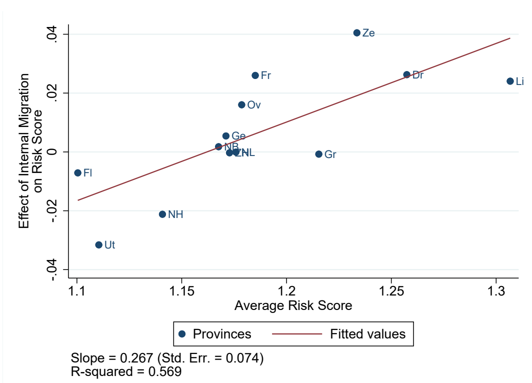
(c) Place effects calculated by including pre-trends for 2 years before the move



(d) Place effects calculated by including pre-trends for 3 years before the move



(e) Place effects calculated by restricting sample for movers to 1 year around the move



(f) Place effects calculated by restricting sample for movers to 2 years around the move

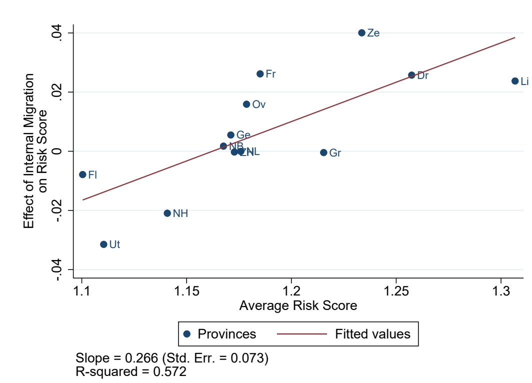
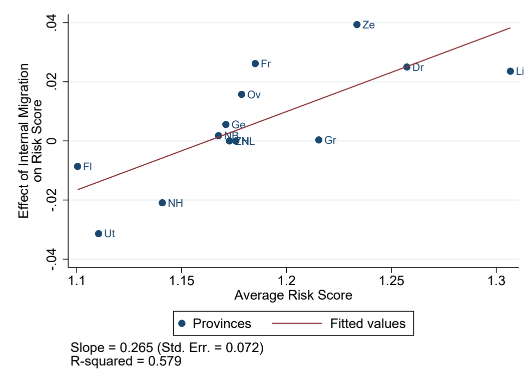
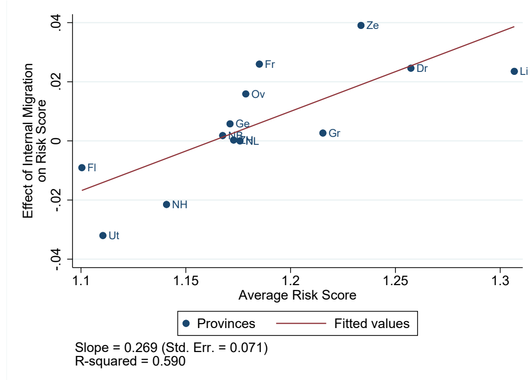


Figure A6: Effect of internal migration on average risk score (contd.)

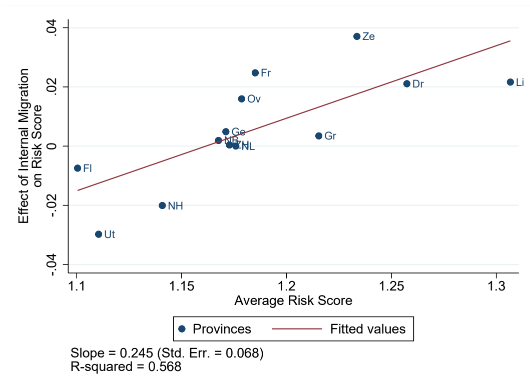
(g) Place effects calculated by restricting sample for movers to 3 years around the move



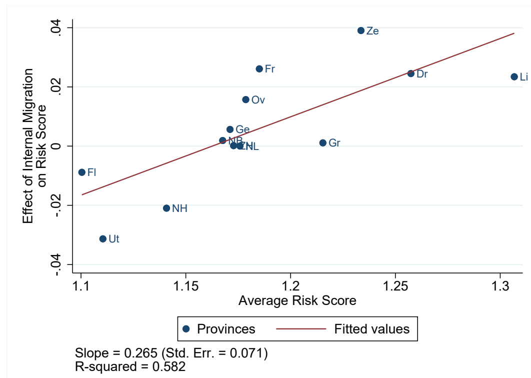
(h) Heterogeneous place effects by age above and below 50



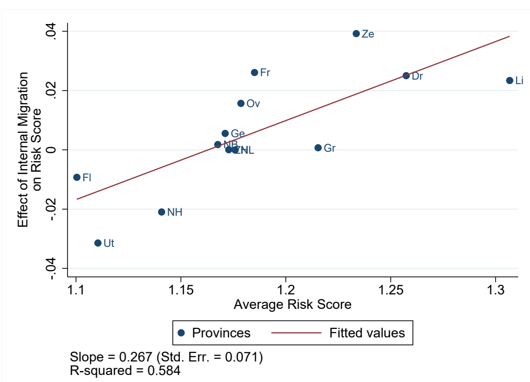
(i) Heterogeneous place effects by risk score (above and below median risk score)



(j) Heterogeneous place effects for patients with and without chronic health conditions



(k) Adjusted for direction of move



(l) Place effects based on province-specific post-trends

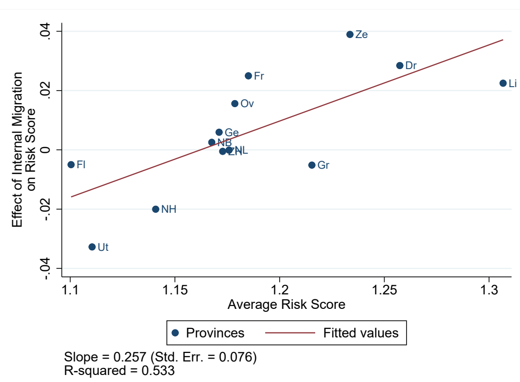
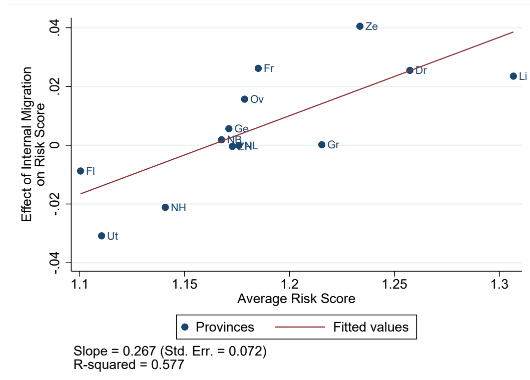
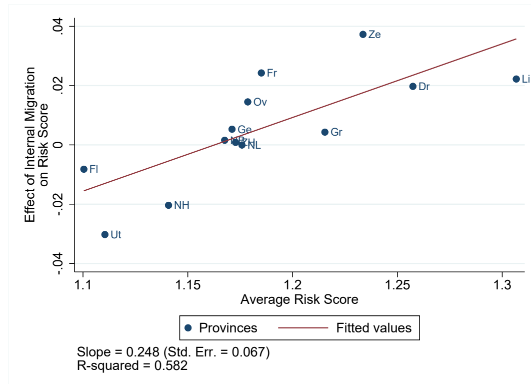


Figure A6: Effect of internal migration on average risk score (contd.)

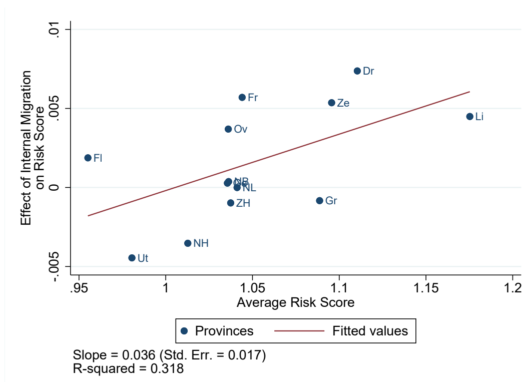
(m) Place effects based on movers post 2015



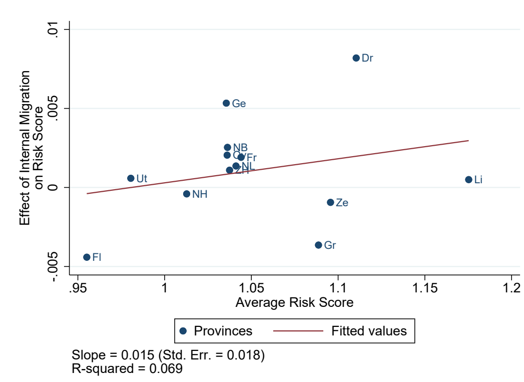
(n) Place effects based on level regression



(o) Effect of internal migration during 2013 to 2018 period

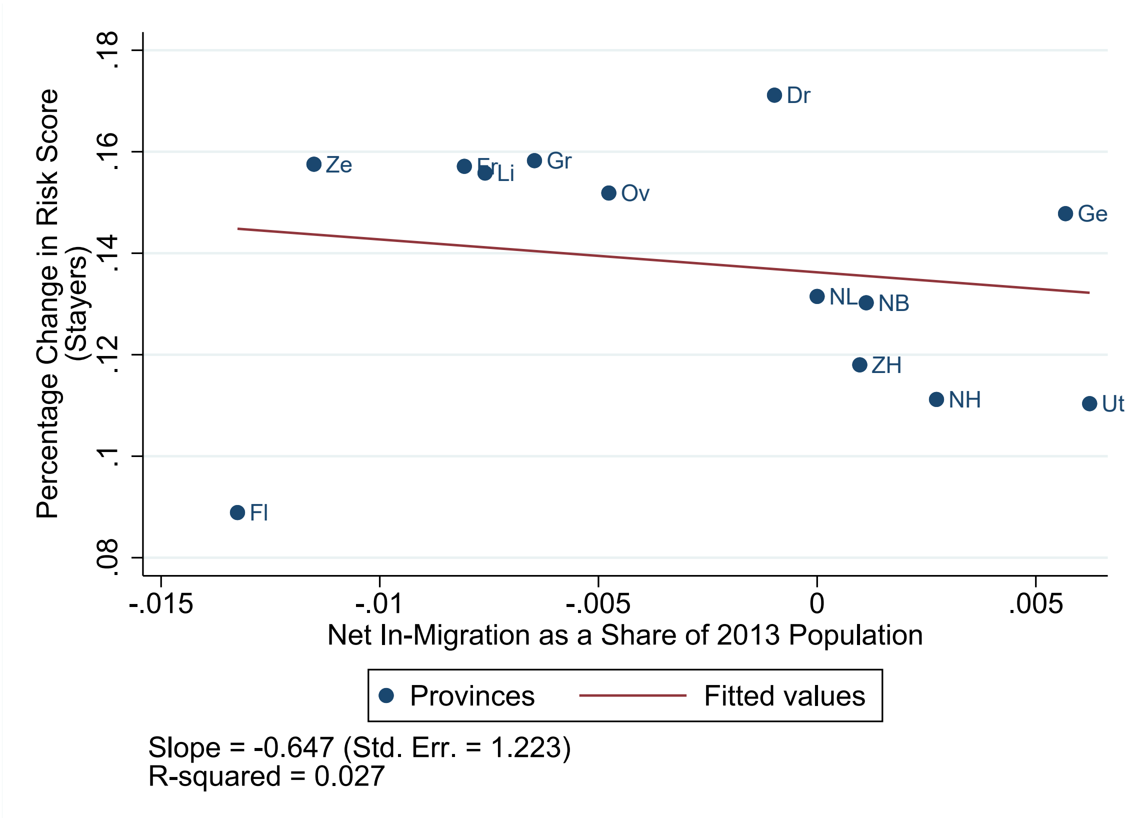


(p) Adjusting for spillover effects during 2013 to 2018 period



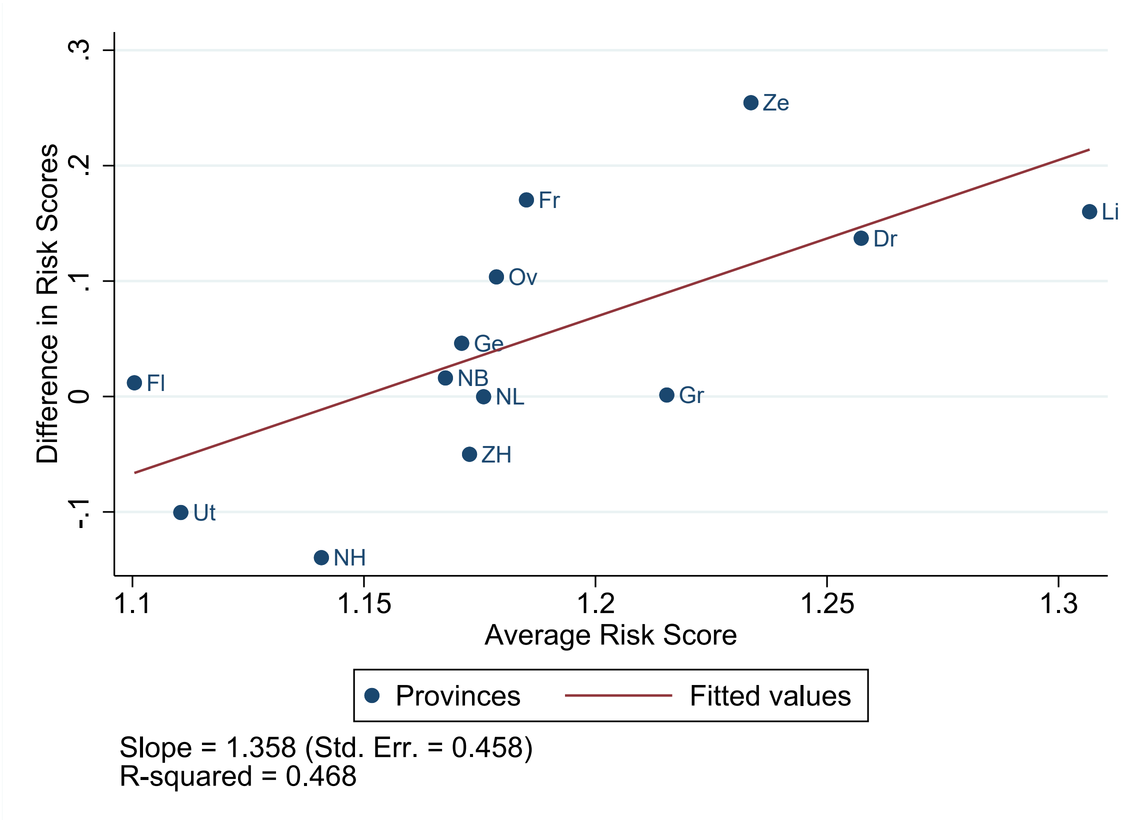
Note: Sample comprises of 12.2 million observations, except for panel (o) and (p) which are constructed for a sample of 15.1 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Figure A7: Correlation between the percentage change in risk score of stayers from 2013 to 2018 and the net in-migration rate of province as a share of 2013 population



Note: the sample includes 15.1 million observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Figure A8: Difference in risk scores between in-migrants and out-migrants by province



Note: The vertical axis shows the difference between average risk scores of in-migrants and adjusted average risk scores of out-migrants. The sample includes 1,620,746 observations. Dr: Drenthe, Fl: Flevoland, Fr: Friesland, Ge: Gelderland, Gr: Groningen, Li: Limburg, NB: Noord-Brabant, NH: Noord-Holland, NL: Netherlands, Ov: Overijssel, Ut: Utrecht, Ze: Zeeland, and ZH: Zuid-Holland.

Table A1: Data availability for the period 1998 to 2018

Description	Observations
Population of Netherlands in 2018	**17,181,084**
Province 2018 is unknown	-5,844
Province 2018 is known	**17,175,240**
Healthcare Cost or Risk Score is not known	-220,970
Healthcare Cost and Risk Score is known	**16,954,270**
Healthcare Cost is Negative or Outlier	-406
Sample to be used	**16,953,864**
Province 1998 is not known	-4,794,644
1. Born after 1998	*3,778,187*
2. Outside Netherlands in 1998	*950,067*
3. Not registered at the Municipality in 1998	*66,390*
Sample used for analysis	**12,159,220**

Note: The three points in italics describe the reason for not having the 1998 province code of the individuals.

Table A2: Individual components for decomposition analysis (healthcare costs)

Province	**Total Effect**	**Population (1998)**	**Net In Migration (1998-2018)**	**Difference in Healthcare Cost Movers & Population (2018)**	**Out-Migrants (1998-2018)**	**Difference in Healthcare Cost In-movers and Out-movers**
Drenthe	89.84	360423	6730	-400.39	72549	483.49
Flevoland	-111.15	241576	28417	-274.17	60215	-316.52
Friesland	74.08	486643	-8872	-372.00	68655	477.01
Gelderland	24.24	1490658	8048	-628.34	218470	188.52
Groningen	12.10	430424	-554	-855.92	85542	55.33
Limburg	67.53	851202	-25099	-802.72	82643	451.77
Noord-Brabant	21.42	1827498	-2001	-650.14	176461	214.46
Noord-Holland	-70.93	1913672	25883	-883.88	233089	-484.22
Overijssel	56.39	836846	-6247	-475.27	115684	382.22
Utrecht	-105.82	875364	34347	-836.13	179019	-357.00
Zeeland	110.30	278771	-5084	-196.07	41597	715.24
Zuid-Holland	-1.77	2566143	-55568	-720.30	286822	-155.42

Note: Total Effect, Difference in Healthcare Cost, and Effect of Selective Migration in Euro. Number of observations is 12.2 million.

Table A3: Decomposition analysis for risk score

Province	**Average Risk Score (2018)**	**Total Effect (Std. Dev.)**	**Effect of Net In-Migration (Std. Dev.)**	**Effect of Selective Migration (Std. Dev.)**
Drenthe	1.257	0.025 (0.00061)	-0.003 (-)	0.028 (0.00061)
Flevoland	1.100	-0.009 (0.00071)	-0.012 (-)	0.003 (0.00071)
Friesland	1.185	0.026 (0.00044)	0.002 (-)	0.024 (0.00044)
Gelderland	1.171	0.006 (0.00030)	-0.001 (-)	0.007 (0.00030)
Groningen	1.215	0.001 (0.00054)	0.0007 (-)	0.0003 (0.00054)
Limburg	1.307	0.024 (0.00027)	0.008 (-)	0.016 (0.00027)
Noord-Brabant	1.168	0.002 (0.00021)	0.000 (-)	0.002 (0.00021)
Noord-Holland	1.141	-0.021 (0.00025)	-0.004 (-)	-0.017 (0.00025)
Overijssel	1.179	0.016 (0.00034)	0.002 (-)	0.014 (0.00034)
Utrecht	1.111	-0.031 (0.00039)	-0.010 (-)	-0.021 (0.00039)
Zeeland	1.234	0.039 (0.00055)	0.001 (-)	0.038 (0.00055)
Zuid-Holland	1.173	0.000 (0.00022)	0.006 (-)	-0.006 (0.00022)

Note: The standard deviation for the total effect is the same as that of the effect of selective migration because only the effect of selective migration is a random variable. The effect of net in-migration is not a random variable. The sample includes 12.2 million observations.

Table A4: Individual components for decomposition analysis (risk score)

Province	**Total Effect**	**Population (1998)**	**Net In-Migration (1998-2018)**	**Difference in Risk Score Movers & Population (2018)**	**Out-Migrants (1998-2018)**	**Difference in Risk Score In-movers and Out-movers**
Drenthe	0.025	360423	6730	-0.150	72549	0.137
Flevoland	-0.009	241576	28417	-0.101	60215	0.012
Friesland	0.026	486643	-8872	-0.113	68655	0.170
Gelderland	0.006	1490658	8048	-0.219	218470	0.046
Groningen	0.001	430424	-554	-0.259	85542	0.001
Limburg	0.024	851202	-25099	-0.269	82643	0.160
Noord-Brabant	0.002	1827498	-2001	-0.241	176461	0.016
Noord-Holland	-0.021	1913672	25883	-0.291	233089	-0.140
Overijssel	0.016	836846	-6247	-0.177	115684	0.104
Utrecht	-0.031	875364	34347	-0.275	179019	-0.101
Zeeland	0.039	278771	-5084	-0.071	41597	0.255
Zuid-Holland	0.000	2566143	-55568	-0.260	286822	-0.050

Note: Total Effect, Difference in Healthcare Cost, and Effect of Selective Migration in risk score points. Number of observations is 14.7 million.

Appendix B

B1: Risk Score Computation

The risk score of individual i in year t is defined as predicted healthcare costs divided by average annual healthcare costs in the year t. We emulate the Dutch risk adjustment model in the year 2015 as described by Layton et al. (2018) and McGuire and Van Kleef (2018). To obtain predicted healthcare costs, we linearly regress healthcare costs of individual i in year t on demographic characteristics, neighborhood characteristics, socio-economic characteristics, and medical conditions, using the following equation:

$$HealthcareCost_i = \alpha + \beta_{Demo} Demo_i + \beta_{NC} NC_i + \beta_{SES} SES_i + \beta_{MC} MC_i + \varepsilon_i \quad (10)$$

For each year t we estimate a separate regression. Therefore, there are no subscripts t in Equation 10. Below, we describe the explanatory variables:

- Demographic Characteristics (Demo): We use binary indicators for age interacted with gender. There are 20 interaction terms each for males and females that correspond to age 0, ages 1 to 4, ages 5 to 89 in 5 year bins, and ages 90+.
- Neighborhood Characteristics (NC): We construct 10 neighborhood clusters. We use hierarchical clustering based on three neighborhood characteristics: share of non-Western immigrants in the neighborhood, urbanization rate, and average distance to a general practitioners' office. While the Dutch risk equalization scheme defines neighborhoods by 4-digit ZIP codes, we use neigborhoods defined by CBS (*wijk* in Dutch) in our analysis because of data limitations. In the year 2018, there were 3086 CBS neighborhoods and 4066 4-digit ZIP codes in the Netherlands, suggesting that they are of roughly comparable size.
- Socio-economic Characteristics (SES): As our first measure of socio-economic

characteristics we use interaction terms of categories for household income and age. There are three categories based on total household income in a given year. The first category includes people in the first three deciles of household income; the second category includes people whose household income falls into the fourth to seventh decile of household income; and the third category includes the top three deciles. Age categories include: below 18 years, ages 18 to 64, and 65+ years. In total, there are 9 interaction terms for household income and age categories. In addition, we include interaction terms of main source of income and age categories. There are five categories for main source of income: disability benefits, general benefits, student grants, self-employment, and other. In total, there are 17 interaction terms of main source of income and age categories. We also include three interaction terms of age categories and household size of 15 persons or more at the same address.

- Medical Conditions (MC): Medical conditions are measured in two ways:
  - Pharmacy Cost Groups (PCGs): Our estimation includes binary indicators for 21 chronic health condition. These health conditions are constructed using information on individuals' prior use of pharmaceuticals. ATC codes are matched to chronic health conditions based on Halfon et al. (2013), Huber et al. (2013), and Nexo et al. (2018). For some health conditions, we were not able to find a direct match based on these studies. We therefore use the WHO Drug Selection Methodology to match these health conditions with ATC codes. We present our matches between chronic health condition and ATC codes in Table B1. Individuals who are not prescribed medicines for any of these chronic health conditions are grouped into the NOPCG (no pharmaceutical cost group) category. Chronic health conditions included in our analysis are based on Layton et al. (2018). Out of the 24 chronic health

conditions mentioned there, we are unable to find individuals who were prescribed medicines for Transplantations, Cystic fibrosis, and Pancreatic disease and Kidney disorders. Thus, we only include 21 chronic health conditions. A limitation of our study is that we do not have information on the number of daily doses prescribed to individuals. We only know whether they were prescribed any pharmaceuticals that match to relevant ATC codes in a given year. As a result, we are over-estimating the share of individuals suffering from chronic health conditions.

– Multiple-year high cost groups (MHCGs): We include seven categories of multiple-year high costs groups: individuals being in the top 0.5% of health-care costs in each of the three prior years, individuals being in the top 1.5% in each of the three prior years, individuals being in the top 4% in each of the three prior years, individuals being in the top 7% in each of the three prior years, individuals being in the top 10% in each of the three prior years, individuals being in the top 15% in each of the three prior years, and individuals being in the top 10% in each of the two prior years. Individuals are classified in only one class, based on the aforementioned order. Individuals who were not included in either of these seven categories were included in the NOMYHCG (no multiple year high cost group) category.

In addition, we include an interaction term of a binary indicator for morbidity and age above or below 65. The morbidity indicator is one if individuals fall in either one of the pharmacy cost groups or multiple year high cost groups. In computing risk scores we follow the Dutch risk equalization scheme in the year 2015 as closely as possible with the available data. For most variables, we use exactly the same variable from the same source as in the risk equalization scheme. However, due to data limitations we omit two types of variables in our estimation that are included in the official scheme. We do not have information on diagnostic-based cost groups based on hospital admissions, and on use of durable medical equipment. We expect that predicted risk scores in our study are still very similar to actual risk scores, since information on pharmacy based cost groups and multiple-year high cost groups already account for costly chronic conditions. The cost groups based on the use of durable medical equipment were added to the risk equalization scheme only in the year 2014.

We estimate the model in Equation 10 separately for each of the years 2013 to 2018. We start in the year 2013 since we need information on healthcare costs for three prior years to compute variables for multiple-year high cost groups. We present estimation results of Equation 10 for the year 2013 in Table B2. The table also presents the population frequency of the variables included in the regression. Predicted healthcare costs are negative for 8 out of 16.1 million observations in the year 2013 and 24 out of 16.3 million observations in the year 2016, mostly for children between the ages 3 to 5. We drop these observations from our sample.

Table B1: Matching chronic health conditions with ATC codes

Chronic Health Condition	**ATC**
Glaucoma	S01E
Thyroid Disorders	H03A, H03B, H03C
Mental Disorders	N06B, N06D
Depressive Disorders	N05A, N05B, N06A
Peripheral Neurotherapy	N02C, N07C
Hypercholesterolemia	C10A, C10B
Diabetes II without Hypertension	A10A
COPD/ Severe Asthma	R03A, R03B, R03C, R03D
Asthma	R01A, R01B, R02A, R05C, R05D
Diabetes II with Hypertension	C02A, C02D, C02K, C03A, C03B, C03D, C03E
Epilepsy	N03A
Crohn's Disease/Colitis Ulcerosa	A07E
Heart Diseases	C01A, C01B, C01C, C01D, C02C, C03C
Rheumatoid Arthritis (TNF-alpha)	L04A
Rheumatoid Arthritis (Others)	H02A, H02B, M01C
Parkinson's Disease	N04A, N04B
Diabetes I	A10B
Transplanations	L04A
Cystic Fibrosis/ Pancreatic Disease	R07
Disorders of Brain/Spinal Cord	N07A, N07B
Cancer	A04A, L01A, L01B, L01C, L01D, L01X, L02A, L03A, V03A
Hormone-sensitive Tumors	L02B
HIV/AIDS	J05A
Kidney Disorders	V09C

Note: The chronic health conditions used for the analysis are based on Layton et al. (2018). Out of the 24 chronic health conditions mentioned here, we are unable to find individuals who were prescribed medicines for Transplantations, Cystic fibrosis or Pancreatic disease and Kidney disorders. Thus, in our results we only have 21 chronic health conditions. The ATC codes are matched to the chronic health conditions based on Halfon et al. (2013), Huber et al. (2013), and Nexo et al. (2018). For some health conditions, we were not able to find a direct match from these studies. We, therefore, used WHO Drug Selection Methodology to match these health conditions with ATC codes.

Table B2: Regression results to estimate healthcare cost, 2013

S. No.	Risk Adjustor Variable	Population Frequency	Coefficient
1	Intercept	100	1608
2	Male. 0	0	0
3	Male. 1-4	1.70	0
4	Male. 5-9	2.90	503
5	Male. 10-14	3.15	315
6	Male. 15-17	1.83	123
7	Male. 18-24	4.33	-2732
8	Male. 25-29	2.95	-2728
9	Male. 30-34	2.92	-2720
10	Male. 35-39	2.98	2789
11	Male. 40-44	3.69	2765
12	Male. 45-49	3.90	-327
13	Male. 50-54	3.80	-204
14	Male. 55-59	3.45	182
15	Male. 60-64	3.22	399
16	Male. 65-69	3.04	1227
17	Male. 70-74	2.09	1664
18	Male. 75-79	1.53	2055
19	Male. 80-84	1.02	2125
20	Male. 85-89	0.52	1875
21	Male. 90+	0.22	1519
22	Female. 0	0	0
23	Female. 1-4	1.62	-189
24	Female. 5-9	2.77	97
25	Female. 10-14	3.01	174
26	Female. 15-17	1.75	491
27	Female. 18-24	4.19	-2398
28	Female. 25-29	2.97	-1795
29	Female. 30-34	2.98	-1594
30	Female. 35-39	3.05	3276
31	Female. 40-44	3.74	2826
32	Female. 45-49	3.89	-333
33	Female. 50-54	3.82	-265
34	Female. 55-59	3.48	-65
35	Female. 60-64	3.22	0
36	Female. 65-69	3.09	745
37	Female. 70-74	2.33	1021
38	Female. 75-79	1.82	1316
39	Female. 80-84	1.48	1450
40	Female. 85-89	1.00	1330
41	Female. 90+	0.64	911

S. No.	Risk Adjustor Variable	Population Frequency	Coefficient
42	No PCG	61.10	-519
43	Glaucoma	1.31	193
44	Thyroid Disorders	2.60	196
45	Mental Disorders	1.35	1025
46	Depressive Disorder	7.53	2029
47	Peripheral Neuropathy	2.15	-50
48	Hypercholesterolemia	11.05	244
49	Diabetes II without hypertension	1.57	1262
50	COPD/Severe asthama	9.28	400
51	Asthama	11.02	-31
52	Diabetes II with hypertension	5.41	342
53	Epilepsy	1.77	1452
54	Crohn's Disease/ Colitis ulcerosa	0.47	879
55	Heart Diseases	4.36	1632
56	Rheumatoid Arthritis (TNF - alpha)	0.66	2055
57	Rheumatoid Arthritis (other)	4.34	1091
58	Parkinson's Disease	0.53	2506
59	Diabetes type I	4.02	378
60	Disorders of Bran/ Spinal Cord	0.20	5478
61	Cancer	1.06	5602
62	Hormone-sensitive tumors	0.39	1122
63	HIV/AIDS	0.57	1221
64	Neighbourhood cluster 1	25.44	0
65	Neighbourhood cluster 2	11.50	19
66	Neighbourhood cluster 3	8.19	37
67	Neighbourhood cluster 4	16.89	-74
68	Neighbourhood cluster 5	18.87	-41
69	Neighbourhood cluster 6	1.92	-119
70	Neighbourhood cluster 7	6.33	42
71	Neighbourhood cluster 8	4.66	17
72	Neighbourhood cluster 9	3.95	28
73	Neighbourhood cluster 10	2.26	-140
74	Age = 0-17 or 65+	37.41	-555
75	Disability Beneficiaries. 15-34	0.53	-603
76	Disability Beneficiaries. 34-44	0.37	-2462
77	Disability Beneficiaries. 45-54	0.64	-1011
78	Disability Beneficiaries. 55-64	1.09	-753
79	General Beneficiaries. 15-34	2.15	-244
80	General Beneficiaries. 34-44	1.11	-1431
81	General Beneficiaries. 45-54	1.38	-345
82	General Beneficiaries. 55-64	3.20	-202
83	Students. 18-34	0.68	1185

S. No.	Risk Adjustor Variable	Population Frequency	Coefficient
84	Self-emplyed. 15-34	1.89	1053
85	Self-emplyed. 34-44	1.39	-235
86	Self-emplyed. 45-54	1.46	461
87	Self-emplyed. 55-64	0.92	-15
88	Other. 15-34	18.67	1041
89	Other. 34-44	10.58	-321
90	Other. 45-54	11.93	311
91	Other. 55-64	8.15	-151
92	No MYHCG	92.76	0
93	2x costs in top-10%	2.63	4502
94	3x costs in top-15%	2.20	6927
95	3x costs in top-10%	0.98	10418
96	3x costs in top-7%	0.72	16213
97	3x costs in top-4%	0.51	31546
98	3x costs in top-1.5%	0.13	74571
99	3x costs in top-0.5%	0.06	4774
100	Address > 15 residents. 0-17	0	0
101	Address > 15 residents. 18-64	0	0
102	Address > 15 residents. 65+	0	0
103	Income deciles 1-3. 0-17	5.02	637
104	Income deciles 1-3. 18-64	14.38	957
105	Income deciles 1-3. 65+	5.80	0
106	Income deciles 4-7. 0-17	8.41	-289
107	Income deciles 4-7. 18-64	24.43	-43
108	Income deciles 4-7. 65+	8.46	0
109	Income deciles 8-10. 0-17	5.29	0
110	Income deciles 8-10. 18-64	23.77	0
111	Income deciles 8-10. 65+	4.43	0
112	No morbidity. 65-	54.80	0
113	Morbidity. 65-	26.51	-121
114	No morbidity. 65+	5.15	187
115	Morbidity. 65+	13.54	0

Note: Number of observations are 16,180,661. The estimates are for the year 2013. The population frequency for the household size interacted with age is very small and hence are shown as 0.

B2: Correcting Standard Errors

We follow a two-step procedure to estimate the effect of internal migration on regional variation in healthcare costs and risk scores. First, we estimate the effect of internal migration on average outcomes, either healthcare costs or risk scores, for every province. In the second step, we examine how these estimated effects of internal migration are related to average outcomes of provinces. The regression equation for this second step is given as:

$$\hat{TE}_j = \alpha + \beta \bar{y}_j + u_j = \alpha + \beta \bar{y}_j + (\varepsilon_j + \omega_j) \tag{11}$$

Here, $\hat{TE}_j$ is the total effect of internal migration on average outcomes in province j. $\bar{y}_j$ is the average outcome variable for province j in the year 2018. We have two components in the error term. The first component (ε_j) comes from the fact that we are approximating a linear relationship between the regressand and regressor in Equation 11. The second component (ω_j) comes from the fact that $\hat{TE}_j$ is estimated in the first stage, and hence the resulting estimation error must be included in the second stage.

We follow Hanushek (1974) and assume that ε_j and ω_j are independent. Moreover, we further impose assumptions on the variance-covariance matrix of the two error components. We assume that ε_j is homoskedastic with $Var(\varepsilon_j) = \sigma^2$ and that $Var(\omega_j) = e_j^2$ with $Cov(\omega_j, \omega_{j'}) = 0 \ \forall \ j \neq j'$. The standard errors ($\sqrt{e_j^2}$) of the total effect of internal migration ($\hat{TE}_j$) for all the provinces are obtained in the first stage. Given these assumptions, we can write the variance-covariance matrix of u_j as:

$$E(uu') = \begin{bmatrix} \sigma^2 + e_1^2 & 0 & 0 \\ 0 & ... & 0 \\ 0 & 0 & \sigma^2 + e_{12}^2 \end{bmatrix}$$

The estimated standard errors in the first stage vary across the 12 provinces, and hence we get heteroskedastic standard errors in the second stage. Therefore, OLS estimates will be inefficient in the second stage. Thus, we estimate a feasible generalized least squares (FGLS) model using an estimate for σ^2.

Following Hanushek (1974) we first run an OLS regression using Equation 11, ignoring the finite sample error problem. The expected variance of residuals from this regression is a function of the two variances (σ^2 and e_j^2) which can be used to solve for σ^2. This gives us an estimate of σ^2 which is then used to run a weighted least-squares regression using Equation 11 with weights given as:

$$W_j = \frac{1}{\hat{\sigma}^2 + e_j^2}$$

In our case, first stage standard errors ($\sqrt{e_j^2}$) are very small, suggesting that the total effects for all provinces are precisely estimated. Therefore, weights are almost the same for all provinces. As a result, the standard errors estimated using OLS and weighted-least squares are essentially the same.

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